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Preface

This thesis is composed of five self-contained chapters on three different areas of research. (1) Electoral institutions and barriers to democratic participation, (2) flexible work arrangements in the context of the Covid-19 pandemic, and (3) technological disruption and international trade. Several unifying themes are joining the chapters. The principal theme is the study of how economic agents respond to unanticipated shocks. In a world marked by global crises, technological disruptions, and fast-paced social change, understanding how agents adapt is crucial to inform economic policy.

The first chapter, *No Surprises, Please: Voting Costs and Electoral Turnout*, examines the consequences of seemingly innocuous shocks to voting costs for electoral participation and voting behavior. Election administrators in Munich, Germany, reassign citizens to vote at a different polling location to improve voting accessibility. This practice changes observable voting costs, i.e., the distance from the polls, only by negligible amounts. Yet, event study estimates show that moving a polling place causes a persistent shift away from in-person to mail-in voting and a transitory drop in overall turnout. We find that the location change itself, paired with inattention to reassignments, are the main drivers of turnout losses. Turnout losses are stronger and persistent in precincts with higher shares of elderly voters. This finding is intriguing, especially against the backdrop that recruiting barrier-free polling locations is a primary reason for reassignments. The results highlight that a well-intentioned policy can carry unintended consequences when seemingly harmless changes to voting costs are overlooked. Our findings also demonstrate the importance of convenient access to mail-in voting in compensating for votes lost at the polls. We conclude that increasing the salience of reassignments ahead of election day could further mitigate turnout losses by alleviating inattention.

The themes of location and proximity also pervade the subsequent chapters. When the global Covid-19 pandemic hit, reducing contacts via "social distancing" became a vital public health creed. What followed was an unprecedented shock to traditional work arrangements by shifting major parts of the workforce from offices and cities into remote work. In a series of articles, this thesis presents an empirical assessment of the role of working from home (WFH) in the context of the Covid-19 crisis. Starting with an analysis of differences in accessibility to WFH in chapter two, followed by an evaluation of the importance of WFH for public and economic health in chapter three, chapter four concludes with a first look at the consequences of the WFH shock for the viability of urban centers in the post-pandemic economy.

In chapter two, *Germany's Capacity to Work from Home* (published in the *European Economic Review*, 2023), we develop an index of WFH capacity for the German economy, drawing on rich survey and administrative data. We find that 56 percent of jobs can be done at least partly from home. WFH feasible jobs are mostly located in urban areas and highly digitized industries. Using individual-level data on tasks and work conditions, we show that heterogeneity in WFH feasibility is largely explained by differences in task content. WFH feasible jobs are typically characterized by cognitive, non-manual tasks, and PC-based work. We compare our survey-based measure with popular task-based measures of WFH capacity, which usually rely on determining tasks that are incompatible with WFH, and show that task-based approaches capture variation in WFH capacity across occupations fairly accurately. A simple measure of PC use intensity will generally constitute a suitable proxy for WFH capacity. Finally, we demonstrate that our WFH index is a strong predictor of actual WFH outcomes during the Covid-19 crisis and discuss applications in the context of the pandemic and the future of work.

Chapter three, *My Home is My Castle – Working from Home During a Pandemic Crisis* (published in the *Journal of Public Economics*, 2021), studies the impact of WFH on work relations and public health during the Covid-19 pandemic in Germany. Combining administrative data on SARS-CoV-2 infections and short-time work registrations, survey data, and cell phone tracking data, we find that WFH effectively shields employees from short-time work, firms from Covid-19 distress, and the population from infection risk. Counties with a higher share of teleworkable jobs register fewer short-time work applications and fewer SARS-CoV-2 cases. At the firm level, an exogenous increase in the uptake of WFH significantly reduces the probability of filing for short-time work and the probability of reporting adverse effects of the crisis. Health benefits of WFH appear mostly in the early weeks of the pandemic and diminish once tight confinement rules are implemented. This effect is driven by lower initial mobility levels in counties with more teleworkable jobs and subsequent convergence in traffic levels once confinement was implemented. Our results imply that lockdowns and incentivizing WFH are substitutive policies to slow the spread of Covid-19.

The forced experiment in WFH has radically disrupted traditional face-to-face work. And evidence is mounting that, indeed, much of the transition to remote will stick (Barrero et al., 2021b; Aksoy et al., 2022). This fact has tempted pessimistic observers to herald the onset of the post-urban era, in which agglomeration forces that pull workers into the city centers are finally overcome by technology (Glaeser and Cutler, 2021). But can this premonition be backed by data? Chapter four, *The Future of Work and Consumption in Cities after the Pandemic*, asks if the new geography of work has lasting implications for the viability of urban centers. We estimate the impact of WFH on the micro-geography of offline consumer spending in five big German metro areas. Our analysis draws on novel postcode-level survey information on local WFH patterns and card transaction data by Mastercard from January 2019 to May 2022. A major challenge in identifying the causal effect of WFH is that local WFH uptake is likely correlated with other determinants of spending changes. We address this problem by estimating intention-to-treat effects based on a measure of "untapped WFH potential", defined as the share of residents with a teleworkable job who did not WFH before the pandemic. The measure approximates the local scope to expand WFH and is orthogonal to sources of spending disruptions during the pandemic. We show that untapped WFH potential explains local growth in WFH during the crisis and prospective growth based on employer plans and employee desires. Difference-in-differences estimates reveal that local spending increases by 2-3 percent per standard deviation increase in untapped WFH potential. Intriguingly, the effects are only significant in non-lockdown periods and after Covid-19 restrictions are permanently lifted. We provide suggestive evidence that null effects during lockdowns are explained by temporary shifts to online spending when mandatory business closures preclude regional relocation of offline spending. The results also have implications for the geography of consumption by relocating spending away from previously consumption-intensive areas and city centers: Moving from the 25th to the 75th percentile in the distribution of untapped WFH potential is associated with a 26 percent increase in distance to the city center and causes a 15 percent increase in local spending.

The Covid-19 pandemic proved that digital tools enable radically different ways of organizing life and work. The technology rooting this transformation is, of course, broadband Internet. The last chapter, *Broadband Internet and the Pattern of Trade*, evaluates the consequences of this pivotal technology for the world economy. Specifically, I study how the deployment of first-generation broadband Internet shaped the pattern of international trade. I develop a Ricardian model of trade in which countries differ along three dimensions: their size, their level of human capital, and the quality of their broadband infrastructure. In every country, firms employ workers who must coordinate their activities across a range of complementary tasks, giving rise to communication costs. To mitigate these inefficiencies, firms must devote a portion of their resources to improving intra-firm information transmission. However, the gains from investing in communication technology crucially depend on the country's broadband infrastructure. I show that in a two-country world economy featuring free trade, the country with a better

effective quality of communication, defined as the product of firm-level communication investments and country-level broadband infrastructure, specializes in more complex goods. The model predicts that this will be the country that provides a more efficient broadband network and is populated by better-educated workers. I study this implication empirically by estimating a Gravity model covering bilateral trade among 109 countries and 85 industries between 1998 and 2016. To account for endogeneity of broadband deployment, I adopt the IV strategy proposed by Czernich et al. (2011) in which the first stage corresponds to a non-linear model of broadband diffusion determined by pre-existing voice telephony and cable TV networks. The results indicate that comparative advantage in more complex industries inferred from the data is consistent with the pattern of comparative advantage predicted by the theory.

Keywords:	Elections, remote work, broadband, consumer spending, international trade, Covid-19
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Jean-Victor Alipour, March 2023

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1 No Surprises, Please: Voting Costs and Electoral Turnout*

1.1 Introduction

Organizing elections that foster trust in the electoral process and encourage voter participation is a key challenge for modern democracies. In recent years, a number of controversies have brought the importance of electoral administration into the public spotlight. Leading up to the 2020 presidential election, reforms at the US Postal Service led former President Obama to accuse then-President Trump of attempting to “actively kneecap” the Postal Service to sway voter turnout in his favor. In Germany, the 2021 Berlin Marathon impeded the accessibility of polling places to the extent that the Constitutional Court decided that the entire State Election must be repeated.[1] But while large-scale controversies quickly become the subject of public scrutiny, supposedly benign or well-intentioned policies can pose an overlooked barrier to democratic participation.

This article presents empirical evidence on the consequences of a seemingly innocuous practice for voter participation: the relocation of polling places. We analyze a natural experiment in Munich, the third-largest city in Germany, where election administrators aim to “facilitate [voting] as much as possible” (Federal Election Code, Section 12:2). Upholding this objective involves recruiting new polling places with better accessibility and controlling precinct sizes to prevent congestion at polling locations. A by-product of these policies is that some eligible citizens are assigned to vote at a different polling location than before. Observable voting costs are only marginally affected by this practice: 90 percent of reassignments that occurred in the eight elections between 2013 and 2020 changed citizens' walking distance to their assigned polling location by less than one kilometer. Given the insignificance of any single vote for the election outcome, classical voting theory suggests that even such small shocks to voting costs may heavily impact turnout (Downs, 1957); either positively (e.g., due to shorter travel distance or better accessibility of the building), or

* This chapter is based on joint work with Valentin Lindlacher.

[1] Reportedly, the 2021 Berlin Marathon was only one of several complications, including a reduced number of voting booths at polling locations, wrong ballot papers, and irregular opening hours of polling places, that, according to the Berlin Constitutional Court led to “chaotic conditions” and “completely overloaded” polling places. Ultimately, the Federal Parliament (*Bundestag*) will decide about a possible repeat of the Federal Election, which was held on the same day as the State Election.

negatively (e.g., due to unfamiliarity with the new polling place or longer travels). More recent voting literature contrasts this view by highlighting the significance of expressive reasons for voting, such as a sense of civic duty, self-expression, ethics, or social pressure (Ali and Lin, 2013; Pons and Tricaud, 2018; Funk, 2010; Dellavigna et al., 2017). Given the importance of these motives, small voting costs are typically considered negligible for voter turnout. Thus, relocating polling places may prove irrelevant to voter turnout. We contribute to this debate by estimating the causal impact of polling place reassignments on the evolution of electoral turnout and the mode of voting.

Understanding the determinants of voter turnout has engaged a vast literature, which has increasingly focused on the role of electoral institutions in recent years.[2] Given the importance of voting *in person* in most democracies, provisions governing voting at the polling place are surprisingly understudied. While observational research suggests that polling place accessibility (e.g., in terms of proximity) can be relevant for turnout, few studies establish causality; notably, Cantoni (2020) uses a regression discontinuity design at precinct boundaries in the US, showing that differences in distance to the polling location explains differences in voter turnout.[3] *Moving* a polling place typically alters the proximity to the polling location. But the practice may also induce unobservable changes to voting costs with ambiguous consequences on voting behavior. Turnout differences could also reflect gradual adjustments of voting behavior or a new voting habit in response to a reassignment shock (Fujiwara et al., 2016). Thus, a comprehensive empirical framework requires a dynamic perspective.

The prevalence of polling place relocations in election organization, often due to routine polling place turnover, also justifies scrutiny of this practice. In Munich, reassignments are nonpolitical and uncontroversial. But this is not always true in other democracies, especially where election laws and administration are politically charged. The closing of polling sites in the US frequently raise concerns over politically motivated efforts to reduce voting access for

[2] For instance, studies have evaluated the role of personal characteristics (e.g., education, religiosity, overconfidence) (Milligan et al., 2004; Gerber et al., 2016; Ortoleva and Snowberg, 2015) or contextual factors (Cantoni and Pons, 2022), and specifically electoral institutions including ID laws (Cantoni and Pons, 2021), registration procedures (Braconnier et al., 2017), voting technology (Fujiwara, 2015), or compulsory voting regimes (Bechtel et al., 2018; Hoffman et al., 2017).

[3] Cantoni's results are consistent with observational research (Haspel and Knotts, 2005; Fauvelle-Aymar and François, 2018; Gibson et al., 2013; Bhatti, 2012; McNulty et al., 2009; Dyck and Gimpel, 2005; Gimpel and Schuknecht, 2003). However, these studies do not account for potential endogeneity, leaving room for biased estimates due to unobserved confounders or selection problems. Using the same identification strategy, Bagwe et al. (2022) find smaller effects of distance on voter participation in Pennsylvania and Georgia. Other studies have investigated the turnout effects of polling place opening hours (Potrafke and Roesel, 2020; Garmann, 2017).

certain groups, particularly racial minorities (Amos et al., 2017; Curiel and Clark, 2021; Chen et al., 2022). Partisan motives and unobserved determinants of polling place relocations pose a key challenge to causal identification of their turnout effects. The existing literature thus offers scant evidence on the consequences of the practice. Brady and McNulty (2011) use matching techniques to account for nonrandom polling place closures in the context of the 2003 LA gubernatorial recall election.[4] Comparing voters who had their polling location moved *further away* with voters without a change, the study documents a turnout decline associated with polling place reassignments. By contrast, Clinton et al. (2021) find no measurable association between turnout changes and moving polling places between two presidential elections in North Carolina.

We depart from the existing literature in four important ways. First, our empirical framework significantly improves on the identification of turnout effects of reassignments. We study a panel covering the eight elections held between 2013 and 2020 and demonstrate that polling place reassignments occur "as good as randomly". Specifically, we show that *i)* current turnout (by mail, in-person, and overall) is unrelated to reassignments in future elections conditional on election and precinct fixed effects (parallel pretrends), *ii)* the timing of reassignments is uncorrelated with changes in observable precinct characteristics, and *iii)* reassignments do not systematically skew toward a increasing or decreasing the distance to the polling location. A second key novelty is the evaluation of effect *persistence* by analyzing turnout up to three elections after reassignment. Understanding the dynamics of voting behavior adaptations is crucial to assess the cost of the practice in terms of both participation and representativeness. Third, the panel structure also allows us to shed light on a much-debated determinant of voting: habit formation. Habitual voting implies that the act of voting itself increases its consumption value and thereby the likelihood of voting in the future (Fujiwara et al., 2016). While scholars have long been aware that turnout differences tend to be persistent (see e.g., Plutzer, 2002; Green and Shachar, 2000; Brody and Sniderman, 1977), causal evidence for habit formation has proved inconclusive.[5] Fourth, this is the first study to estimate the causal

[4] Specifically, the authors match on age, past turnout, and distance to the polling place in the previous election.

[5] Meredith (2009) demonstrates that voters who had just turned eighteen at the time of the 2000 US general election are also more likely to cast their ballot in the subsequent election than their peers who fell short of the age threshold. Gerber et al. (2003) provide evidence suggesting that get-out-the-vote campaigns increase turnout in subsequent elections. Fujiwara et al. (2016) propose election-day rainfall as an exogenous and transitory shock to voting costs and find that the decrease in turnout induced by rainfall also reduces turnout in subsequent US presidential elections. By contrast, compulsory voting in Switzerland and Austria showed no persistent effects on turnout after its abolition (Bechtel et al., 2018; Gaebler et al., 2020). Similarly, Potrafke and Roesel (2020) find that longer opening hours of polling places increase contemporaneous turnout but do not affect turnout in subsequent elections.

impact of reassignments and distance to the polling location outside the US in the context of a multi-party system with proportional representation. We use aggregate party votes to estimate the partisan consequences of moving polling locations; an aspect lacking in the existing literature. Moreover, Germany counts among the few countries to offer universal access to mail-in voting. Thus, our setting is well suited to test the importance of convenient alternatives to voting at the polling place.[6]

To fix ideas, we present a simple rational choice model of voting that combines three key ingredients. First, polling place reassignments alter the cost of voting in person by changing the travel distance to the polling location; second, reassignments always generate a disutility from engaging with an unfamiliar environment, which is independent of distance. Third, we allow for *inattention* to reassignments as citizens in Munich, unlike in the US, are not explicitly informed of *changes* to their polling location. This introduces the possibility that a fraction of eligible voters is surprised by a reassignment or does not notice the change at all. Our model delivers three key predictions. First, reassignments generate asymmetric turnout effects by distance: increasing distance always reduces turnout at the polling place by making it less attractive relative to mail-in voting and abstention; however, decreasing distance does not raise polling place turnout, unless it is enough to compensate for the reassignment disutility. Second, inattention amplifies the shift toward abstention when reassignments make in-person voting more costly. This is due to inattentive polling place voters who are surprised by reassignments after the deadline for requesting mail-in ballots has passed. Some inattentive voters who would have switched to mail-in voting instead abstain from turning out, thereby increasing turnout losses relative to a scenario without inattention. Third, inattention attenuates turnout gains when reassignments reduce travel distance. Intuitively, inattention creates inertia among abstainers who do not notice reassignments at all.

Our empirical results suggest sizable and persistent effects of polling place relocations. We use an event study design that focuses on turnout dynamics around the time that a precinct is assigned to a different polling place. Our estimates suggest that, on average, reassignments cause a *persistent* substitution between the modes of voting. Turnout at the polling place falls by 1.0–1.3 percentage points immediately after the change, mirrored by an increase in mail-in turnout. Remarkably, the substitution is only *partial* in the first post-reassignment election, causing overall turnout to fall temporarily by 0.4–0.6 percentage points. Given the well-intentioned nature of the policy and the marginal changes to proximity from the polling

[6] Only 5 percent of countries globally and 27 percent of OECD countries (including Germany, parts of the US, Canada, and the UK) offer access to mail-in voting for all eligible voters (International Institute for Democracy and Electoral Assistance (IDEA)).

place, a declining turnout is notable. The magnitude of the drop is comparable to reducing the number of early (in-person) voting days in the US by 2–3 (Kaplan and Yuan, 2020), and would be enough to offset the positive turnout effect of an additional newspaper during the turn of the twentieth century in the US (Gentzkow et al., 2011).

Next, we examine a key dimension of reassignment heterogeneity: changes in proximity to the polling location. We estimate an event study specification that allows for differential treatment effects between reassignments that increased versus decreased distance to the polling place. In line with our model, we find strikingly asymmetric effects. When reassignments increase distance, the shift towards mail-in voting and the temporary drop in total turnout are amplified. By contrast, distance reductions generate no statistically significant turnout effects, on average. Our model suggests that the reassignment disutility may offset potential turnout gains of reducing travel time. Indeed, we find evidence of gains in polling place turnout when the polling location moves at least 17 percent closer to voters. These gains come almost exclusively from former mail-in voters. We only find weak evidence of increases in overall participation in extreme cases of distance declines. The latter result is consistent with inattentive abstainers, who remain abstainers even when the polling location moves very close. However, we cannot rule out alternative explanations for the lack of positive participation effects. Overall, we find that the change in distance accounts for less than 60 percent of the turnout effects, highlighting the relocation itself as a barrier to voting overlooked by election administrators.

We explore the mechanism explaining the drop and subsequent recovery of voter participation found when reassignments do not decrease travel distance. Results suggest that the recovery is entirely explained by an increase in mail-in rather than polling place turnout. This is at odds with the hypothesis that temporary abstainers return to vote in person after familiarizing themselves with their new polling place. Instead, the pattern is consistent with inattention to reassignments. Inattentive polling place voters are surprised by reassignments after the deadline for requesting mail-in ballots has passed. Consequently, some inattentive voters who would have switched to mail-in voting abstain in the current election and only turn to mail-in voting in the subsequent election. Our results thus highlight the importance of offering access to mail-in voting to compensate for votes lost at the polls. This speaks to previous research suggesting that the availability of convenience voting systems can increase participation rates (Thompson et al., 2020; Barber and Holbein, 2020; Kaplan and Yuan, 2020; Hodler et al., 2015; Gerber et al., 2013). Moreover, the results are incompatible with the hypothesis that voting is habit forming. The fact that turnout declines only temporarily after reassignments is inconsistent with the view that abstaining instilled a new habit. Moreover, the fact that turnout losses are immediately recovered is incompatible with the hypothesis that voting (or abstaining) is habit-forming. Instead, the persistent substitution of in-person for mail-in voting and the recovery in voter participation is consistent with rational behavior in response to a positive shock to voting costs that is temporarily amplified by inattention. The mechanism implies that increasing the salience of reassignments ahead of Election Day to remedy inattention (e.g., by explicitly notifying affected citizens) could alleviate detrimental turnout effects.

Our baseline estimates obscure a great amount of heterogeneity. In particular, we find that turnout effects vary significantly by the age composition of the local electorate. We estimate a triple difference model that traces the differential turnout trend for precincts with a higher share of elderly eligible voters before and after the reassignment. A primary reason for polling place turnover during our observation period is the city council's resolution to recruit new barrier-free venues, which are supposed to improve access for elderly voters and citizens with physical impairments. However, our estimates suggest that total turnout drops more in elderly-heavy precincts after reassignment and *does not* fully recover in subsequent elections. Using a similar estimation strategy, we find that the shift from in-person to mail-in voting is significantly weaker in precincts with a higher fraction of migrant citizens; yet, the change in overall turnout is not statistically different. We find no evidence that reassignments depress turnout stronger in less affluent precincts (measured by the average quoted rent) nor in precincts with a higher share of households with children.

The presence of heterogeneous treatment effects may undermine the representativeness of the electoral outcome. Our results suggest it does not. Turnout effects of reassignments are similar across parties, and party vote shares do not change significantly, on average. This finding is likely explained by the lack of heavy spatial segregation along party lines in Munich, ensuring that polling place relocations are not concentrated among a particular party's supporters.

The next section describes the institutional setting. Section 1.3 outlines the conceptual framework guiding our empirical analysis. Section 1.4 describes how we build our estimation panel and outlines our empirical strategy. We present our main results in Section 1.5. Section 1.6 analyzes heterogeneous effects across precinct characteristics and explores potential partisan consequences of reassignments. Section 1.7 concludes.

1.2 Institutional Background: Elections and Polling Place Reassignments

1.2.1 Elections in Munich

Our panel covers the eight elections held in Munich between 2013 and 2020. These include elections to the four legislative bodies that reflect the federal system in Germany: the *Bundestag* (federal parliament), which constitutes the main body of the central government, the Bavarian *Landtag* (state parliament), the *Stadtrat* (Munich city council), which governs the city alongside the mayor, and the European Parliament, which effectively exercises some of the power of the federal government since Germany is a member of the European Union. All elections follow the principles of proportional representation but differ with respect to the electoral rules. In Appendix A.3, we briefly describe the key features of the different electoral processes.

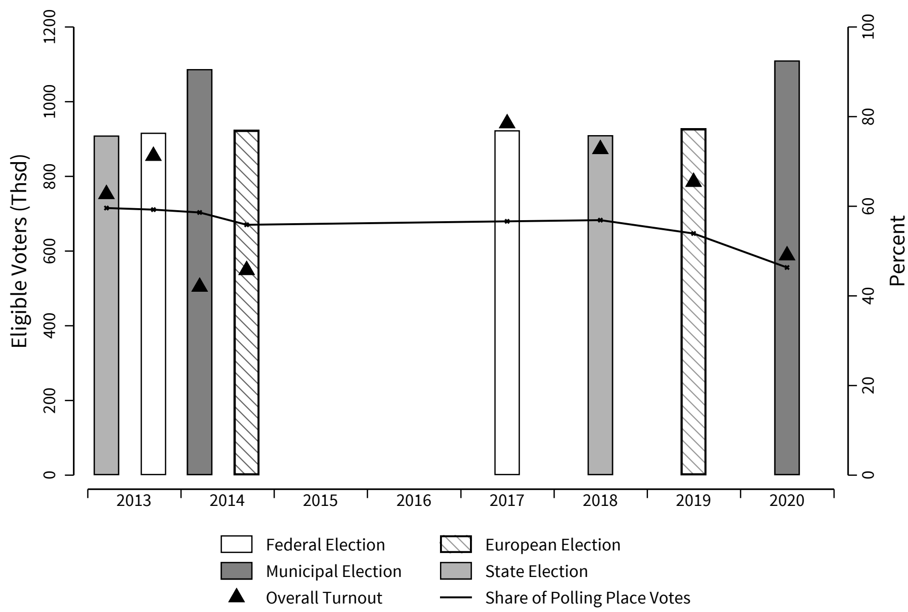
Eligible voters are automatically entered into the electoral roll. Voting is not compulsory and mail-in voting is available to all eligible voters without separate photo identification. Every person on the roll receives an election notification via mail no later than 21 days before the election. The letter includes information about the election date, the location and opening hours of the polling place, and whether it offers barrier-free access for people with physical impairments. There is no explicit information about any *changes* to the polling location—neither in the election documents nor in a separate notification. This contrasts with the US, where changes to precinct borders typically trigger the requirement to notify affected voters (Cantoni, 2020; Clinton et al., 2021). Eligible voters may cast a ballot in person at their assigned polling place on Election Day. In this case, they must present their election notification and a photo ID at the voting station. Eligible voters who instead wish to vote by mail must request a "polling card" (*Wahlschein*) by returning a form included in the election notification no later than two days before the election.[7]

Figure 1.1 illustrates the election timeline in our panel. Two elections were held in 2013 and 2014 (but not on the same day), and one was held every year between 2017 and 2020. The vertical bars illustrate the number of eligible voters (left axis). The triangles and the solid line trace the evolution of total turnout and the share of votes cast at the polling place, respectively (right axis). The number of eligible voters is distinctively higher in municipal elections, in

[7] In principle, the polling card also entitles one to vote at another polling place in the city; however, typically, more than 98 percent of ballots cast using polling cards are mail-in votes. And more than 90 percent of voters requesting a polling card actually cast a vote.

which EU foreigners living in Munich are also entitled to vote.[8] Total turnout tends to increase over time when comparing the same election type; the share of votes cast in person typically lies between 50 and 60 percent and declines slightly over time.[9]

Figure 1.1 : Timeline and Turnout of Elections Held between 2013 and 2020



Notes: The figure presents the number of eligible voters (vertical bars), total turnout (triangles), and the share of polling place votes (solid line) for the eight elections included in our sample. The shading of the bars reflects the different election types. Between 2013 and 2020, two state elections, two federal elections, two European elections, and two municipal elections were held in Munich. The data are from the Munich Elections Office (*Wahlamt*).

1.2.2 Polling Place Reassignments

Elections are organized by the Munich Elections Office (*Wahlamt*). Employees of the Elections Office are nonpartisan civil servants and have no direct incentives to manipulate the electoral process. In every election, the electorate is geographically partitioned into more than 600 voting precincts based on eligible citizens' registered home addresses.[10] Precincts constitute the smallest administrative unit and serve to enable a manageable election process. We use information from the official electoral rolls provided by the Munich Elections Office to

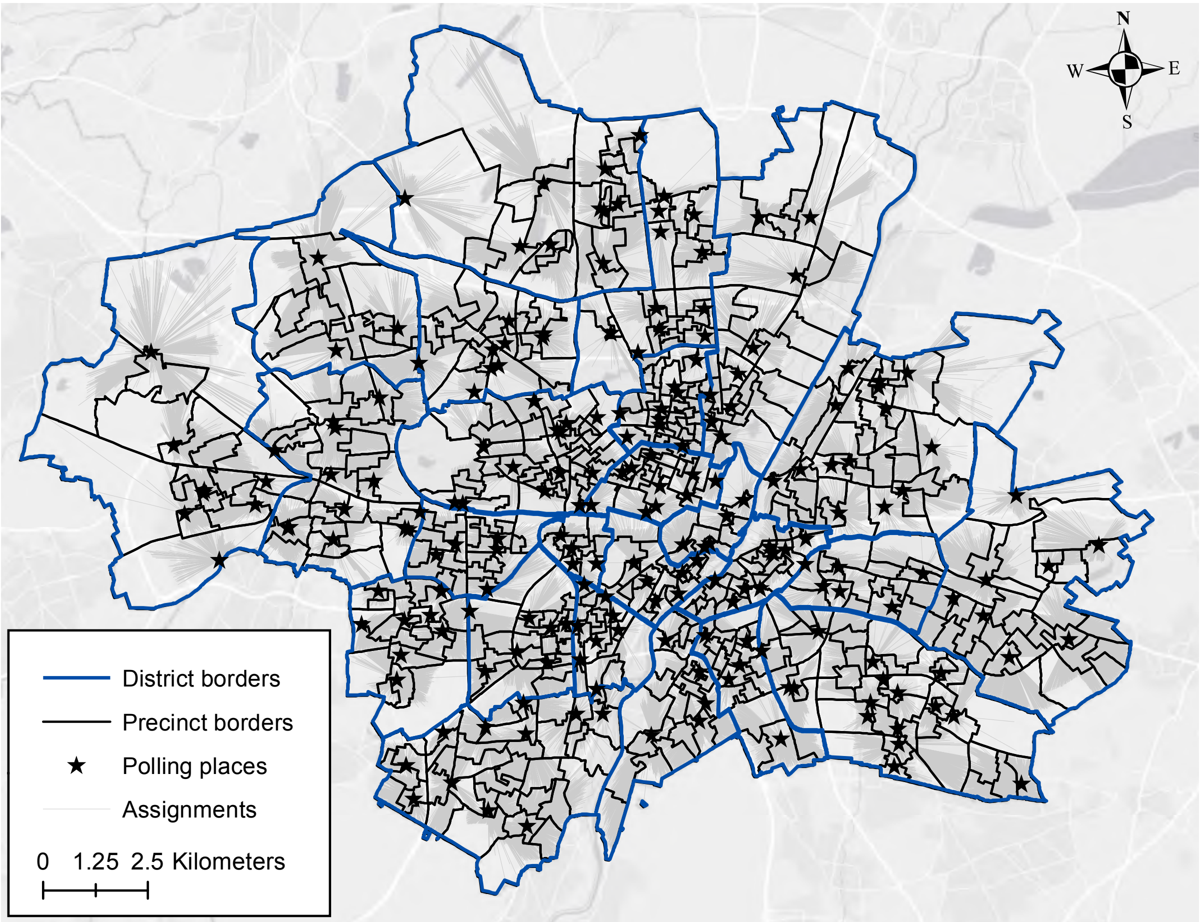
[8] For instance, in the 2020 Municipal Elections, 17.5 percent of eligible voters were foreign EU citizens. Foreign EU citizens who wish to vote in European elections in Munich instead of their country of origin must lodge a registration request.

[9] With more than half of all votes cast by mail, the 2020 Municipal Election held during the Covid-19 pandemic marks an exception.

[10] Citizens are required by law to notify the city's Registration Office (*Meldeamt*) within two weeks of moving into a new residence. This also applies to citizens who move within a municipality.

georeference polling locations and residential addresses in every election in our panel.[11] Figure 1.2 depicts a typical electoral map. The black boundaries delineate the 618 precincts; blue lines delineate the 25 city districts. A polling place, depicted by black stars, is assigned to each precinct, but it is not uncommon that a single venue, typically a school, accommodates the polling place of several neighboring precincts located in the same district. The gray lines indicate the assignment of home addresses to polling places.

Figure 1.2 : Electoral Map of Munich for the 2018 State Election



Notes: The map shows the delineations of the 25 city districts (blue lines) and the 618 voting precincts (black lines) in Munich for the 2018 State Election. Black stars mark the locations of polling places. Gray lines connect the addresses of eligible voters to their assigned polling place. The data are from the official electoral rolls provided by the Munich Elections Office (*Wahlamt*).

Recruitment of Polling Locations One source of variation in polling place assignments comes from turnover in the venues that are used to host polling places. These venues are typically public properties, usually schools (71 percent of all venues), but also Church-affiliated

[11] We identify and geolocate 154,156 residential addresses from the 2018 electoral roll, of which we are able to match 141,642 to a unique precinct in every election (92 percent).

facilities (11 percent), and retirement homes (5 percent).[12] In each election year, district inspectors (*Bezirksinspektoren*) are charged with recruiting potential locations and verifying they meet the required standards. While recruitment usually focuses on venues that were used in the past, new polling place requirements, competing events on Election Day, building closures, or ongoing construction work may leave some locations unavailable. There is no documentation of the reasons why venues become inactive or new venues are recruited. Based on correspondence with the Elections Office, we identify two primary reasons for turnover in polling locations during our observation period. First, following a resolution of the city council (*Stadtrat*), the Elections Office prioritized recruiting locations with barrier-free access for elderly people and voters with physical impairments after 2014.[13] Second, Munich's school construction program (*Schulbauoffensive*), which involved investments of more than 3.8 billion Euros in refurbishing educational facilities starting in 2016, forced buildings to close down for several years. We reviewed public documents on the investment plans and found that in 70 percent of the cases in which schools were no longer used to host polling places, the election date fell within the specified construction period. Overall, we observe 293 distinct venues that were used in at least one election between 2013 and 2020. The number of operated venues is typically around 200 in any given election. Appendix Figure A.3 illustrates the activity status of polling venues over time.

Precinct Reconfigurations The second source of variation in polling place assignments comes from reconfigurations of precinct boundaries and the allocation of existing polling places. The law requires that precincts be drawn so that "participation in the election is facilitated as much as possible" (Federal Election Code, Section 12:2). Besides monitoring proximity to polling locations and recruiting barrier-free venues, the Elections Office's main objective is to minimize congestion risk at polling places. In practice, this involves controlling precinct sizes (to maintain an average of 1,500 eligible voters per precinct) and adjusting the number of polling places hosted by the same venue in case it serves multiple precincts.[14] As a result, precincts may be merged, split, or entirely assigned another (existing) polling place. According to the Elections Office, precinct boundaries were rarely revised before 2017 due to the cost of spatial monitoring. Instead, changes in precinct size were addressed by adjusting

[12] See Appendix Figure A.2 for an overview of venue types.

[13] Specifically, the resolution demanded that the number of barrier-free polling places be doubled between 2014 and 2017 and that a share of at least 75 percent should be reached by 2020. According to documents provided by the Elections Office, a share of 80 percent was achieved by 2018.

[14] The law specifies that a precinct may not accommodate more than 2,500 eligible voters in any election. See Appendix Figure A.1 for a density plot of precinct size across all elections.

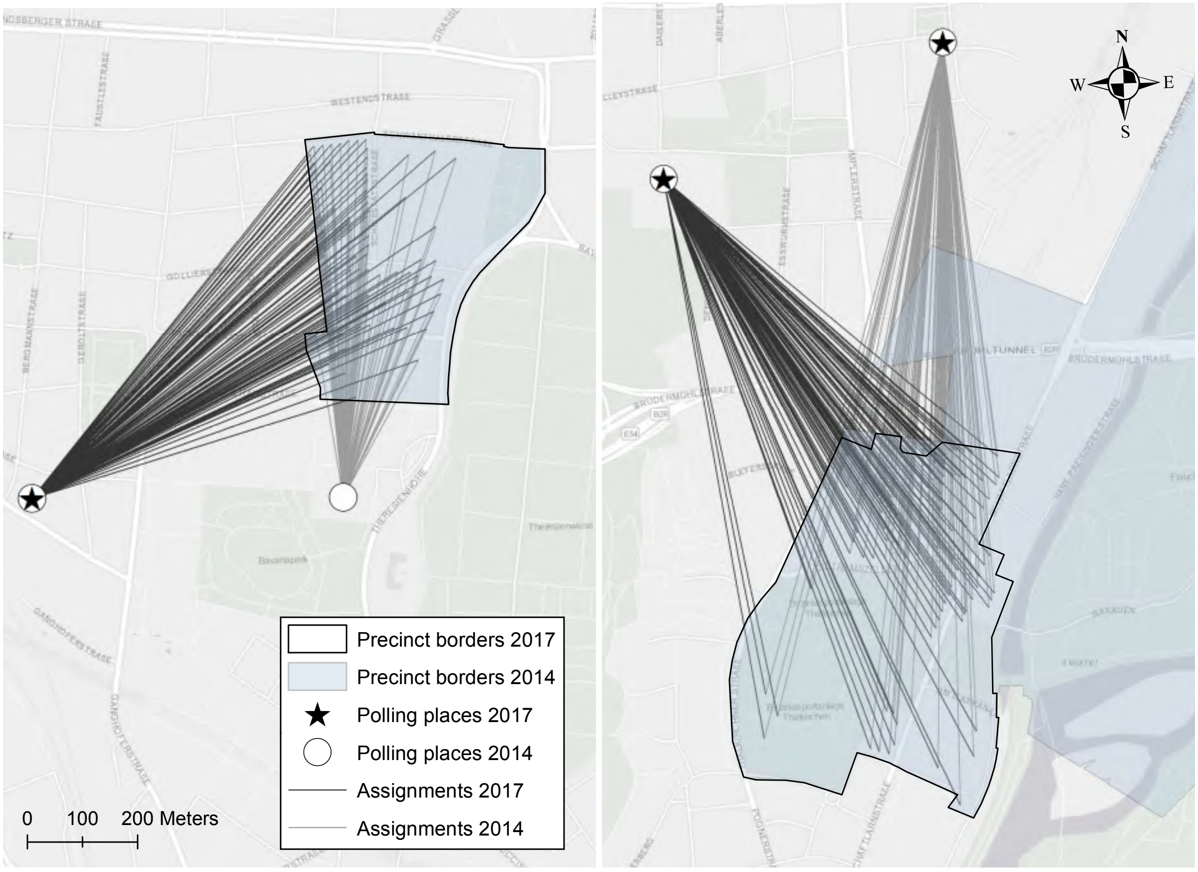
the number of poll workers at polling places. The introduction of a new urban planning technology in 2017 facilitated spatial monitoring and enabled more precise delineation of precincts. This resulted in a major re-division of the city and a significant reduction in the variance of precinct sizes (see Appendix Figure A.1). The number of precincts declined from 702 to 617 in 2017 and remained at 618 in 2018 and 2019. In 2020, the number increased again to 755 to accommodate a larger number of eligible voters during municipal elections and to account for social distancing provisions during the Covid-19 pandemic.

We illustrate two instances of polling place reassignments between 2014 and 2017 Figure 1.3. The black borders delineate precincts as of 2017. The blue-shaded areas demarcate precincts as of 2014. The dark (light) gray lines connect eligible voters' addresses to their assigned polling place in 2017 (2014). In Panel (a), the pub that served as the precinct's polling place in 2014 was not recruited in the subsequent election. Instead, the precinct was assigned to another polling place (a public school) about nine walking minutes west of the old location. In the example, the relocation led to an increase in the average distance to the polling place. Panel (b) illustrates an instance in which a precinct's boundaries were redrawn. A new precinct (black borders) was carved out from the original precinct (light blue area). Voters living in the newly created precinct were consequently reassigned from the polling place at the top of the map to the location further south. Unlike in the preceding example, both polling places remained in operation in 2017.

Figure 1.4 documents the fraction of residential addresses reassigned to a different polling place relative to the previous election.[15] There were no reassignments in the 2013 Federal Election and the 2014 European Election, as other elections were held earlier in the same year. Before 2017, the Elections Office addressed changes in precinct size mainly by adjusting the number of poll workers at the polling locations so that reassignments due to precinct border adjustments were limited. In 2017, 41 percent of home addresses were assigned to a different polling place, mainly caused by the major consolidation of precincts (enabled by a new urban planning technology) and due to updated requirements for polling places (especially regarding barrier-free buildings). Munich's school construction program contributed to the turnover of polling venues starting in 2017. In 2020, reassignments were primarily due to the increased number of precincts and the recruitment of suitable venues to meet social distancing provisions during the Covid-19 pandemic. Overall, 42 percent of all addresses are never subject to reassignments between 2013 and 2020, 26 percent are reassigned once, and

[15] Reassignments in the 2013 State Election are determined relative to polling place assignments in the 2009 Federal Election.

Figure 1.3 : Illustration of Polling Place Reassignments



(a) Polling location recruitment **(b) Precinct reconfiguration**

Notes: The figure illustrates two instances of polling place reassignments between the 2014 European Election and the 2017 Federal Election. Dark (light) gray lines connect the residential addresses of eligible voters to their 2017 (2014) polling location. In Panel (a), the precinct was reassigned to a different polling place (black star) as the old polling location became inactive (white circle). Panel (b) illustrates a precinct reconfiguration. Black borders delineate a newly created precinct that was spun off from a larger precinct. Citizens living within the black borders were thus reassigned from the polling place in the north to the location in the northwest of the map. Both locations were active in 2014 and 2017.

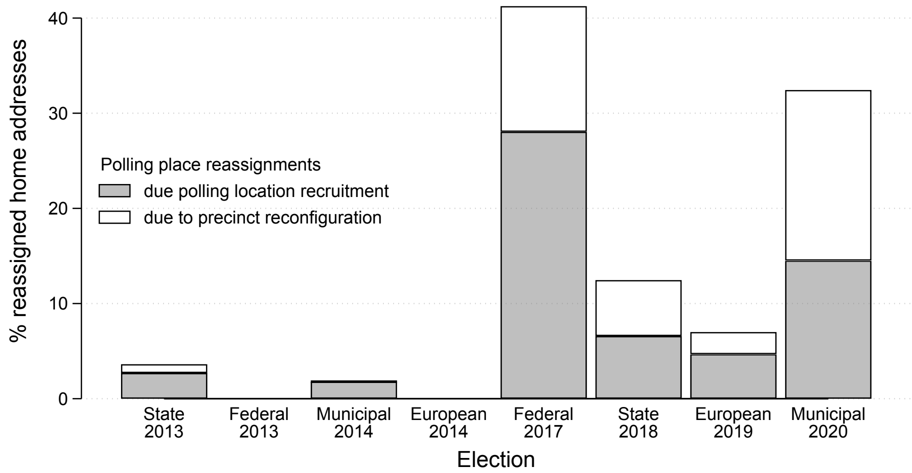
24 percent twice (see Appendix Figure A.4).[16]

Figure 1.5 plots the distribution of street (walking) distances between home addresses and polling places (left panel), and the distribution of distance *changes* conditional on reassignment across all elections (right panel).[17] Negative values indicate that the new polling place moved closer (relative to the previous election); positive values correspond to

[16] On average, an address is reassigned once during our observation period. When an address is reassigned more than once, the median period between the first and second reassignment is three elections.

[17] We use the osrmtime package (Huber and Rust, 2016), which makes use of *Open Source Routing Machine (OSRM)* and *OpenStreetMaps (OSM)*, to calculate street distances, defined as the shortest walking distance between two points using the public road network.

Figure 1.4 : Share of Addresses Assigned to Different Polling Place Relative to Previous Election



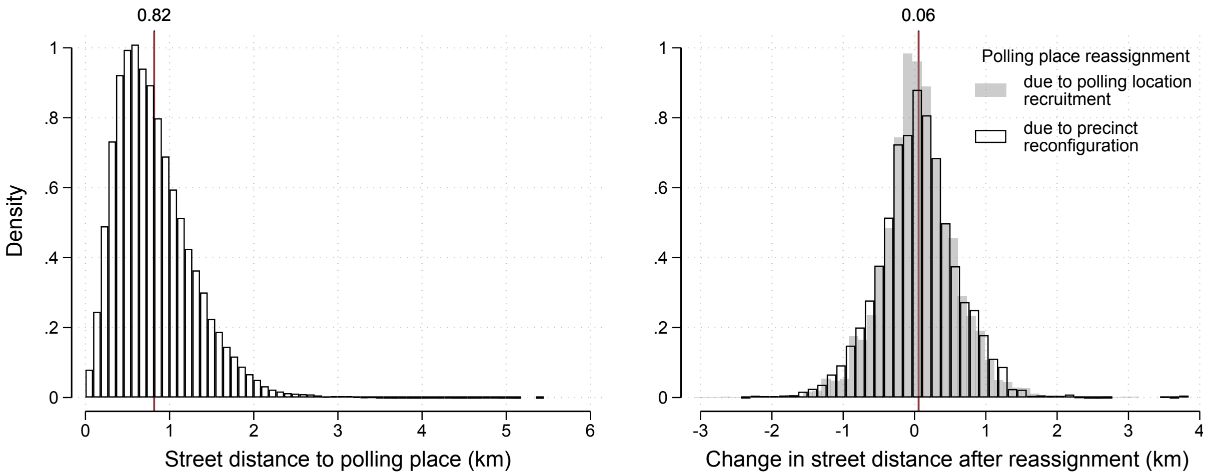
Notes: The figure plots the share of reassigned residential addresses relative to the previous election. The election preceding the 2013 State Election is the 2009 Federal Election (not shown). Reassignment can be due to the reconfiguration of precincts or due to the recruitment of a different polling venue.

a relocation further away. We distinguish between changes due to recruitment of polling locations and due to the reconfiguration of precincts. For 90 percent of residential addresses, the polling place is less than 1.4 kilometers away, which roughly corresponds to a 17-minute walk (median: 0.74 km, mean: 0.82 km). The overall distribution of distance changes is closely centered around zero (median: +0.04 km, mean: +0.06 km) and approximately symmetric (skewness: 0.2), indicating that polling places are not systematically located closer or further away after reassignment. Splitting by reason of reassignment leaves the moments of the two distributions nearly unchanged. The different sources of reassignments thus do not systematically produce different shocks to observable voting costs. More than 90 percent of reassignments change the walking distance by less than one kilometer, suggesting that the practice generates only marginal shocks to voting costs overall.

1.2.3 A Precinct-Level Panel

We use official election results from the Munich Elections Office to estimate the impact of polling place relocations on voter turnout. One limitation for our empirical exercise is that the highest granularity of turnout is at the precinct level. Thus, we aggregate reassignments and distance from the polling location from the address level to precinct delineations. To obtain a constant unit of observation, we impose *time-invariant* precinct borders corresponding to the 2018 configuration for aggregation. This way, we obtain a panel of 618 precincts with harmonized boundaries that we observe over eight elections between 2013 and 2020. We turn to the details of the empirical strategy to identify the causal effects of reassignments on

Figure 1.5 : Density of Street Distance and Change in Proximity to the Polling Place



Notes: The figures present density plots for the street distance between residential addresses of eligible voters and their assigned polling places (left plot, $N = 1,133,136$) and the *change* in distance conditional on assignment to a different polling place relative to the previous election (right plot, $N = 142,062$) for the eight elections between 2013 and 2020. Vertical lines highlight the mean of the distribution.

turnout in Section 1.4.

1.3 Conceptual Framework: Voting Costs, Inattention, and Turnout

To inform the empirical exercise, we present a simple rational choice model of voting drawing on the "calculus of voting" framework (Riker and Ordeshook, 1968). The unit of observation in our causal analysis is the precinct. Thus, our thought experiment considers a precinct that is struck by a polling place reassignment. The counterfactual is a twin precinct without any change. The purpose of the model is to convey key intuitions about $i)$ the mechanisms through which polling place reassignments alter the costs of voting, $ii)$ how the shock to voting costs affects precinct-level turnout at the polling place, via mail, and overall, and $iii)$ how turnout effects may change when we allow a fraction of the population to be inattentive to reassignments.

Model Setup Suppose a precinct populated by a unit mass of eligible voters, indexed $i \in \mathcal{I} = [0, 1]$, and two periods in which an election is held $t \in \mathcal{T} = \{0, 1\}$. In each period, individuals can vote in person at their assigned polling place, vote by mail, or abstain from voting. There are benefits to voting $B \geq 0$, which are assumed to be constant across time and individuals.[18] The benefits and costs of abstaining are zero. Voting by mail generates costs $c_i^m > 0$, which are constant over time. We assume that there are two types of individuals in the population; a fraction $\alpha \in (0,1)$ of type L with low costs of mail-in voting, $c^{mL} \leq B$, and a fraction $(1-\alpha)$ of type H with high costs of mail-in voting, $c^{mH} > B$. Thus, the net utility of voting by mail for individuals of type H is negative and these citizens will never vote by mail. Whether an individual is of type L or H is exogenous and independent of other parameters.

Now, suppose that the entire electorate is reassigned to a different polling place between periods 0 and 1. Voting benefits and the costs of voting by mail are unaffected; however, reassignments change the costs of voting at the polling place, $c_{i,t}^p$, which are a function of travel distance to the polling place, $dist_{i,t} \geq 0$, and a constant $q_t \geq 0$:

$$c_{i,t}^p = \gamma dist_{i,t} + q_t, \tag{1.1}$$

where $\gamma > 0$ is a preference parameter, constant across time and individuals, and q_t is a reassignment disutility from engaging with an unfamiliar environment, arising if and only if the polling location changes. Thus, $q_0 = 0$ in period 0 and $q_1 > 0$ in period 1. For simplicity, the reassignment disutility is assumed to be constant across individuals.[19] Without loss of generality, we assume that individuals are ordered on the interval $\mathcal{I} = [0,1]$ such that the travel distance is continuous and strictly increasing in i. Formally, $\sigma : \mathcal{I} \times \mathcal{T} \to \mathbb{R}^+$ and we let $dist_{i,t} = \sigma(i,t) \equiv k_t i$, with $k_0 = 1$. Thus, the ranking is described by a linear function with the slope parameter $k_t > 0$. Reassignments alter the distance proportionally for every individual via a change of the slope k_t. For instance, $k_1 = 1.2$ corresponds to a 20 percent increase in distance to the polling location for the entire electorate.

Turnout in Period 0 Individuals chose the option that confers the highest net utility. Figure 1.6a draws the net utilities of voting by mail for types H and L ($U^{mH} \equiv B - c^{mH}$ and $U^{mL} \equiv B - c^{mL}$, respectively) and the net utility of voting in person ($U_{i,0}^p \equiv B - c_{i,0}^p$). Since distance is strictly increasing in i, $U_{i,0}^p$ is downward sloping. Imposing parameter restrictions such that the sets of polling place voters, mail-in voters, and abstainers are nonempty, there exist two thresholds $z^0, u^0 \in [0,1]$ such that $U_{i,0}^p = U^{mL}$ if $i = z^0$ and $U_{i,0}^p = 0$ if $i = u^0$.

[18] Voting benefits can reflect the expected utility if the preferred party wins a greater number of seats and any direct utility from the act of voting itself (i.e., expressive motives).

[19] In the framework proposed by Brady and McNulty (2011), q_t would capture what the authors label "search costs", i.e., a positive shock to the cost of voting in person that is independent of the change in distance. Brady and McNulty (2011) do not formally separate between search costs and distance effects; thus, our model extends their conceptual framework.

Denote $\mathcal{P}^0 \subset \mathcal{I}$ the set of individuals voting in person in period 0. $\mathcal{P}^0$ includes all individuals for whom the net utility of voting in person is greater than zero and exceeds the net utility of voting by mail: $\mathcal{P}^0 = \{i \in [0,1] : U^p_{i,0} \geq U^m_i \text{ and } U^p_{i,0} \geq 0\}$. Thus, turnout at the polling place corresponds to the mass of $\mathcal{P}^0$, which we denote $m(\mathcal{P}^0)$:

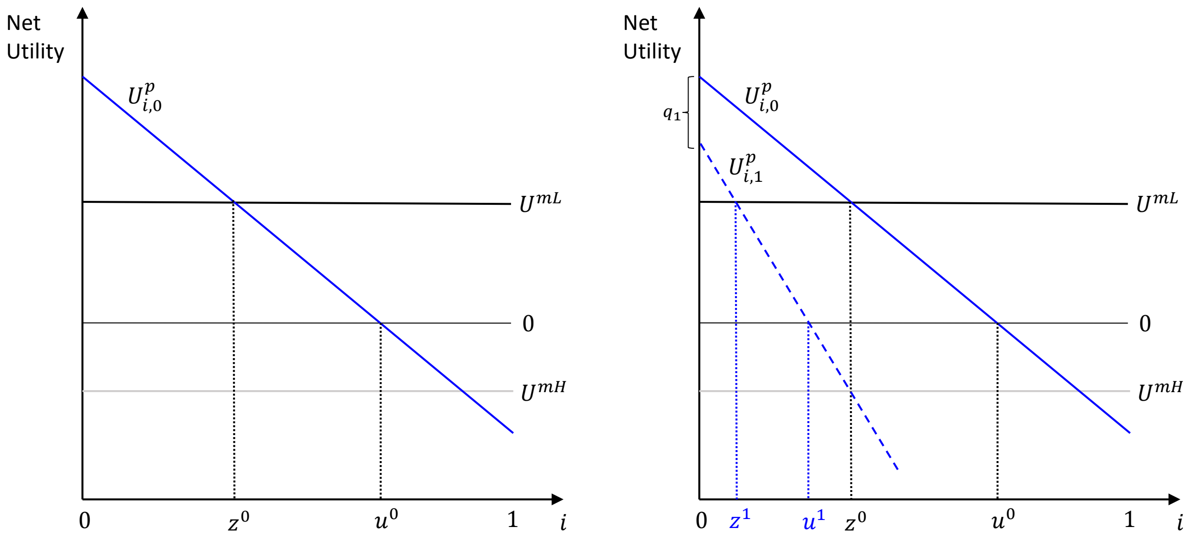
$$\text{Polling place turnout: } m(\mathcal{P}^0) = z^0 + (1-\alpha)(u^0 - z^0) \in (0,1) \tag{1.2}$$

Intuitively, all individuals $i \in [0, z^0]$ with a net utility of voting in person $U^p_{i,0} \geq U^{mL} > 0$, plus a share $(1-\alpha)$ of individuals of type H on the interval $[z^0, u^0]$, who have high costs of voting by mail, turn out at the polling place. Similarly, the set of mail-in voters, $\mathcal{M}^0$, corresponds to individuals with low costs of mail-in voting and a net utility exceeding the utility of voting at the polling place: $\mathcal{M}^0 = \{i \in [0,1] : U^m_i = U^{mL} \text{ and } U^{mL} > U^p_{i,0}\}$. Thus, turnout by mail and overall turnout are given by:

$$\text{Mail-in turnout: } m(\mathcal{M}^0) = \alpha(1 - z^0) \in (0,1) \tag{1.3}$$

$$\text{Total turnout: } m(\mathcal{T}^0) = m(\mathcal{P}^0) + m(\mathcal{M}^0) = u^0 + \alpha(1-u^0) \in (0,1) \tag{1.4}$$

Figure 1.6 : Net Utility of Voting in Period 0 and Period 1



(a) **Period 0: No reassignment**

(b) **Period 1: Reassignment**

Notes: The figure illustrates the utility functions of voting by mail and at the polling place. The net utility of abstaining is zero. Individuals are ranked by distance from their polling location on the interval $[0,1]$. Panel (a) shows the utility function of polling place voting before the polling place reassignment, $U^p_{i,0}$. Panel (b) draws the utility function of polling place voting after the entire population is reassigned to a different polling location that proportionally increased travel distance, $U^p_{i,1}$.

Change in Turnout in Period 1 Figure 1.6b illustrates the impact of a reassignment that *increased* the distance to the polling place. The utility function of in-person voting in period 1, $U^p_{i,1}$, shifted downwards because of the reassignment disutility q_1 and is steeper due to the proportional distance increase. Imposing that reassignments never create empty sets of mail-in voters, in-person voters, or abstainers, we obtain new cutoffs, $z^1, u^1 \in [0,1]$ such that $U^p_{i,1} = U^{mL}$ if $i = z^1$ and $U^p_{i,1} = 0$ if $i = u^1$. These cutoffs determine turnout in period 1 equivalently to period 0. Then, we can express turnout in period 1 relative to period 0 as a function of relative change in distance k_1 due to reassignment:

$$\hat{\mathbf{P}}(k_1) \equiv \frac{m(\mathcal{P}^1)}{m(\mathcal{P}^0)} = \frac{z^1 + (1-\alpha)(u^1 - z^1)}{z^0 + (1-\alpha)(u^0 - z^0)} \tag{1.5}$$

$$\hat{\mathbf{M}}(k_1) \equiv \frac{m(\mathcal{M}^1)}{m(\mathcal{M}^0)} = \frac{\alpha(1-z^1)}{\alpha(1-z^0)} \tag{1.6}$$

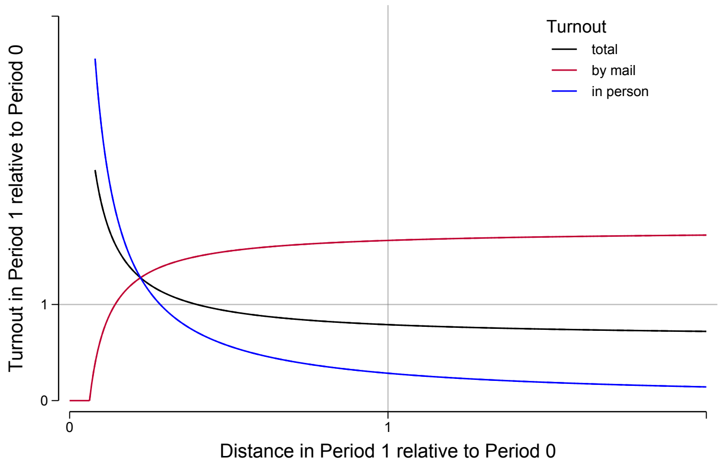
$$\hat{\mathbf{T}}(k_1) \equiv \frac{m(\mathcal{T}^1)}{m(\mathcal{T}^0)} = \frac{u^1 + \alpha(1-u^1)}{u^0 + \alpha(1-u^0)}, \tag{1.7}$$

where all cutoffs $z^0, z^1, u^0, u^1 \in [0,1]$ are determined by exogenous parameters. Figure 1.7 illustrates how turnout changes in response to a relative change in distance. Right of the vertical unity line, distance increased due to reassignment. The greater the increase, the lower polling place turnout in period 1 relative to period 0 as more individuals are discouraged from turning out in person. Larger increases in distance cause more people to switch to mail-in voting, increasing turnout by mail relative to period 0 (red line). At the intersection with the vertical unity line, i.e., when distance is held constant, polling place turnout is lower and mail-in turnout greater than in period 1 due to the reassignment disutility q_1. For a reassignment to increase in-person turnout, distance must decline enough to compensate for the reassignment disutility. Similarly, overall turnout falls in period 1 unless the reassignment reduces the distance to the polling location sufficiently to incentivize abstainers to start voting at the polling place.

Inattention to Reassignments To notice a reassignment, citizens need to review the address of the polling place stated in the election notification, which is mailed a few weeks before election day. Unlike in the US, citizens in Munich are not separately informed of changes to precinct boundaries or their previous polling location. Thus, *inattentive* voters may be surprised by a reassignments or not notice at all that their polling place has moved. Conceptually, we introduce inattention as follows:

i) a fraction $\theta \in [0,1)$ of polling place voters, $i \in \mathcal{P}^0$, are surprised by reassignments *after*

Figure 1.7 : Turnout Effects of Polling Place Reassignments



Notes: The figure illustrates turnout at the polling place (blue line), via mail (red), and overall (black) in period 1 relative to period 0 as a function of the relative change in distance to the polling location after a reassignment.

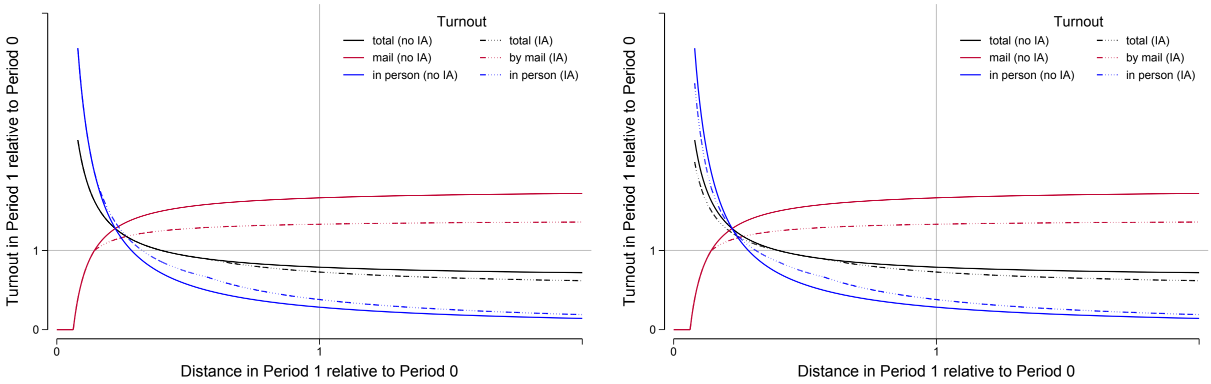
the deadline for requesting a mail-in ballot has passed. Citizens who choose to vote in person need to present the election notification to poll workers at the polling place. Thus, inattentive individuals may open the notification only shortly before going to vote and only notice then that it has been moved. In period 1, these citizens can only choose to vote at the *new* polling location or switch to abstention.

ii) a fraction $\pi \in [0,1)$ of abstainers, $i \in \mathcal{A}^0$, do not notice the reassignment at all and remain abstainers in period 1.

iii) mail-in voters, $i \in \mathcal{M}^0$, are never inattentive. Since mail-in ballots must be requested by opening the election notification and returning a form, we assume that mail-in voters always notice a reassignment.

Figure 1.8 illustrates how turnout changes after a reassignment when there is no inattention (solid lines) and when a fraction of the electorate is inattentive to reassignments (dashed lines). In Figure 1.8a only a fraction of in-person voters is inattentive, $\theta \in (0,1)$ and $\pi = 0$. In this case, inattention changes the turnout effects when a reassignment makes in-person voting unattractive to polling place voters (by not sufficiently reducing or increasing travel distance). Inattentive voters who would otherwise have switched to mail-in voting are left with choosing between turning out at the new polling location or switching to abstention. Thus, inattention *attenuates* the shift from in-person toward mail-in voting and *amplifies* the shift toward abstention. The decline in total turnout relative to a situation without inattention becomes stronger with increasing distance.

Figure 1.8 : Turnout Effects of Reassignments with Inattentive Voters



(a) Fraction of in-person voters is inattentive, $\theta \in (0, 1), \pi = 0$

(b) Fractions of in-person voters & abstainers are inattentive, $\pi, \theta \in (0, 1)$

Notes: The figure illustrates the turnout at the polling place (blue line), via mail (red), and overall (black) in period 1 relative to period 0 as a function of the relative change in distance to the polling location after a reassignment. Dashed lines draw the relationship between turnout change and distance change when a fraction of the electorate is *inattentive* to reassignments. In Panel (a), only a fraction of in-person voters, $i \in \mathcal{P}^0$ is inattentive. In Panel (b) an additional fraction of abstainers, $i \in \mathcal{A}^0$, is inattentive.

Figure 1.8b illustrates a scenario in which fractions of in-person voters and abstainers are inattentive, $\pi, \theta \in (0, 1)$. This alters turnout effects relative to a situation without inattention only in cases in which reassignments *reduce* distance enough to make in-person voting attractive for previous abstainers. When a fraction of abstainers is inattentive, increases in polling place turnout and overall participation are attenuated.

To summarize, the model delivers the following key predictions:

- **Asymmetric effects by distance:** An *increase* in travel distance always makes voting at the polling place less attractive, prompting a shift away from in-person voting toward mail-in voting and abstention. By contrast, a *decrease* in travel distance makes polling place voting only more attractive if the reduction is enough to compensate for the reassignment disutility.

- **Attenuated turnout gains under inattention:** Inattention weakens the increase in total turnout when distance declines. The effect comes from inattentive abstainers who remain abstainers even when the new polling place is conveniently located nearby.

- **Amplified turnout losses under inattention:** Inattention amplifies the shift from in-person voting to abstention when in-person voting becomes unattractive (due to an increase in travel distance and/or the reassignment disutility). The effect comes from inattentive voters who would have switched to mail-in voting but missed the deadline for requesting a mail-in ballot.

1.4 Empirical Strategy

1.4.1 Main Specification: An Event Study Design

We use an event study framework to trace out changes in voting behavior around polling place relocations. In the baseline, we define the event as the *first* election in which the *entire* electorate in a precinct is assigned to a different polling place. Reassignment of the entire precinct constitutes the modal case, both among reassignments due to recruitment of polling locations (60 percent) and due to precinct reconfigurations (16 percent); overall, we capture 40 percent of all instances in which reassignments occur using this definition (see Appendix Figure A.5). In the baseline, we also trim precinct time series from the time a second reassignment occurs to ensure that we capture the effects of a single reassignment rather than a series of changes.[20] We test the sensitivity of the results to alternative assumptions in Section 1.5. Let $E_p \in \{1, 2, ..., 8\}$ denote the election in which precinct p is fully reassigned for the first time (the event), and $\tau \equiv t - E_p$ denote time relative to the event. Then, our preferred specification is given by:

$$Y_{pt} = \sum_{k \neq -1} \mu^k \mathbb{1}(\tau = k) + \mathbf{X}'_{pt}\phi + \delta_p + \delta_{d(p)t} + \varepsilon_{pt}, \tag{1.8}$$

where an outcome Y_{pt} (e.g., turnout at the polling place, via mail, and overall) in precinct p and election t is regressed on election indicators relative to the event and a series of control variables and fixed effects. Specifically, we include precinct effects δ_p, which absorb any time-invariant factors that influence the outcome, and election fixed effects $\delta_{d(p)t}$ that we allow to be district-specific. Election fixed effects account for common shocks, such as differences in voting propensity across elections or the weather on Election Day. The motivation for interacting election fixed effects with district indicators is twofold. First, unlike precincts, districts are directly contested in some elections. In state and federal elections, the 25 districts are combined into several single-member constituencies, where residents directly elect their representatives. In Municipal Elections, citizens also elect a local district committee as the representative body. Systematic differences in voting incentives across districts may affect the validity of our estimates if, for example, close races are anticipated in certain constituencies (Bursztyn et al., 2022). Secondly, polling place recruitment is performed by local district inspectors. Thus, election×district fixed effects can also account for systematic differences in

[20] Out of 278 treated precincts, 150 (54 percent) are treated exactly once (Appendix Figure A.6).

recruitment practices by comparing outcomes only within district-election cells. The vector $\mathbf{X}$ comprises a set of time-varying precinct characteristics.[21] The error ε_{pt} represents unobserved precinct$\times$election shocks to the outcome that are assumed to be uncorrelated with the regressors of interest. Then, the event-time coefficients $\hat{\mu}^k$ trace the differential time path of the outcome in treated relative to untreated precincts before and after the reassignment. Specifically, estimates $\hat{\mu}^{k,\tau\geq 0}$ deliver the average effect of reassignment on treated units in election τ=k after the event.

The two identifying assumptions for interpreting the effect estimates as causal are *i)* that polling place reassignments and changes in distance are not related to other determinants of voting behavior (that are not accounted for by fixed effects), and *ii)* that the expectation of changes in turnout does not drive polling place reassignments. A violation of the assumptions would occur if, for instance, the Elections Office systematically consolidated adjacent precincts that showed a stronger tendency to turn out by mail to save the costs of operating polling places. In this case, treatment effect estimates could merely reflect a pre-existing trend.[22] Although these assumptions cannot be tested directly, we present several indirect tests, including a balancing exercise, a pretend analysis, and results from alternative specifications to bolster our confidence in the causal interpretation of the findings.

A few final estimation details. First, because votes by mail are recorded only at the district level, we are confined to relying on *requested* polling cards as a proxy for mail-in votes. As noted above, about 90 percent of requested cards are returned as ballots, and more than 98 percent of these ballots are mail-in votes. Second, since not all event-time indicators are identified in the presence of precinct fixed effects, we choose the election before the reassignment $\tau = -1$ as our reference period and normalize μ^1 to zero. We then estimate the whole range of event-time indicators and report the coefficients for the four elections before and three elections after reassignment. Third, we cluster standard errors at the precinct level to account for the correlation of model errors over time. We test the sensitivity of our results to alternative assumptions about the variance-covariance matrix in Section 1.5. Fourth, specifications are

[21] Specifically, controls include the precinct size (log of the number of residents and the share of residents eligible to vote), the age structure of the electorate (share of eligible voters aged 18–24, 25–34, 35–44, and 45–59), the share of EU foreigners in the electorate, the share of native German residents, the share of non-native German residents, the share of single residents, the share of married residents, the average duration of residence (in years), the share of households with children, and the average quoted rent per square meter. Information on local rents is from the RWI Institute for Economic Research. All other data are provided by the Munich Statistical Office.

[22] According to the Elections Office, past and expected turnout are not considered when redrawing precinct boundaries.

weighted by precinct size (i.e., the number of eligible voters) to recover the conditional mean association between turnout and polling place reassignments at the individual level. Finally, we estimate Equation 1.8 using OLS to produce our baseline results. As pointed out by several recent contributions, OLS two-way fixed effect (TWFE) estimates may yield biased results with staggered treatment and heterogeneous effects.[23] The reason is that the TWFE estimator uses already-treated precincts as controls for newly-treated precincts, thereby violating the parallel trend assumption in the presence of treatment effect dynamics. The treatment timing in our setting is illustrated in Appendix Figure A.6. Of 618 precincts, 340 are never treated, and most of the treated precincts had their polling location changed in the 2017 Federal Election (62 percent).[24] To account for the staggered treatment timing, we also estimate the event study using the estimators proposed by Borusyak et al. (2022), Callaway and Sant'Anna (2021), Sun and Abraham (2021), and de Chaisemartin and D'Haultfœuille (2020). A discussion of the different estimators and their underlying assumptions is beyond the scope of this paper. For recent reviews, see Roth et al. (2022) and de Chaisemartin and D'Haultfoeuille (2022).

1.4.2 Balancing Test

Under our identifying assumptions, the timing of reassignments is uncorrelated with other determinants of turnout. One approach to assess the comparability of treated and untreated precincts is to examine whether precinct characteristics are balanced conditional on election and precinct fixed effects. Since the fixed effects account for time-invariant factors, the residual correlation provides information on the association between treatment timing and *changes* in precinct characteristics. We present the balancing test results in Figure 1.9.

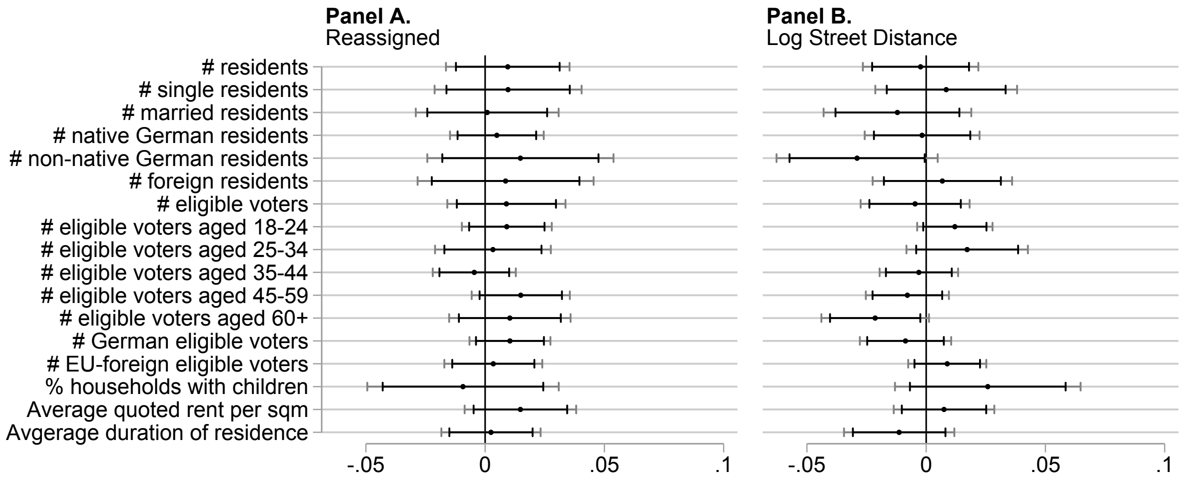
Panel A shows estimates and confidence bands from univariate OLS regressions of a dummy identifying reassignments that changed the polling location for the entire precinct on precinct characteristics, conditional on election and precinct fixed effects. Each estimate comes from a separate regression. All characteristics are standardized to have mean zero and unitary standard deviation. The estimates are close to zero and insignificant, suggesting that treatment timing is uncorrelated to observable changes in precinct characteristics. The dependent variable in Panel B is the log of average street distance. Out of seventeen estimates, only two are marginally significant at the 10 percent level. Still, F-tests cannot reject the null that the coefficients are jointly zero in any panel, indicating that the fixed effects perform well

[23] See e.g., Athey and Imbens (2022); de Chaisemartin and D'Haultfœuille (2020); Borusyak et al. (2022); Goodman-Bacon (2021); Sun and Abraham (2021).

[24] 14 percent (13 percent) of precincts have their polling place moved in the 2020 Municipal Election (2018 State Election), and the remainder is treated in other elections. Appendix Figure A.7 maps the spatial distribution of polling place relocations.

in eliminating any correlation between treatment and precinct characteristics. Coefficients and test statistics are reported in Appendix Table A.2. We also present correlations for reassignments due to polling location recruitment and precinct reconfigurations, separately. Again, we find no evidence that changes in observable precinct characteristics co-occur with polling place relocations.

Figure 1.9 : Balancing Test on Precinct Characteristics



Notes: Panels A and B report OLS estimates from separate univariate regression on standardized precinct characteristics conditional on election and precinct fixed effects. The dependent variables are an indicator identifying full reassignments to a different polling place (Panel A) and the log of average street distance to the polling location (Panel B). Confidence intervals are drawn at the 90 and 95 percent levels using standard errors clustered at the precinct level. F-tests cannot reject the null that coefficients are jointly equal to zero in any panel. The coefficients and test statistics are reported in Appendix Table A.2. Information on local rents is from the RWI Institute for Economic Research. All other precinct characteristics are obtained from the Munich Statistical Office.

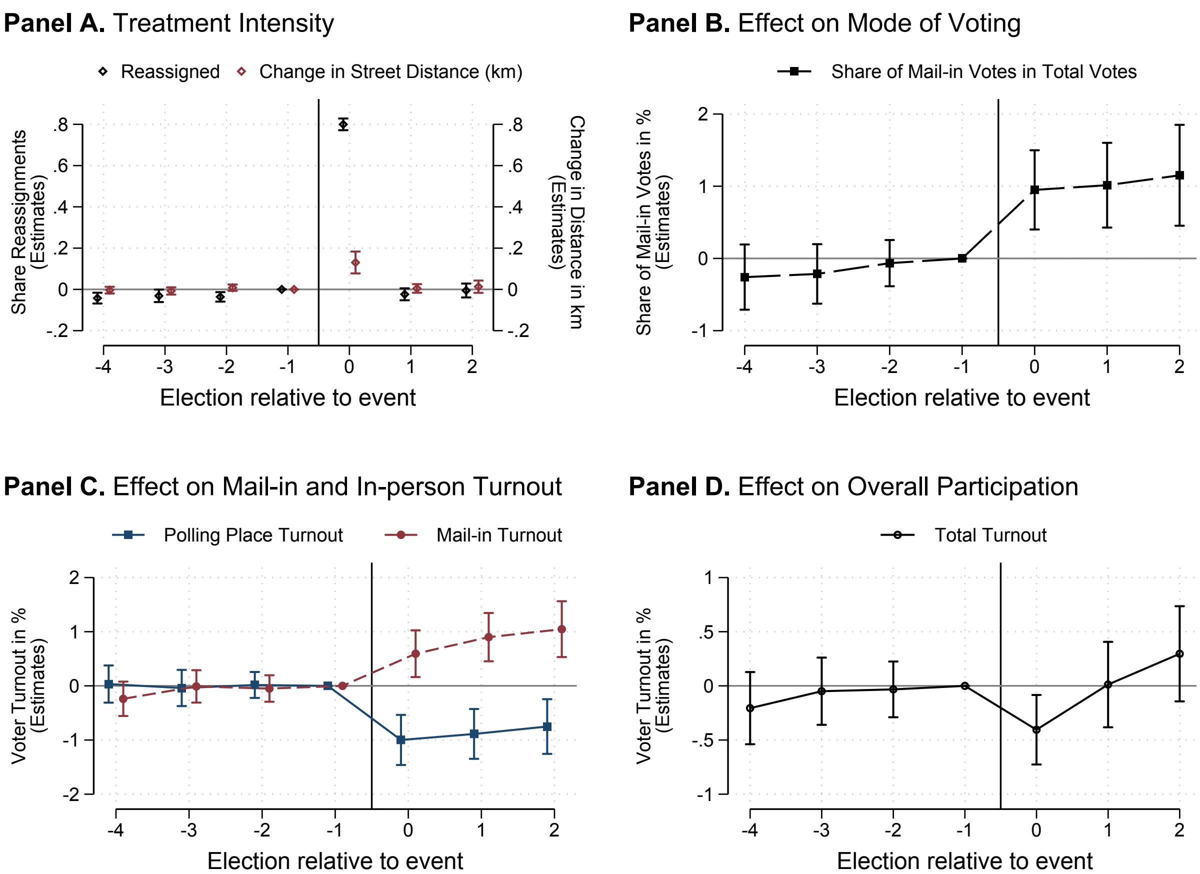
1.5 Main Results

1.5.1 Average Effects on Turnout and the Mode of Voting

We start by estimating the average effects of polling place reassignments on treated precincts. Figure 1.10 plots event-time estimates based on Equation 1.8 using different outcomes in Panels A–D. The event corresponds to the first election in which the entire precinct is assigned to a new polling place. As emphasized above, we exclude all precinct-election observations beyond any second event so that we pick up the effects of only one instance of treatment. Panel A illustrates the average treatment intensity according to this event definition by using the share of reassigned addresses and the *change* in proximity to the polling location (relative to the preceding election) as dependent variables, respectively. Since reassignments at intensities below 100 percent are allowed to occur before and after the event, the coefficients in $\tau \neq 0$ are not precisely equal to zero, and the coefficient in $\tau = 0$ is less than one (left axis).

Importantly, the design captures a sharp reassignment shock relative to the baseline. The coefficients on the change in distance (right axis) suggest that, on average, the distance to the polling location increases by 0.13 kilometers due to the event. This represents a moderately larger increase compared to the overall distribution of proximity changes caused by reassignments presented in Figure 1.5.

Figure 1.10 : The Effect of Reassignments on Turnout and the Mode of Voting



Notes: The figure presents event study results based on Equation 1.8. The event is defined as the first time in which the entire precinct is reassigned to a different polling place. All specifications include time-varying covariates listed in Section 1.4.1. Regressions are weighted by the number of eligible voters. Confidence intervals are drawn at the 95 percent level using standard errors clustered at the precinct level. The point estimates and standard errors underlying the results in Panels C and D appear in Column (2) of Appendix Table A.3.

Panels B–D plot event-time coefficients for different outcomes of voting behavior. The first notable feature is that event-time coefficients preceding the reassignment are close to zero and not statistically significant in any panel. The absence of pretrends provides important evidence in support of the identifying assumption; trends in outcomes across comparison groups evolve in parallel except through the treatment. By contrast, we observe a sharp and persistent increase by 1 percentage point in the share of votes cast by mail immediately after reassignment (Panel B). The results in Panel C show that this jump can only be partly explained by substitution between modes of voting: in-person turnout falls by 1 percentage point immediately after reassignment (equivalent to 3 percent at the mean), while mail-in turnout increases by only 0.6 percentage points (2 percent). Thus, the shift to mail-in voting is not large enough to completely compensate for votes lost at the polls, generating a decline in total turnout by 0.4 percentage points (0.7 percent) in Panel D. This result is consistent with reassignments producing a positive shock to the cost of voting in person on average, making mail-in voting relatively more attractive and inducing some voters to abstain from turning out.

The estimates further show that the shift from polling place to mail-in voting persists in the two elections after the initial jump, suggesting that the shock to voting costs is lasting. Remarkably, however, the decline in total turnout completely recovers in the subsequent election and is not statistically different from zero afterward. One possible explanation for this recovery is that the reassignment shock to voting costs wanes over time. For example, temporary abstainers may familiarize themselves with their new polling place and return to vote there after one election. An alternative explanation is that the initial turnout decline is driven by inattention to reassignments. As proposed in Section 1.3, inattentive polling place voters are surprised by the reassignment *after* the deadline for requesting a mail-in ballot has passed. Some inattentive voters who would otherwise have switched to mail-in voting consequently abstain from voting in the first election after reassignment. But aware of the change, they switch to voting by mail in the subsequent election, recovering the drop in turnout. In Section 1.5.3, we make the case that the transitory decline in overall turnout is consistent with inattention and inconsistent with the waning cost hypothesis. The argument is that the recovery is demonstrably driven by an increase in mail-in turnout, not in-person turnout.

Albeit transitory, the turnout decline caused by changing a polling place is sizable. To put the estimates into perspective, the average decline in participation is roughly equivalent to reducing the number of early (in-person) voting days in the US by 2–3 (Kaplan and Yuan, 2020). Moving a polling place would also be enough to offset the positive turnout effect of an additional newspaper around the turn of the twentieth century in the US (Gentzkow et al., 2011).

A central insight of Figure 1.10 is that the estimates *do not* support the hypothesis that (non)voting is habit forming. If abstaining from voting was habit-forming (by increasing its consumption value), the initial decline in turnout would carry over to subsequent elections, even in a hypothetical scenario in which the costs of voting were entirely restored to pre-treatment levels. Our estimates are clearly inconsistent with this pattern. This result contrasts with Fujiwara et al. (2016), who find that a decline in past turnout due to rainfall on Election Day also reduces current turnout, and are in line with Bechtel et al. (2018), who show that compulsory voting in Switzerland did not instill a voting habit by increasing turnout after its abolition.

The full set of our results based on Equation 1.8 and some of its variants appear in Appendix Table A.3. Column (1) reports event-time estimates *excluding* time-varying controls. Column (2) presents the results of our preferred specification, which includes controls. This reduces standard errors across the board without significantly affecting point estimates. In Column (3), we estimate the event study using the full sample instead of trimming the time series once a second treatment occurs. Results remain very similar to the estimates in Column (2). Column (4) replaces election$\times$district fixed effects with election indicators. Again, the results show little sensitivity to the alternative specification; importantly, pre-event coefficients remain statistically insignificant, corroborating our identification strategy. In Column (5), we test the robustness of the baseline estimates to an alternative event definition. Here, the event corresponds to the first election in which at least 50 percent of a precinct is reassigned.[25] The estimated effect sizes are slightly more pronounced compared to our preferred model, but the main conclusions hold. In Appendix Figure A.8, we re-estimate the model of Column (4) using several novel estimators that account for staggered treatment timing (Borusyak et al., 2022; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021; de Chaisemartin and D'Haultfœuille, 2020). The estimates remain very similar to the TWFE-OLS estimates, suggesting that heterogeneity in treatment timing does not compromise our estimates of interest.

We also show that the results are robust to alternative assumptions about the variance-covariance matrix in Appendix Table A.4. One might be concerned, for instance, that model errors are correlated within districts. This may be the case because adjustments to the boundaries of adjacent precincts are not performed across but only within districts. Moreover, it is not uncommon that polling places of several precincts (within a district) are located in the same building. In these cases, closing a venue might affect several adjacent precincts

[25] Using this treatment definition, we capture 60 percent of all instances in which a positive share of addresses is reassigned (see Appendix Figure A.5).

simultaneously. We reproduce our preferred specification (from Column 2 of Table A.3) with standard errors clustered at the precinct level for comparison in Column (1). Column (2) shows that standard errors are only marginally larger when correcting for two-way clusters at the level of precincts (to account for error correlation over time) and at the level of districts in each election (to account for within-district-election correlation). Next, we test robustness to using wild bootstrapped standard errors clustered at the precinct level (Column 3) and at the district level (Column 4), as recommended by MacKinnon et al. (2022). All treatment effects remain statistically different from zero. Finally, we verify that wild bootstrap clustering at the district level does not affect conclusions in the model using election fixed effects instead of election×district fixed effects. Column (5) shows that all effects remain statistically significant.

In Appendix A.4, we test if the different reasons for reassignments (polling location recruitment versus precinct reconfiguration) carry different turnout effects. We find they do not.

1.5.2 The Role of Distance to the Polling Location

The baseline turnout estimates are informative about the effects of an average reassignment. However, they mask a key dimension of reassignment heterogeneity: the change in distance to the polling location. In this section, we analyze the role of this central aspect of polling place accessibility and shed light on the mechanisms underlying the change in voting behavior documented above. To this end, we estimate two modified versions of Equation 1.8.

Effect Heterogeneity by Change in Distance First, we allow for different treatment effects between reassignments that increased versus decreased distance to the polling place. Formally, let N_p^+ be an indicator equal to 1 for precincts where reassignment caused an *increase* in average distance to the polling location. N_p^- denotes the analogous indicator for cases in which distance *decreased*. Then, the modified event study specification takes the following form:

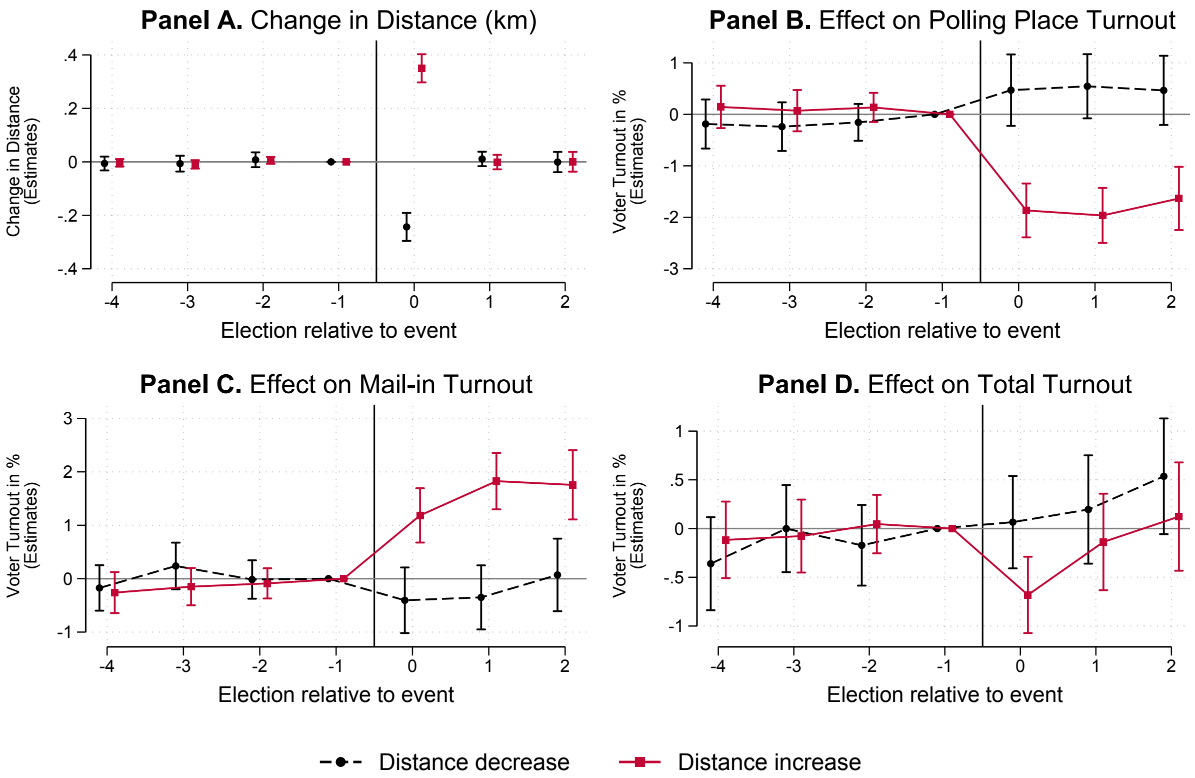
$$Y_{pt} = N_p^+ \times \sum_{k \neq -1} \beta^k \mathbb{1}(\tau = k) + N_p^- \times \sum_{k \neq -1} \alpha^k \mathbb{1}(\tau = k) + \mathbf{X}'_{pt}\phi + \delta_p + \delta_{d(p)t} + \varepsilon_{pt}, \quad (1.9)$$

where the coefficients $\hat{\beta}^k$ and $\hat{\alpha}^k$ trace the differential time path of turnout separately for the two groups defined by N_p^+ and N_p^-. Note that since we do not condition on distance in Equation 1.8, the baseline estimates $\hat{\mu}^k$ correspond to a weighted average of $\hat{\beta}^k$ and $\hat{\alpha}^k$. As before, the specification includes election×district fixed effects, a vector of precinct indicators, and time-varying controls.

The results are presented in Figure 1.11. Each panel report estimates and 95 percent confidence intervals on interaction terms between event-time indicators and a dummy identifying reassignments that generated an average increase (black coefficients) and decrease (red coefficients) to the polling location, respectively. Panel A shows that distance increases by 350 meters, on average, when the new polling location is moved further away. When the new polling place is moved closer, the reduction is about 240 meters. Consistent with our model, turnout effects are strikingly asymmetric when comparing cases that increased versus decreased distance from the polling place. Panel B suggests that reassignments that generate a greater travel distance cause a sharp and persistent decline in polling place turnout. The estimate on the immediate effect is -1.87 ($p <$0.01), which is equivalent to a 6 percent decline at the mean and nearly double the average effect. By contrast, when reassignments reduce the distance to the polling place, in-person turnout tends to rise only slightly, albeit not statistically significant. Panels C and D show a similar picture. The impact on mail-in turnout is statistically insignificant when the new polling location is closer and strongly positive when relocated further away. In total, participation declines only in precincts in which distance increases. The drop amounts to 0.68 percentage points, which is 20 percent greater than the average effect. Our model proposes that reassignments always cause a disutility from engaging with an unfamiliar environment. The results suggest that when reassignments reduce the distance to the polling location, lower travel time and the reassignment disutility offset each other on average. Consequently, we find minimal substitution between the modes of voting. By contrast, the reassignment disutility is compounded by additional travel costs when the new polling location is further away. This generates a significant shift from in-person to mail-in voting and a sizable drop in overall participation.

Our model implies that the distance to the polling place must decline enough to compensate for the reassignment disutility to make in-person voting relatively more attractive than mail-in voting or abstaining. To test these mechanisms, we estimate a version of Equation 1.9 in which we allow treatment effects to vary by *three* reassignment types in Figure 1.12: those that produce a "large" distance decrease, "little" distance change, and a "large" distance increase. While the shift from polling place to mail-in voting is visibly attenuated when distance barely changes, the decline in overall participation remains comparable to cases in which distance strongly increased. This pattern bolsters the case that the reassignment disutility alone imposes a burden on voters beyond travel time. By contrast, when the new polling place is relocated significantly closer to voters, substitution is *reversed*; mail-in turnout declines (albeit not statistically significant), mirrored by a significant and permanent increase in polling place turnout. Overall participation increases slightly; however, the estimate is not statistically

Figure 1.11 : Effect Heterogeneity by Change in Proximity to the Polling Location



Notes: The figure presents event study results based on Equation 1.9. Each panel report estimates on interaction terms between event-time indicators and a dummy identifying reassignments that generated an average increase (black coefficients) and decrease (red coefficients) to the polling location, respectively. The event is defined as the first time in which the entire precinct is reassigned to a different polling place. Regressions are weighted by the number of eligible voters. Confidence intervals are drawn at the 95 percent level using standard errors clustered at the precinct level. Point estimates and standard errors are reported in Appendix Table A.5.

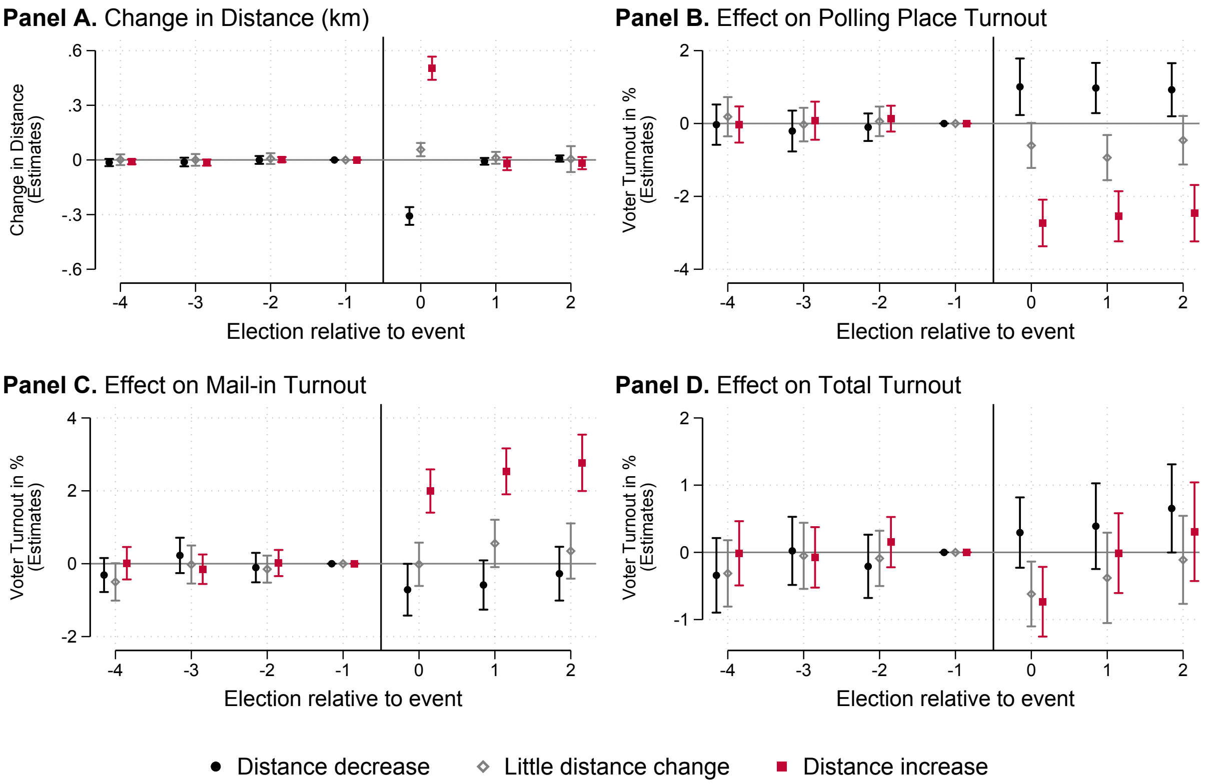
significant.[26]

Although we do not observe changes in voting behavior at the individual level, the pattern is consistent with our rational choice model of voting. However, one concern with relying on aggregate measures of distance changes is that they may mask substantial heterogeneity within precincts. For example, an increase in *average* distance to the polling location could mask that a nontrivial portion of the local electorate experienced a decrease in distance. We, therefore, estimate a specification using a sample in which we remove such ambiguous cases. Specifically, we restrict the treatment group to precincts where the reassignment

[26] In Appendix Figure A.9, we estimate treatment effects by four reassignment types; those that produced a small distance reduction, a large reduction, a small increase, and a large increase. The results paint a similar picture; i.e., large distance reductions generate a sizable substitution from away from mail-in toward in-person voting; yet, we find no significant effects on total turnout. Small distance reductions are insufficient to compensate for reassignment disutility, resulting in a decline in polling place turnout. Finally, distance increases always cause a shift away from in-person towards mail-in voting and abstention.

consistently increased (decreased) the distance to the polling place for at least 90 percent of home addresses and to precincts where reassignments induced only “little distance change” to all citizens. In the latter group, we include only cases where the polling place moved less than 800 meters from the old location.[27] We estimate a version of Equation 1.9 allowing for different treatment effects in each group. The estimates in Appendix Figure A.10 show that, reassuringly, the results hold.

Figure 1.12 : Effect Heterogeneity by Change in Proximity to the Polling Location (3 bins)



Notes: The figure presents event study results based on a version of Equation 1.9 in which event-time dummies are interacted separately with three mutually exclusive indicators for average distance increase, little average distance change, and average distance decrease due to reassignment. The event is defined as the first time in which the entire precinct is reassigned to a different polling place. Regressions are weighted by the number of eligible voters. Confidence intervals are drawn at the 95 percent level using standard errors clustered at the precinct level. Point estimates and standard errors are reported in Appendix Table A.6.

Decomposition Exercise: Distance and Reassignment Disutility In our second exercise, we introduce the log of average street distance to the polling location as a covariate in Equation 1.8. Since the specification includes precinct fixed effects, the identifying variation comes from changes in distance *within* a precinct, which are generated by reassignments only. The results allow us to decompose the baseline effects into a portion explained by the change

[27] 800 meters corresponds to the median change in distance between new and old polling locations.

in distance and into a residual that reflects reassignment costs that are independent of the change in proximity. In our model, these costs correspond to the reassignment disutility (e.g., from engaging with an unfamiliar environment), which always increases the costs of voting at the polling place.[28]

The results are presented in Table 1.1. The outcomes are turnout at the polling place in Columns (1) and (2), turnout by mail (Columns 3 and 4), and overall turnout (Columns 5 and 6). Odd columns use election$\times$district fixed effects; even columns use election fixed effects. Absorbing the distance effect attenuates the event-time estimates relative to the baseline results (Column 2 and Column 4, Table A.3). However, the estimates remain mostly statistically significant, consistent with the notion that reassignments induce a disutility beyond the change in travel distance. The estimate on log distance is negative and statistically significant in Columns (1) and (2), suggesting that polling place turnout falls by 0.33 percentage points when distance increases by 10 percent. To compensate for votes lost at the polls due to reassignment disutility, the polling place would thus have to move 17 percent closer to voters, on average. Increasing distance has the opposite effect on mail-in turnout (Columns 3 and 4); however, the effect size does not completely offset the negative impact on in-person turnout: on average, increasing distance by 10 percent results in a drop in overall participation by 0.08 percentage points (Columns 5 and 6). Interestingly, the event-time estimates on mail-in turnout turn insignificant in the first post-event election and become more than twice as large and significant in the subsequent election. Again, this pattern is consistent with inattentive voters delaying the switch from polling place to mail-in voting by one election because they missed the opportunity to request a mail-in ballot. If these voters predominantly abstain from participating before turning to mail-in voting, this would explain the temporary decline in total turnout. We test this mechanism as the driver of the turnout recovery in the next section. Comparing the point estimates with the baseline results suggest that distance accounts for 35–39 percent of the reassignment effect on in-person turnout (over the three post-event elections), and for 19–25 percent of the drop in overall turnout in the first post-reassignment election. Thus, although distance effects are sizable and significant, only less than half of the turnout effects are attributable to changes in distance.

The insight that the mere relocation is the primary driver of turnout effects relative to distance changes is important. Election officials monitor the proximity to the polling locations. But that the relocation of a polling place itself may pose a barrier to voting has so far been overlooked.

[28] Brady and McNulty (2011) label the costs that arise on top of increased travel distance “search costs”, which result from the time of looking up and going to the new polling location.

Table 1.1 : Event Study Estimates Conditional on Log Street Distance

	Turnout at the Polling Place		Turnout by Mail		Total Turnout	
	(1)	(2)	(3)	(4)	(5)	(6)
Log Street Distance	-3.31***	-3.36***	2.56***	2.56***	-0.75***	-0.79***
	(0.26)	(0.26)	(0.25)	(0.26)	(0.22)	(0.23)
Reassignment $(t-4)$	0.02	-0.15	-0.23	-0.07	-0.21	-0.22
	(0.17)	(0.19)	(0.16)	(0.17)	(0.17)	(0.17)
Reassignment $(t-3)$	-0.08	-0.09	0.02	-0.07	-0.06	-0.17
	(0.17)	(0.20)	(0.15)	(0.20)	(0.16)	(0.17)
Reassignment $(t-2)$	0.03	0.16	-0.06	-0.16	-0.03	0.00
	(0.12)	(0.14)	(0.12)	(0.14)	(0.13)	(0.15)
Reassignment $(t+0)$	-0.55***	-0.65***	0.25	0.21	-0.30*	-0.44***
	(0.21)	(0.22)	(0.21)	(0.23)	(0.16)	(0.17)
Reassignment $(t+1)$	-0.62***	-0.63***	0.70***	0.69***	0.07	0.06
	(0.20)	(0.23)	(0.20)	(0.22)	(0.20)	(0.20)
Reassignment $(t+2)$	-0.44*	-0.44*	0.81***	0.78***	0.37	0.33
	(0.23)	(0.24)	(0.24)	(0.26)	(0.23)	(0.24)
R^2	0.98	0.97	0.96	0.95	0.99	0.99
Fraction of effect explained by distance	0.39	0.35	0.35	0.34	0.25	0.19
Observations	4,672	4,672	4,672	4,672	4,672	4,672
Precinct FE	×	×	×	×	×	×
Election-District FE	×		×		×	
Election FE		×		×		×

Notes: The table presents event study results based on different versions of Equation 1.8 in which the log of average street distance is included as a covariate. The dependent variables are voter turnout (0–100) at the polling place (Columns 1 and 2), by mail (Columns 2 and 4), and overall (Columns 5 and 6). Odd columns use election×district fixed effects, even columns use election fixed effects. The fraction of the effect explained by distance corresponds to the average decrease of point estimates when controlling for distance compared to baseline estimates (reported in Column 2 and Column 4 of Table A.3) over the three post-event periods (for in-person and mail-in turnout) and in the first-post event period (for total turnout), respectively. The event is defined as the first time in which the entire precinct is reassigned to a different polling place. All specifications include time-varying covariates listed in Section 1.4.1. Regressions are weighted by the number of eligible voters. Standard errors are clustered at the precinct level and reported in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1.$

Existing causal estimates of distance to the polling location on turnout use cross-sectional variation near precinct borders in a regression discontinuity design (Cantoni, 2020). Based on the negative distance effects, one might be tempted to prescribe a policy of simply relocating polling places closer to voters to increase turnout. Our results highlight that such a policy may, in fact, not deliver the expected outcome as distance reductions come at the cost of changing the polling location.

Our estimated distance effects on overall turnout—based on temporal variation—are smaller than estimated by Cantoni (2020). Cantoni's estimates imply that a 1 standard deviation greater distance (0.25 miles) reduces turnout in US elections by 1–3 percentage points. Based on the specification in Column (5) of Table 1.1 and replacing the log of street distance with linear distance, we estimate a decline of 0.3 percentage points (p <0.01) for every 1 standard deviation increase in distance (0.21 miles). Unlike in most US elections studied by Cantoni, mail-in voting in German elections is universally accessible. Thus, a potential reason for the discrepancy is the convenient access to mail-in voting, which we find to compensate significantly for votes lost at the polling place. Our estimates imply that a 1 standard deviation jump in distance decreases *in-person turnout* by 1.4 percentage points, which is in line with the effect range estimated by Cantoni.

1.5.3 Mechanism: What Drives the Recovery in Overall Turnout?

Perhaps intriguingly, the decline in total turnout is recovered after one election, even when reassignments strongly increase the distance to the polling place. This pattern could be explained by inattention to reassignments. As formally introduced in Section 1.3, inattention implies that some voters delay switching to mail-in voting by one election and instead temporarily abstain from turning out. The reason is that they are surprised by the reassignment *after* the deadline for requesting mail-in ballots has passed. However, an alternative explanation could be the waning of the initial shock to voting costs. Waning costs imply that voters temporarily abstain from turning out and return to voting in person, for instance, because they familiarized themselves with their new polling place. Thus, while inattention implies that the recovery in the subsequent election is driven by an increase in *mail-in* voting, waning costs imply that the recovery is driven by an increase in turnout *at the polling place*.

A visual inspection of the baseline estimates in Figure 1.10, Panel C lends some support for the inattention hypothesis as the effect size estimates on mail-in turnout further increase between the first and the second post-reassignment election. This pattern is even more pronounced for estimates on reassignments that caused an increase in distance to the polling location (Panels B and C, Figure 1.11). Polling place turnout, on the other hand, tends to *decline* between the first and second post-event election, inconsistent with the waning-costs hypothesis.

Formally, we test whether the event-time indicators in the first and second election after reassignment differ; and whether the sign of the difference implies an increase in mail-in or in-person turnout, respectively. We use estimates restricted to cases that generated a *greater* distance to the polling location (i.e., $\hat{\beta}^1 - \hat{\beta}^0$ from Equation 1.9) to rule out ambiguity due to cases that may produce a *negative* shock to voting costs. Indeed, we find that the difference for mail-in turnout is positive and statistically significant (0.64, p <0.01). The difference for in-person turnout is negative, albeit not statistically significant (-0.10, $p > 0.1$). Another approach is to test the difference of the event-time coefficients holding distance to the polling location constant as proposed in the previous section and reported in Columns (4) and (5) of Table A.3. In this specification, turnout effects are driven by the reassignment disutility. Again, the test suggests that mail-in turnout further *increases* in the second election after reassignment (0.45, $p < 0.01$), while polling place turnout, if anything, marginally decreases (-0.07, $p > 0.1$). Hence, the results strongly support the hypothesis that the recovery in overall turnout is driven by inattentive voters switching from nonvoting to mail-in voting, and are inconsistent with the waning-cost hypothesis.

To rule out that the results are merely an artifact of using the TWFE estimator, we replicate the tests using the novel DiD estimators that explicitly account for heterogeneity in treatment timing (Borusyak et al., 2022; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021; de Chaisemartin and D'Haultfœuille, 2020). The event study results are plotted in Appendix Figure A.12 for specifications using a restricted sample excluding reassignments that caused a distance *decrease*, and in Appendix Figure A.11 for specifications controlling for the log of street distance. In addition, Appendix Table A.7 reports the difference of the event-time coefficients in the second and the first post-reassignment election for mail-in, in-person, and overall turnout according to the five estimators. The robustness check supports our conclusion that the transitory decline in voter participation is driven by inattention to reassignments. According to all estimators, mail-in turnout further increases in the second post-event election; the difference is statistically significant in almost all cases. Instead, there is no evidence that in-person turnout drives the recovery in total turnout: half of the estimated differences are negative, and none are statistically significant.

In our model, we also consider the case in which a fraction of abstainers is inattentive to reassignments (e.g., because they never open the election notification). In this scenario, inattention attenuates the increase in total turnout when reassignments reduce the distance to the polling location. Intuitively, some individuals would have turned out at their new (closer) polling location if informed but, instead, remain abstainers. It is impossible to empirically identify this type of inattention since we cannot rule out that the observed reductions in travel distance are not enough to make polling place voting attractive for abstainers. However, the lack of positive turnout effects, even in cases in which reassignments significantly reduce distance, points toward inattention as a contributor to the inertia of abstainers.

1.6 Effect Heterogeneity and Partisan Consequences of Reassignments

The baseline event study estimates deliver average turnout effects for precincts that had their polling place moved. Yet importantly, the results may obscure heterogeneity across voter groups. Uncovering sources of heterogeneity is central for several reasons. First, policymakers may be particularly concerned about reassignments imposing a disproportional burden on minorities or economically disadvantaged people. Second, if reassignments are more likely to discourage certain groups from turning out, the representativeness of the election outcome may be at risk. Thus, we devote this section to analyzing effect heterogeneity, starting with differences across demographic groups followed by partisan consequences of reassignments.

1.6.1 Heterogeneity across Precinct Characteristics

Who responds to reassignment shocks? To explore heterogeneity across voter groups, we estimate a version of Equation 1.8 by adding a set of interaction terms between event-time indicators and a variable Z_p along which we allow for heterogeneity. Z_p is measured at the precinct level and chosen to be time-invariant. Then, the modified specification corresponds to a triple-difference estimator that allows for the effects of reassignments to evolve over time:

$$Y_{pt} = \sum_{k \neq -1} \gamma^k [Z_p \times \mathbb{1}(\tau = k)] + \sum_{k \neq -1} \theta^k \mathbb{1}(\tau = k) + \mathbf{X}'_{pt}\eta + \pi_p + \pi_{d(p)t} + \epsilon_{pt}, \tag{1.10}$$

where θ^k are the coefficients on the standard event-time dummies, $\mathbf{X}$ is a vector of time-varying covariates, and π_p and $\pi_{d(p)t}$ denote precinct and election×district fixed effects, respectively. For intuition, suppose that Z_p is a dummy identifying precincts with an above-average share of elderly eligible voters. Then, the estimates $\hat{\gamma}^k$ trace the differential turnout trend in "old" relative to "young" precincts before and after the polling place relocation. Note that all first and second-order interaction terms required for identification of the triple-difference estimator are included in the specification or absorbed by the fixed effects.

In practice, we estimate Equation 1.10 separately for different Z_p's, each corresponding to a standardized precinct characteristic (i.e., unitary standard deviation and mean zero) measured in 2013 (the first year in our panel). Hence, the triple-difference estimates measure the difference in turnout among treated units when Z_p is increased by one standard deviation.

The results appear in Figure 1.13. In each panel, the left plot shows the triple difference estimates for turnout at the polling place and via mail; the right plot shows the differential trends for overall turnout. The main conclusions from this exercise are that precincts with a higher share of elderly eligible voters show a greater decline in polling place turnout and a weaker shift toward mail-in voting when reassigned. This results in a stronger drop in overall participation (Panel A). The effects on total turnout are statistically significant and *persistently* negative, suggesting that participation rates among elderly voters are permanently depressed. Indeed, an F-test that the *overall* effect on total turnout is equal to zero in the two subsequent elections ($H_0 : \hat{\gamma}^1 + \hat{\theta}^1 = \hat{\theta}^2 + \hat{\gamma}^2 = 0$) is rejected at the 5 percent level (F=3.85, p=0.03). In precincts with a larger share of younger eligible voters, the impact of reassignments is visibly attenuated (Panel B): the estimated effects are negative for mail-in turnout and positive for polling place and overall turnout. This is unsurprising, given that a greater share of first-time voters implies a higher proportion of individuals who do not experience reassignments. We find no measurable differences for precincts with a higher fraction of households with children nor for precincts where housing is more expensive (Panels C and D). Panel E shows that the substitution between modes of voting is significantly weaker in precincts with a higher fraction of Germans with a migrant background; yet, overall turnout appears not statistically different. This finding might reflect that migrants are not used to mail-in voting from their country of origin or are more likely to be unfamiliar with the process of requesting a mail-in ballot (e.g., due to language barriers).[29] The findings contrast with Cantoni (2020), who finds that a greater distance to the polling location reduces turnout stronger in areas with higher minority and low-income presence.

Two remarks are in place. First, since inference is not based on (quasi-)random sources of variation, the results of the heterogeneity analysis can only be interpreted as suggestive of the mechanisms underlying differential turnout trends. For instance, other characteristics correlated with Z_p (e.g., unobserved aspects of voters' socioeconomic status) could constitute the actual *cause* of differential effects of reassignments. Second, we did not account for the change in distance to the polling location generated by reassignments in the regressions. To rule out the possibility that differential trends are merely the result of correlation between Z_p and proximity to the polling place, we re-estimate all specifications conditional on the log of street distance. Appendix Figure A.13 shows that the conclusions still hold.

1.6.2 Partisan Consequences of Reassignments

The presence of heterogeneous turnout effects across voter groups may threaten the representativeness of the electoral outcome. We examine this concern by estimating the

[29] For instance, election notifications, which include information on requesting polling cards to vote by mail, are only sent out in German.

partisan consequences of reassignments. One limitation is that we observe party outcomes at the precinct level only for votes cast *in-person*. Party votes from mail-in ballots are only recorded at the *district level*. As there are only 25 districts (compared to 618 precincts), estimates based on district-level observations are likely underpowered. Consequently, we first analyze party results at the polling place using our precinct panel. The results help us understand whether reassignments disproportionately dissuade specific party supporters from turning out at the polling place. Next, we verify if the conclusions hold in the district-level panel using party outcomes from mail-in ballots.

We estimate Equation 1.8 for two outcomes: party turnout, defined as the number of party votes relative to the number of eligible voters, and party vote share, defined as the number of party votes relative to the number of total votes. For expositional convenience, we group the outcomes of the six largest parties that were on the ballot in every election during our observation period into a "left-wing" and a "right-wing" cluster according to the parties' platforms.[30]

The results presented in Figure 1.14 suggest that in-person turnout declines slightly more for right-wing parties after reassignment (left plot, Panel A); however, the effects are not statistically different from each other in any period (right plot, Panel A). Panel B presents the results for party vote shares, which is the relevant metric for determining the composition of parliament. None of the estimates are statistically significant from zero (left plot, Panel B) nor statistically different from each other (right plot, Panel B). Thus, assuming that voters who switch to voting by mail do not simultaneously switch their party preference because of reassignment, the results suggest negligible partisan consequences. We present the results for all parties individually in Appendix Figure A.14. Again, the estimates do not suggest that any party particularly gains or loses from reassignments. We also find null effects when estimating a modified event study specification using a district-level panel and party outcomes from mail-in votes, corroborating the results (Appendix Figure A.15).

The null effects on the electoral outcomes are reassuring from an administrator's perspective. Polling place relocations are not notably concentrated geographically (Appendix Figure A.7). In addition, the absence of significant spatial segregation along party lines in Munich ensures that polling place relocations are not particularly targeted at a particular party's supporters. The vulnerability to adverse effects is markedly higher for democracies with two-party systems and strong partisan segregation. Thus, our results should not imply that electoral consequences

[30] We use the left-right categorization suggested by ParlGov (`parlgov.org`) to group parties. Left-wing parties include SPD, *Grüne*, and *Die Linke*; right-wing parties include CSU, *Freie Wähler*, and FDP.

of polling place relocations are universally benign.

1.7 Conclusion

Voting is the backbone of democracy. Yet, the likelihood of a pivotal vote is negligible, raising the possibility that seemingly innocuous changes to voting costs affect electoral turnout. Election officials in Munich recruit new polling places to improve their accessibility and control precinct sizes to prevent congestion, producing plausibly exogenous variation in the assignment of polling places. We study the turnout effects of relocating polling places using an event study design. Results suggest that polling place reassignments induce a persistent substitution away from in-person voting toward mail-in voting and a transitory decline in total turnout by 0.4–0.6 percentage points (0.7–1.0 percent). The effects are amplified when the polling place is moved further away and insignificant, on average, when reassignments reduce the distance to the polling location. Our findings suggest that, for the most part, changes in turnout are attributable to the relocation itself rather than changes in proximity to the polling place. This result cautions about targeting distance to the polling place as the sole accessibility factor (Cantoni, 2020), as distance reductions come at the cost of relocation.

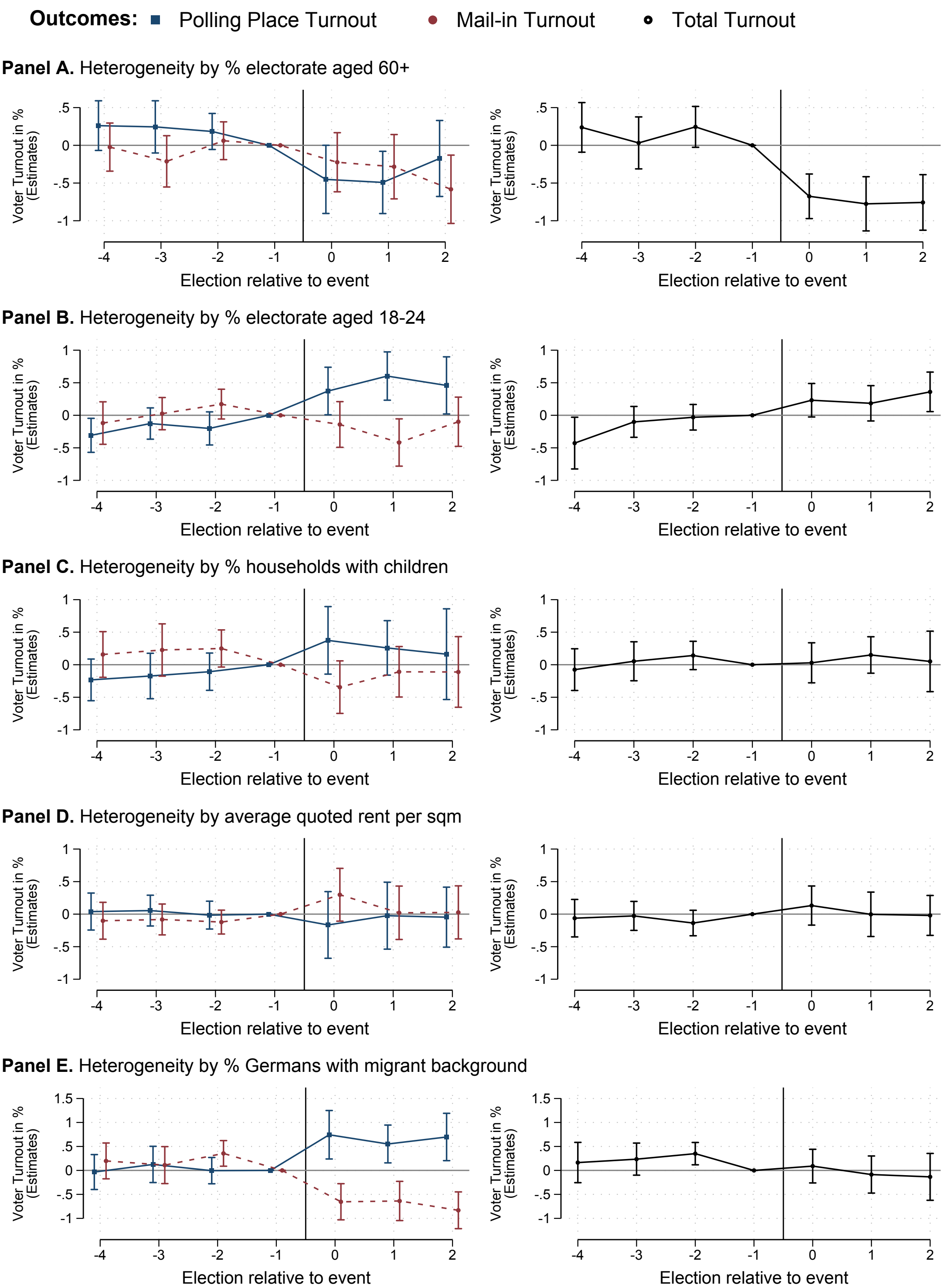
Heterogeneity analyses suggest that reassignments cause a stronger and more persistent turnout decline in precincts with a higher share of elderly eligible voters. The result is intriguing, given that recruiting new barrier-free locations was a primary motivation for reassigning polling places during our observation period. Thus, our findings highlight that a well-intentioned policy can have unintended consequences when small changes in voting costs are overlooked. We do not find evidence that moving polling locations adversely affected the electoral outcome by altering party shares. However, democracies characterized by spatial voter segregation along party lines and two-party systems may be more vulnerable to partisan consequences, justifying particular scrutiny of this practice.

We find that inattention to reassignments likely explains the drop and subsequent recovery in total turnout. Inattentive citizens are surprised by reassignments after the deadline for requesting mail-in ballots has passed. Consequently, some inattentive, who would have switched to voting by mail, instead temporarily abstain and turn to mail-in voting only in the subsequent election. Increasing the salience of polling place relocation is a possible effective remedy against turnout losses by mitigating inattention.

Finally, our results highlight the role of mail-in voting in compensating for the decline in turnout at the polling place. Mail-in voting is rather uncommon by international comparison.[31] Thus, in contexts in which the substitution between modes of voting is limited, negative turnout effects of reassignments are likely larger and more persistent, underscoring the importance of monitoring this practice outside of Germany.

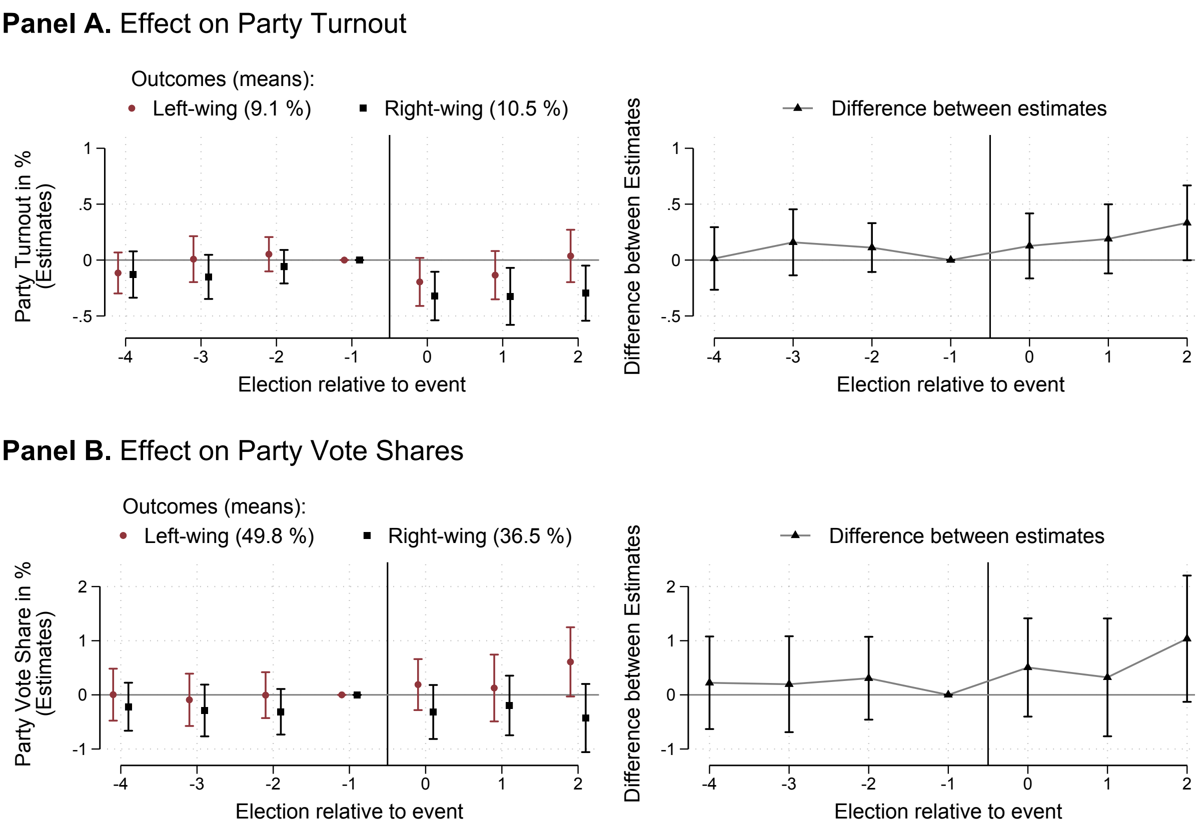
[31] Only 5 percent of countries globally and 27 percent of OECD countries (including Germany, parts of the US, Canada, and the UK) enable mail-in voting for all eligible voters (International Institute for Democracy and Electoral Assistance (IDEA)).

Figure 1.13 : Effect Heterogeneity by Precinct Characteristics



Notes: The figure presents event study results based on the triple difference estimator introduced in Equation 1.10. Each panel uses a different heterogeneity dimension Z_p and plots the triple-difference coefficients $\hat{\gamma}^k$ for the three outcomes, polling place turnout, mail-in turnout, and overall turnout. The event is defined as the first time in which the entire precinct is reassigned to a different polling place. All specifications include time-varying covariates listed in Section 1.4.1. Regressions are weighted by the number of eligible voters. Confidence intervals are drawn at the 95 percent level using standard errors clustered at the precinct level. Point estimates and standard errors are reported in Appendix Table A.8.

Figure 1.14 : Effects of Reassignments on Party Outcomes at the Polling Place



Notes: The figure presents event study results based on Equation 1.8. The outcomes are party turnout (Panel A) and party vote shares (Panel B) at the polling place. Party turnout is defined as the number of votes relative to the number of eligible voters for left-wing and right-wing parties, respectively. Party vote share is defined as the number of votes relative to total votes for left-wing and right-wing parties, respectively. The right plot in each panel presents estimates and confidence bands for the difference between event-time indicators in each period. The event is defined as the first time in which the entire precinct is reassigned to a different polling place. All specifications include time-varying covariates listed in Section 1.4.1. Regressions are weighted by the number of eligible voters. Confidence intervals are drawn at the 95 percent level using standard errors clustered at the precinct level.

2 Germany's Capacity to Work from Home*

2.1 Introduction

In the wake of the Covid-19 pandemic and the associated containment measures, working from home (WFH) has experienced an unprecedented boom. Survey evidence suggests that 42 (Bloom, 2020) to 50 percent (Brynjolfsson et al., 2020) of U.S. workers worked from home during April and May 2020.[1] Similar shifts are recorded in Europe, with nearly 60 percent of workers in Finland and the Netherlands switching to WFH due to the crisis and close to 40 percent in Germany (Eurofound, 2020). Around the globe, WFH constituted a central measure to reduce physical proximity among workers while maintaining economic activity. At the same time, the transition to WFH is likely to permanently change the organization of work for several reasons: First, companies that switched to WFH incurred fixed costs from digitizing work processes, upgrading IT infrastructure, implementing digital communication tools, and training employees in their usage (Barrero et al., 2021b). Second, evidence shows that WFH policies can represent a competitive advantage in attracting qualified labor (Mas and Pallais, 2017; Barrero et al., 2021b) and generate sizable productivity gains when implemented (Angelici and Profeta, 2020; Bloom et al., 2014; Choudhury et al., 2021; Harrington and Emanuel, 2021). Thus, once fixed costs are borne and WFH stigma lifted, a permanent expansion of WFH relative to the pre-crisis level is plausible. This raises two interrelated questions: How many and what type of jobs can be done from home?

We estimate the German economy's overall capacity to work from home and present a WFH capacity index for occupations, industries, and regions. Our analysis draws on administrative employment statistics and individual-level information from the 2018 BIBB/BAuA Employment Survey. The dataset covers more than 17,000 employees and includes information on pre-pandemic WFH uptake and individual WFH feasibility as well as the task content of jobs. Unlike task-based measures popularized by Dingel and Neiman (2020), hereinafter DN, our WFH index is based on the self-assessment of employees and is thus independent of plausibility judgments about the compatibility of tasks with WFH.[2] Moreover, rather than employing US

* This chapter is based on joint work with Oliver Falck and Simone Schüller, and was published in the *European Economic Review*, 2023.

[1] Bick et al. (2021, Fig. 1) report a 44.8 percent WFH share for May 2020.

[2] Specifically, DN propose a task exclusion approach to measure WFH capacity, which involves defining a set of tasks or work conditions that cannot be performed at home.

estimates of occupation task content, we use country-specific data to provide an accurate account of feasibility constraints of WFH in the German economy.[3]

We find that a total of 56 percent of jobs can be done from home. WFH feasible jobs are typically located in urban, densely populated areas, and in highly digitized industries. Importantly, unlike most previous studies, our measure is not limited to jobs that can be done from home *entirely* but also includes partial WFH. Including partial WFH feasible jobs captures feasibility constraints and thus the potential to maintain social distance at work more accurately (Adams-Prassl et al., 2022; Bick et al., 2021).[4] Therefore, our measure provides a useful benchmark to evaluate or design policies aimed at containing Covid-19. We show that estimated WFH capacity is highly predictive of WFH outcomes during the pandemic and present further applications of our measure, such as analyzing the role of WFH in reducing infection risk and mitigating the economic shock of the pandemic in Germany.

Besides data on WFH feasibility, the BIBB/BAuA Survey also includes detailed information on the task content of jobs. A key novelty of our paper is that we can use this information to link heterogeneity in WFH feasibility to differences in task profiles at the individual job level and thus identify single tasks and work conditions that are most (or least) conducive to WFH. We show that a job's task content is an important determinant of WFH feasibility and find that the significance of background characteristics (e.g., gender) substantially declines once accounting for task profiles. WFH feasible jobs typically require more cognitive, non-manual tasks, and in particular, the use of a computer. The results further contribute to understanding within- and across-occupation heterogeneity regarding WFH feasibility documented in the literature (Adams-Prassl et al., 2022; Gottlieb et al., 2021) and with respect to occupational task content in general (Autor and Handel, 2013; Lewandowski et al., 2022).

Drawing on our findings, we compare employees' self-assessment of WFH feasibility with alternative task-based measures in the spirit of DN, which usually rely on determining tasks that are incompatible with WFH. We show that task-based measures perform well in capturing differences in WFH capacity across occupations. In settings with limited information on self-reported WFH or job tasks, a simple measure of PC use intensity will generally provide a suitable proxy of WFH capacity.

[3] E.g., Gottlieb et al. (2021) and Lewandowski et al. (2022) demonstrate that cross-country differences in task content within the same occupations are sizeable.

[4] Focusing only on jobs that can be performed from home entirely tends to underestimate actual capacities in the economy, as evidence on actual WFH rates during the Covid-19 lockdown shows (Brynjolfsson et al., 2020, 2022).

About half of the employees who could work from home did not do so before the pandemic. Most of this untapped capacity was due to employer-side rather than employee-side restrictions. We analyze the selection into actual WFH conditional on WFH feasibility and show that individuals with lower levels of education and income were less likely to realize WFH opportunities. We discuss an application of our measure of untapped WFH capacity, showing that during the pandemic, employers' WFH offers increased most in occupations with previously larger unused potentials. As such, our measure also provides a suitable input to models used to analyze the spatial division and the organization of work in the post-pandemic era.[5]

In Section 2.2, we describe how we construct our WFH capacity index and discuss alternative approaches in the literature. In Section 2.3, we present evidence of heterogeneity in WFH capacity across occupations and analyze the determinants of WFH feasibility and untapped WFH at the individual level. We further present the geographical and industry-level distribution of WFH capacity. Section 2.4 is dedicated to WFH in the context of the Covid-19 pandemic. We test how well our measure predicts WFH outcomes during the pandemic and discuss applications of our WFH measures. In Section 2.5, we compare our survey-based measures of WFH capacity with alternative task-based measures. Section 2.6 concludes.

2.2 Measuring WFH Capacity

2.2.1 Approaches to Measuring WFH Capacity in the Literature

Our paper relates to a recent strand of research aimed at quantifying WFH capacities, i.e., how many jobs can potentially be done from home. In their influential paper, DN determine job characteristics that arguably *preclude* the possibility of entirely working from home (e.g., working outdoors) based on O*NET task data and classify occupations as either compatible or incompatible with WFH. Combining the classification with the prevalence of each occupation in the economy, the authors find that a maximum of 37 percent of U.S. jobs can entirely be performed from home. This task-exclusion approach to measure WFH capacity has become very popular. Several studies have proposed variants of this method and applied them to numerous countries.[6] Estimates for the German economy vary widely, including 17 (Pestel, 2020), 29 (Boeri et al., 2020), 37 (Dingel and Neiman, 2020) 42 percent (Fadinger and Schymik,

[5] All measures are available for download at the occupation level (2-digit and 3-digit KldB-2010 and ISCO-2008 occupations), the industry level (88 2-digit NACE industries), and the county level (401 NUTS-3 level regions) at: `https://github.com/jvali1/alipouretal_wfh_germany/tree/master`.

[6] See e.g., Barbieri et al. (2022), Boeri et al. (2020), Del Rio-Chanona et al. (2020), Fadinger and Schymik (2020), Gottlieb et al. (2021), Holgersen et al. (2021), Mongey et al. (2021), OECD (2020), Pestel (2020) or Yasenov (2020).

2020). The range of estimates is sizable, reflecting different judgments about which job characteristics are incompatible with WFH as well as different data limitations.

A common theme of these studies is the focus on jobs that can potentially be performed *entirely* at home. We argue that excluding jobs in which only part of work can be carried out at home might miss important adjustments in the economy for several reasons: First, recent survey evidence indicates that most workers can do some (rather than all or none) of their job tasks at home (Adams-Prassl et al., 2022). This finding is also in line with the observation that full-time WFH rates before the pandemic were typically low, e.g., 3.5 percent in Germany (BIBB/BAuA Survey 2018), 5.1 percent in the U.K. (Watson, 2020), and around 4 percent in the U.S. (Mas and Pallais, 2020, Fig. 1). Second, evidence suggests that partial WFH has both contributed to maintaining economic activity (measured via the likelihood of job loss or short-time work) and mitigating the spread of Covid-19 (Adams-Prassl et al., 2020; Alipour et al., 2021a; Bick et al., 2021). This is corroborated by the fact that measures of full-time WFH capacity have underestimated actual WFH rates during the pandemic lockdown (see Brynjolfsson et al., 2020 for this observation in the U.S. context). Hence, the pandemic-related WFH shock and its ramifications for the economy are not solely driven by the subset of employees with full-time WFH feasible jobs but also include those who can do partial WFH. A policy-relevant measure of WFH capacity should therefore account for both types of jobs.

Another set of studies draws on pre-pandemic employment surveys in which individuals directly report their WFH practices to measure WFH capacity—see e.g., Alon et al. (2020), Hensvik et al. (2020) and Papanikolaou and Schmidt (2022) using the American Time Use Survey. An advantage of this approach is that assessments of job suitability for WFH are independent of researchers' own judgments. A drawback is that most pre-pandemic surveys inquire about actual WFH prevalence rather than feasibility.[7,8] During the pandemic, the focus of surveys has shifted toward the latter. For instance, Adams-Prassl et al. (2022) surveyed about 25,000 U.S. and U.K. employees in April and May 2020 about the fraction of job tasks they can perform at home and document sizable variation within occupations.

[7] In the American Time Use Survey (ATUS), respondents are asked *"As part of your (main) job, can you work at home?"*, which still conveys employer-side restrictions.

[8] A notable exception is Mas and Pallais (2020), who employ questions about the fraction of work a respondent can do from home (module 82 of the 2017 Understanding America Survey). However, the sample size (N =625) is relatively low to draw meaningful conclusions about occupational, sectoral, or regional distributions of WFH feasibility.

2.2.2 A New Survey-Based Approach

Our approach leverages information from a nationally-representative survey for Germany, in which employees are asked about WFH feasibility, regardless of whether the employer actually offers WFH. We draw on information from 17,160 employees (aged 18-65, excluding the marginally employed) from the 2018 wave of the BIBB/BAuA Employment Survey (Hall et al., 2020).[9] The survey elicits information on (pre-pandemic) actual WFH and, importantly, asks employees (who never work from home) about the *possibility* of working at home, specifically: *"If your company would allow you to work at home temporarily, would you accept this offer?"— Yes; No; Is not possible with my work*. We define a job as *WFH feasible* if the respondent does not rule out the possibility of WFH at her job or if she reports ever working from home.[10] Thus, our binary measure captures the full range of WFH feasibility, including jobs suitable for full or partial relocation to the home office. It is worth noting that an individual reporting that WFH is "not possible" does not necessarily correspond to 0 percent WFH feasible tasks as measured by Adams-Prassl et al. (2022), who elicit WFH feasibility on a continuous scale. It is likely that our measure additionally includes a judgment by employees as to what fraction of WFH feasible tasks makes WFH meaningfully possible in their job. Importantly, a measure of WFH feasibility should capture which jobs *can* be performed from home, i.e., whether WFH is technologically feasible, independent of worker characteristics. We show in Section 2.3.2 that individual-level variation in our measure is indeed largely explained by differences in job tasks and work conditions. We use the term *WFH capacity* to refer to the aggregate of WFH feasible jobs in an occupation, a region, or an industry. In the overall economy, 56 percent of jobs are WFH feasible. We break down actual WFH rates (pre-pandemic) by frequent and occasional WFH. Employees reporting ever working from home did so on average 6.6 hours a week (median $=$ 4 hours), distributed across 2.6 weekdays (median $=$ 2 weekdays). Table 2.1 presents our terminology and the survey questions used in this context.

Furthermore, using the information on employees' pre-pandemic WFH uptake, we can assess the level of *untapped WFH capacity*, defined as the fraction of employees never working from home despite having a WFH feasible job. Untapped capacities represent a useful metric to gauge the scope for increases in WFH usage at the extensive margin during and beyond the pandemic. In principle, untapped capacities can be due to limitations on the employer side (e.g., lacking infrastructure, no WFH policies) or on the employee side (e.g., personal preference for working from business premises, poor working conditions at home). We broadly

[9] BIBB: Federal Institute for Vocational Education and Training (*Bundesinstitut für Berufsbildung)*; BAuA: Federal Institute for Occupational Safety and Health (*Bundesanstalt für Arbeitsschutz und Arbeitsmedizin*).

[10] See Mergener (2020) and Brenke (2016) for similar definitions of WFH feasibility at the employee level.

categorize untapped capacities using the information on whether employees with a WFH feasible job would accept or decline their employer's offer to WFH. We assume that employees who would accept the offer face practical constraints from their employer (employer-side restrictions), while those who would reject the offer have no desire to WFH (employee-side restrictions). We discuss employer-side and employee-side restrictions in Section 2.3.3.

Table 2.1 : Terminology & Survey Questions

Survey Question		Answer Categories
[A]	*"Do you work for your company (even if only occasionally) from home?"*	Yes; No.
[B]	*"How frequently [do you work from home]?"*	always; frequently; sometimes; rarely.
[C]	*"If your company would allow you to work at home temporarily, would you accept this offer?"*	Yes; No; Is not possible with my work.
Term	**Definition**	**Level**
actual WFH	Dummy identifying individuals who report working from home in survey question [A].	individual
frequent WFH	Dummy identifying individuals who report working "always" or "frequently" from home in survey question [B].	individual
occasional WFH	Dummy identifying individuals who report working from home "sometimes" or "rarely" in survey question [B].	individual
WFH feasibility	A job is *WFH feasible* if the respondent does not rule out that WFH is possible in her job in survey question [C] or if she reports ever working from home in survey question [A]. WfH feasibility thus captures whether it is technologically feasible to perform a job at least partly from home.	individual
untapped WFH	Respondent never works from home (based on question [A]) but has a WFH feasible job. We assume employer-side (employee-side) restrictions to WFH if respondent would (would not) accept offer to WFH based on question [C].	individual
WFH capacity	Share of WFH feasible jobs in an occupation, a region, or an industry.	aggregate
untapped WFH capacity	Share of employees never working from home but with a WFH feasible job.	aggregate

Notes: The table outlines our terminology and the mapping of questions in the 2018 BIBB/BAuA Employment Survey into WFH concepts.

2.3 WFH Capacities in Germany

2.3.1 Occupational WFH Capacities

Figure 2.1 depicts WFH capacities and (pre-pandemic) rates of actual WFH by occupation at the 2-digit level of the German Classification of Occupations (KldB 2010). The corresponding values are reported in Appendix Table B.1.[11] The total size of the bars corresponds to occupations' WFH capacity, i.e., the percentage of WFH feasible jobs. The difference between total capacity and actual WFH is equal to (pre-pandemic) untapped WFH capacity, i.e., the fraction of employees who do not work from home despite having a WFH feasible job. Finally, untapped capacity is decomposed into the fraction of employees who do not work from home due to employer- and employee-side restrictions, respectively. The results show large differences across occupations. WFH capacities range from about 16 percent for "Drivers and Operators of Vehicles" to roughly 97 percent for computer scientists and ICT workers. The distribution of WFH capacities also suggests a substantial variation within occupations as all values range strictly between 0 and 100 percent and show no evident clustering at the extremes. This heterogeneity also holds for narrower occupation groups in our data. Indeed, the portion of the variation in individual-level WFH feasibility explained by occupations increases only marginally from 27 to 30 percent when comparing 2-digit occupations (36 groups) to 3-digit occupations (139 groups). This corroborates important insights of Adams-Prassl et al. (2022) and Gottlieb et al. (2021), namely, that much of the relevant variation in WFH feasibility is driven by differences across jobs belonging to the *same* occupation.

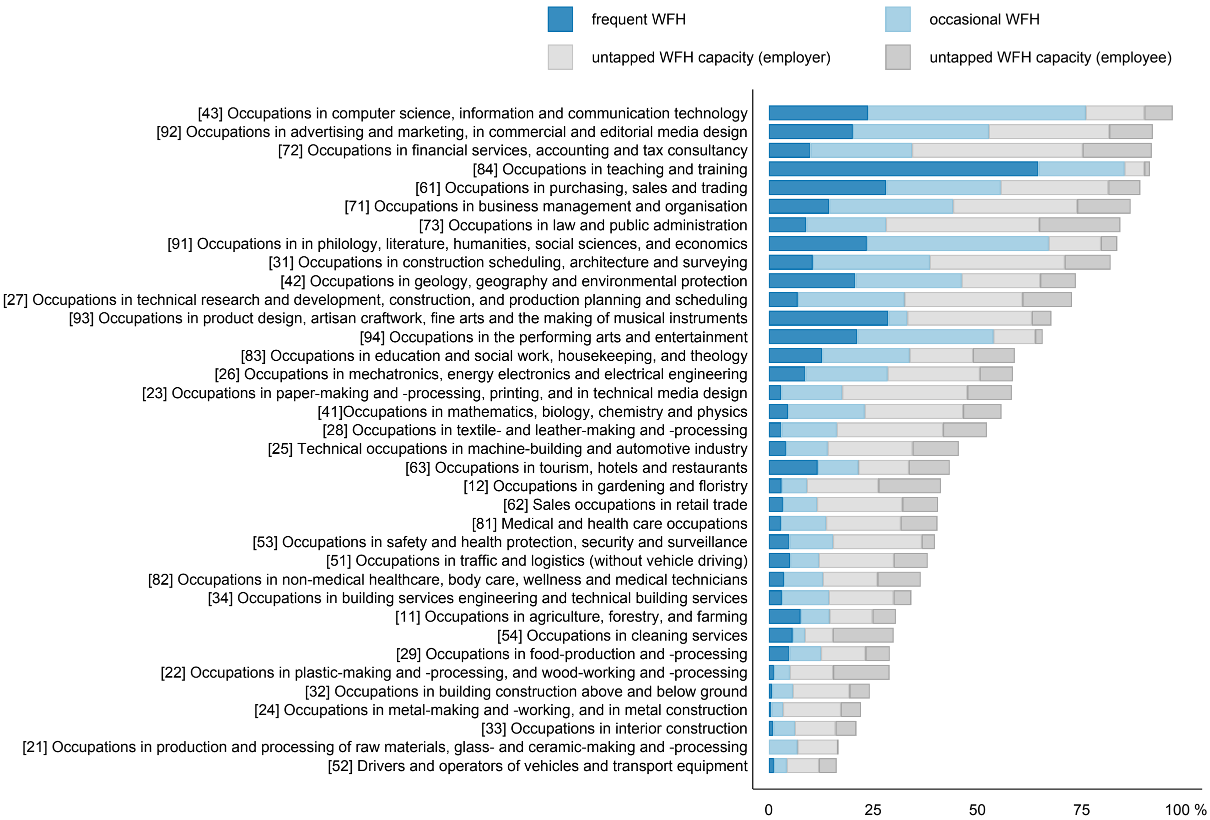
Although WFH feasibility should, *a priori*, be independent of worker or employer tastes and characteristics, actual WFH is clearly subject to selection based on varying attitudes and needs. For instance, teachers and instructors (KldB$=$84) show a WFH rate of 85 percent pre-pandemic, amounting to about 91 percent of total WFH capacity. It is common for teachers to prepare their courses at home and employers typically do not restrict this arrangement. Overall, about one in four workers report ever working from home, implying that before the pandemic only less than half of the economy's WFH capacity (56 percent) was used.

2.3.2 Determinants of WFH Feasibility

The evident heterogeneity in WFH feasibility across and within occupations begs the question about its determinants. The unique combination of individual-level information on WFH feasibility, worker characteristics, and task profiles allows us to shed light on the source of this heterogeneity.

[11] We also report the results for ISCO-08 classification (1-digit and 2-digit level) in Appendix Tables B.2 and B.3.

Figure 2.1 : Capacity to Work from Home by Occupation



Notes: The figure displays WFH capacities and pre-pandemic WFH usage by occupation (2-digit KldB). The underlying values are reported in Appendix Table B.1. Data from the 2018 BIBB/BAuA Employment Survey.

A key novelty of our analysis is that we can identify job tasks and work conditions that are most and least conducive to WFH feasibility in a way that is independent of researcher judgment. To this end, we estimate individual WFH feasibility as a function of job features and worker characteristics. Employees report, for instance, how often they carry heavy loads, monitor machines, or use a computer on the job—the full list including population means is reported in Appendix Table B.4. Omitting this information is likely to severely overestimate the importance of demographic characteristics, such as gender or education, due to selection into different occupations or different jobs within an occupation. We code each job task as one if respondent i indicates that she performs it frequently (and zero otherwise) and estimate the following linear probability model:

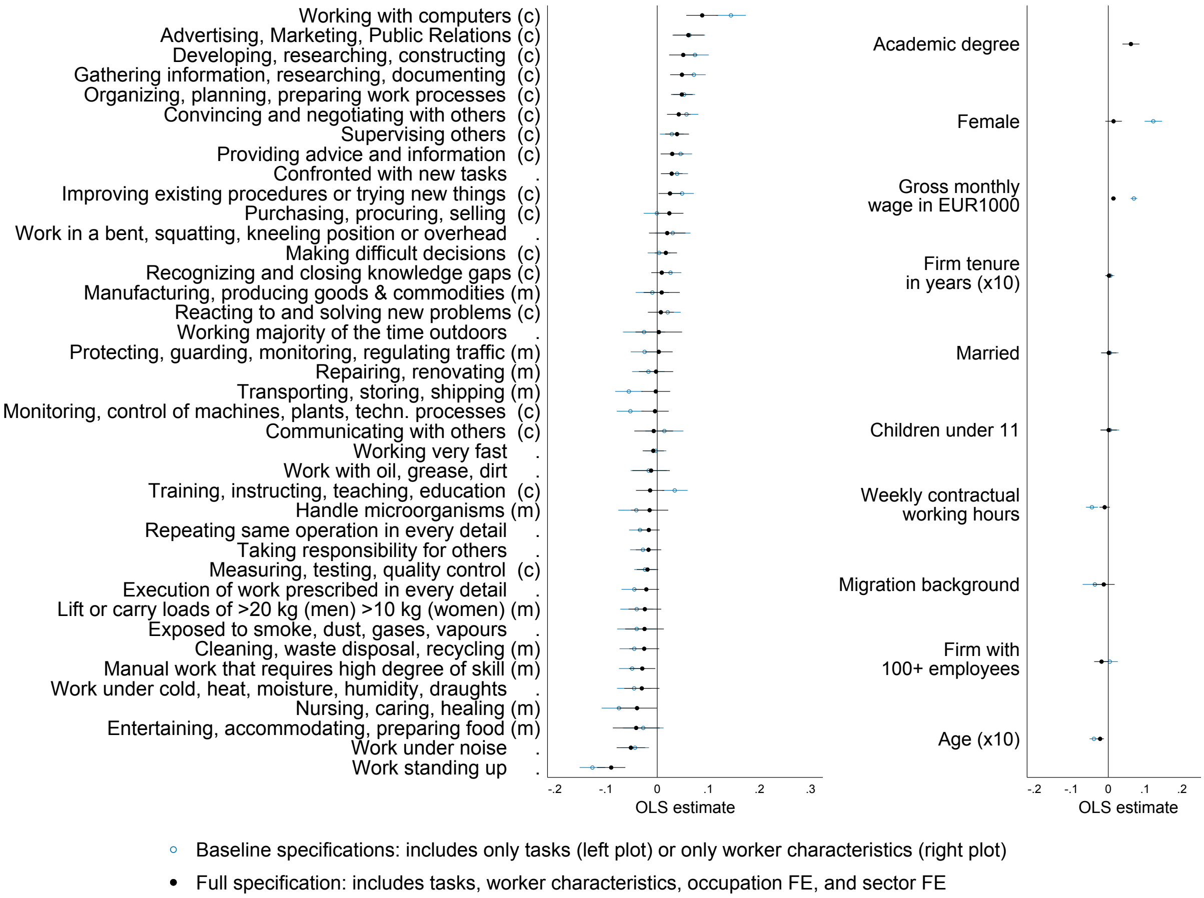
$$WFH\_feasibility_i = \mathbf{T}_i'\delta + \mathbf{X}_i'\gamma + \alpha_{o(i)} + \alpha_{s(i)} + \varepsilon_i, \tag{2.1}$$

where $WFH\_feasibility_i$ is our individual-level WFH feasibility indicator, $\mathbf{T}_i$ is the vector containing tasks and work conditions, $\alpha_{o(i)}$ denotes occupation fixed effects at the 2-digit level, and $\alpha_{s(i)}$ is a set of industry fixed effects (identifying 21 distinct industries). $\mathbf{X}_i$ is a vector of worker characteristics including gender, age, monthly wage, contractual working hours, tenure at the firm, and a set of dummies identifying respondents who are married, have children under the age of 11 living in the household, hold an academic degree, work in a firm with more than 100 employees, or have a migration background, respectively.

The OLS results are presented in Figure 2.2. The left plot shows the estimates associated with job tasks, the right plot presents the estimates for background characteristics. We report the estimates from the full specification (in black) and from two baseline specifications (in blue), which estimate WFH feasibility as a function of only job tasks (left plot) or only individual characteristics (right plot). Cognitive and manual tasks are labeled (c) and (m), respectively. The full set of results including point estimates and their standard errors are reported in Appendix Table B.5. In the baseline specification, job tasks alone explain about 30 percent of the individual variation in WFH feasibility. The estimates imply that the likelihood of WFH feasibility increases strongly when the job requires frequent computer usage (14 p.p.), "advertising, marketing, PR" (6 p.p.) and "developing, researching, constructing" (7 p.p.). By contrast, the job features "work standing up" and "nursing, caring, healing" are the least conducive to WFH, reducing the likelihood of WFH feasibility by 13 p.p. and 7 p.p., respectively. There is an evident pattern indicating that WFH feasibility is positively associated with cognitive tasks and negatively correlated with manual tasks, consistent with previous findings (Mergener, 2020). Controlling for occupation, industry, and background characteristics in the full specification increases the R-squared to 0.37 and attenuates the estimated coefficients for job tasks. For instance, the marginal impact of working with a computer on the likelihood of a job being WFH feasible decreases from 14 p.p. to 9 p.p. Yet, most estimates do not lose their statistical significance. The task content of jobs thus appears to constitute the main determinant of WFH feasibility also within occupations and industries.

The estimation results for worker characteristics show the importance of accounting for job tasks and work conditions (right plot of Figure 2.2). For instance, while women are on average 12 p.p. more likely to work in a WFH feasible job (holding other background characteristics constant), the effect reduces to 1 p.p. and becomes statistically insignificant when accounting for occupation, industry, and job tasks. The estimate for academic degree drops from 29 p.p. to only 6 p.p. in the full specification. Similarly, the estimates for age, migration background, wage, and working hours are much closer to zero in the full specification. In fact, the reductions in estimate sizes are almost entirely driven by conditioning on task profiles. Occupation and industry fixed effects instead only add little explanatory power and cause only marginal changes to the estimates (see full results in Appendix Table B.5).

Figure 2.2 : Determinants of WFH Feasibility



Notes: The figure reports the estimates from regressing WFH feasibility on job tasks/ working conditions, worker characteristics, occupation fixed effects, and industry fixed effects (Equation 2.1). The baseline specifications include only job tasks (left plot) or only worker characteristics (right plot). The full specification includes job tasks, worker characteristics, occupation fixed effects, and industry fixed effects. Estimates are sorted by size in the full specification. Regressions use survey weights. Standard errors are robust to heteroskedasticity. Confidence intervals are reported at the 95 percent level. The full estimation results are reported in Appendix Table B.5.

However, some coefficients on worker characteristics remain statistically different from zero. For instance, holding an academic degree increases the chance of WFH by 6 p.p. and ten-year older employees have on average a 2 p.p. lower likelihood of reporting a WFH feasible job, all else equal. Although small, statistically relevant estimates can reflect two s of bias. One is that our account of task profiles does not capture the full variation in task content. For example, "working with a computer" may encompass significantly different activities for high-skilled and lower-skilled employees. While conducting scholarly research or writing an academic article on a PC may be easily performed at home, serving clients at the counter of a bank is not. Thus, a significant estimate for holding an academic degree may reflect this type of omission. A second reason is measurement error in the sense that respondents may judge the WFH feasibility of the same job differently. For instance, younger employees could be more aware of technological solutions allowing to perform certain tasks at home. The results suggest that these types of biases are limited.

To further assess whether differences in task composition are the main driver of differences in WFH feasibility, we also conduct a variance decomposition exercise following Gottlieb et al. (2021). The results are reported in Appendix Table B.6. We find that tasks and work conditions alone explain 11.6 percent of the variance in WFH feasibility, plus a further 9.6 percent when adding the covariance with occupation fixed effects. By contrast, worker characteristics, occupation fixed effects, and industry fixed effects account for only 0.9 percent, 7.1 percent, and 0.7 percent of the variance, respectively.

2.3.3 Determinants of Untapped WFH

By the start of the Covid-19 pandemic in early 2020, most of the WFH capacity in Germany had remained unexploited. According to the BIBB/BAuA Survey, about two-thirds of the untapped capacity is due to employer-side restrictions, i.e., to employees with WFH feasible jobs, who would like to work from home but do not, and one-third is the consequence of a lack of desire to WFH by employees. Pre-pandemic employer and employee survey evidence, e.g., reported in Grunau et al. (2019), illustrates that the major reasons for employee-side restrictions relate to a high appreciation of presence at the workplace in the corporate culture. Employers additionally mention data protection and data security concerns to be important. The lack of technical means does not range among the primary reasons, neither from the employee nor the employer's perspective. Temporal and spatial distance is seen by both employers and employees as complicating collaboration with colleagues. Another important reason for employee-side restrictions is individuals' desire "to keep private and professional life separate".

To shed light on how untapped WFH correlates with task profiles and worker characteristics, we re-estimate Equation 2.1 separately, using dummies identifying untapped WFH due to employer-side restrictions and due to employee-side restrictions as dependent variables. Individuals reporting working from home at least occasionally constitute our comparison group in both specifications (i.e., workers without WFH feasible jobs are excluded from the analysis). Figure 2.3 reports the results of the full specification (including task profiles, worker characteristics, occupation fixed effects, and industry fixed effects as independent variables). The blue coefficients show point estimates and 95 percent confidence intervals for employee-side untapped WFH, the black coefficients show the results for employer-side untapped WFH. The full results are reported in Appendix Table B.7.

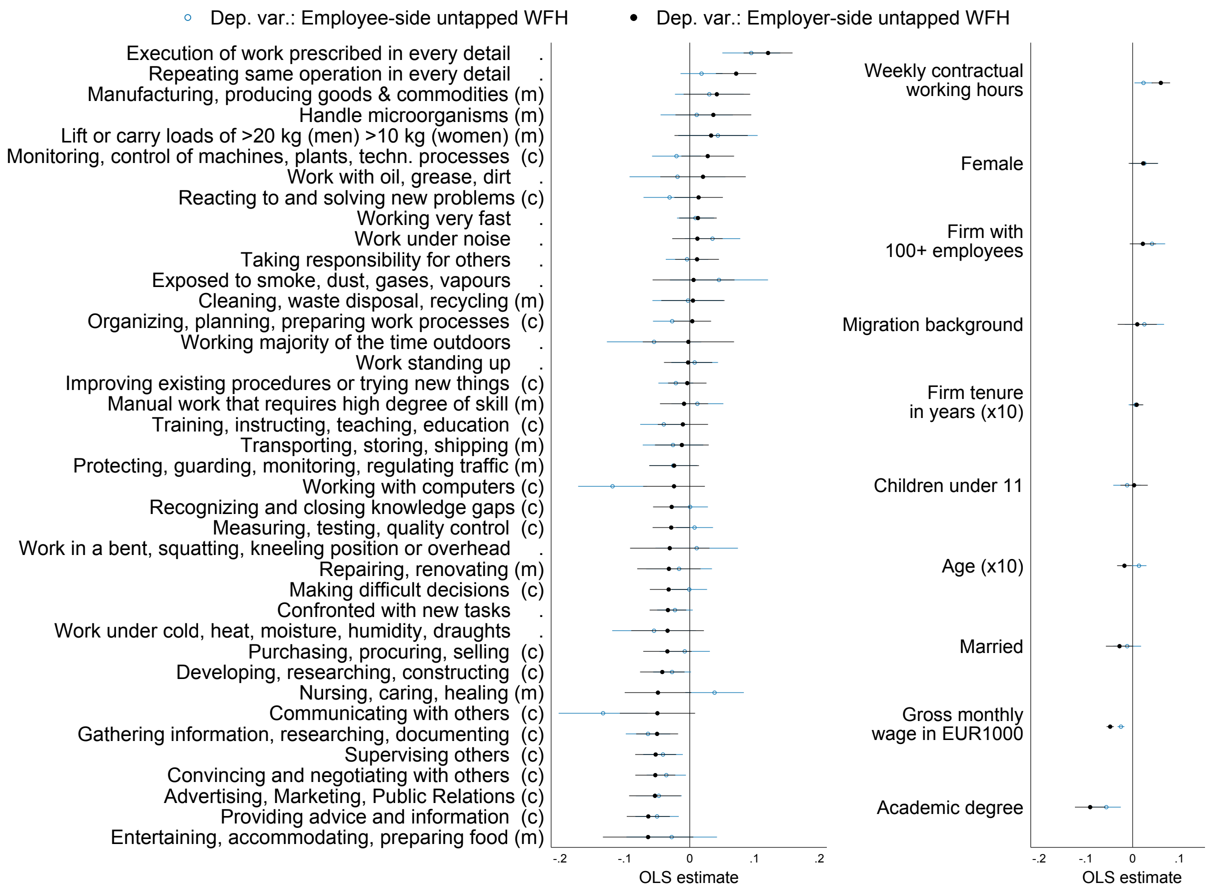
The OLS estimates indicate that working at a larger firm significantly increases the likelihood of reporting employee-side untapped WFH (4 p.p.), but has no statistically significant effect on reporting untapped WFH due to employer-side restrictions (right plot). This result is in line with previous findings, showing that larger firms are more likely to offer WFH arrangements to their employees (see e.g., Grunau et al., 2019). Employee gender, migration background, marital status, or children living in the household are not significantly correlated with the likelihood of untapped WFH. Younger workers are more likely to report employer-side restrictions preventing WFH but are not more likely to work from business premises because they have no desire to WFH. By contrast, workers with higher weekly working hours are significantly more likely to forgo working from home for both employer-side and employee-side reasons. The same is true for workers without an academic degree and workers with lower wages, all else equal.

The fact that higher-skilled workers are more likely to work from home when having a WFH feasible job is also reflected in the OLS estimates for job tasks and work conditions (left plot). Employees who are required to supervise others, conduct research, or negotiate with others are significantly less likely to report WFH restrictions. For example, employees required to provide advice and information are 5 p.p. less likely to forgo WFH due to employee-side restrictions and 6 p.p. less likely to forgo WFH due to employer-side restrictions. By contrast, individuals whose work is prescribed in detail or who conduct highly repetitive work report both employer-side and employee-side restrictions significantly more often.

2.3.4 Distribution of WFH Capacities in the Economy

We measure the aggregate WFH capacity in the German economy as well as the geographical and industry-level distribution of WFH feasible jobs by first collapsing our employee-level WFH feasibility indicator (population-weighted) to the occupation level (2-digit German Classification of Occupations, KldB 2010, excluding military services). Next, we combine the resulting shares with 2019 data from the Federal Employment Agency (BA) on occupational employment counts in the overall economy, in each German county (401 *Kreise* and *kreisfreie Städte*), and in each industry (88 2-digit NACE industries) and aggregate over occupations. We use the same approach to compute (pre-pandemic) rates of actual WFH as well as untapped

Figure 2.3 : Determinants of Untapped WFH



Notes: The figure reports OLS estimates of two separate regressions of untapped WFH on job tasks/ working conditions, individual characteristics, occupation fixed effects, and industry fixed effects (Equation 2.1). Results in blue (black) use employee-side (employer-side) untapped WFH as the dependent variable. The reference group corresponds to employees working from home at least occasionally. Regressions use survey weights. Standard errors are robust to heteroskedasticity. Confidence intervals are reported at the 95 percent level. The full estimation results are reported in Appendix Table B.7.

WFH capacities in industries and counties.

It should be noted that regional employment statistics distinguish between employment at the *county of work* and at the *county of residence*. Using the former to construct our measure yields a distribution of WFH feasible jobs independent of employees' place of residence while using the latter allows measuring local shares of employees who can work from home independent of the location of their job. In the following, we restrict our scope to the former case as both approaches yield very similar results.[12]

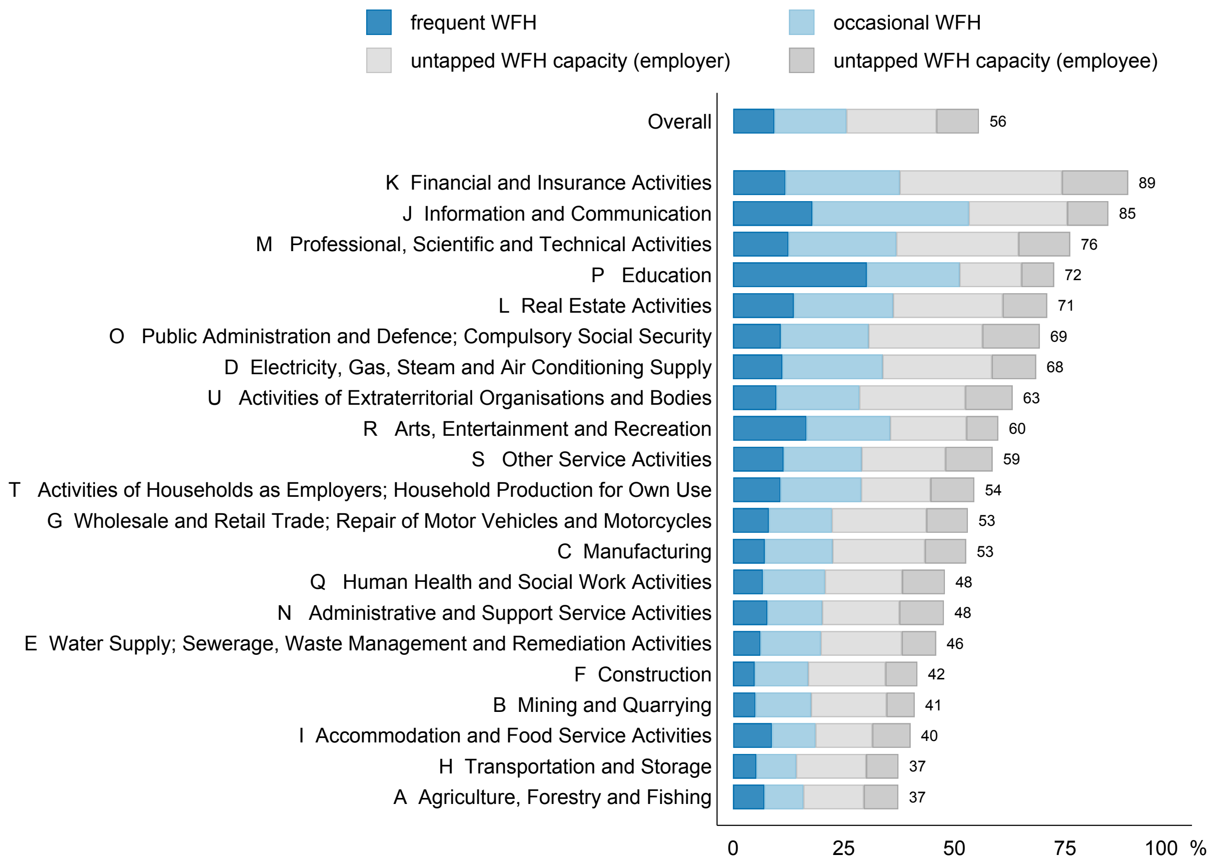
Overall, 56 percent of jobs in Germany can be performed entirely or partly from home.[13] Figure 2.4 reports WFH capacities and pre-pandemic rates of actual WFH for the overall economy and by sector (NACE main sections). The results for all 2-digit industries are reported in Appendix Table B.9. There is a large variation in WFH capacity across industries, with values ranging from 37 percent in the transportation or agricultural sector to nearly 90 percent in highly digitized sectors, such as the ICT sector and the financial sector. In most sectors, actual WFH rates before the pandemic fall far below their capacity. Only employees in education and the ICT sector used well over half of their WFH capacity. In all industries, pre-pandemic untapped capacities are mainly driven by employer-side rather than employee-side restrictions.

Figure 2.5 depicts the geographic distribution of WFH feasible jobs across the 401 German counties. Note that by construction, industry-level and regional variation in WFH capacity is determined by the occupational composition in each industry and county, respectively. The reliability of these results thus rests on the assumption that occupational WFH capacities in different industries or counties do not significantly differ from their national averages reported in Figure 2.1. The map reveals a clear divide between East and West Germany and between densely populated, urban counties and rural counties with lower population density. While on average 59 percent of jobs in West Germany (including Berlin) can be done from home, only 50 percent of jobs are WFH feasible in East Germany. Urban-rural inequalities are even more pronounced: WFH capacity amounts to roughly 65 percent in counties with $500,000$ inhabitants or more, compared to 53 percent in the rest of the country. Figure B.1 in the Appendix shows a strong correlation of 0.88 between WFH capacity and population density across counties, reflecting the specialization of urban centers in digitized, knowledge-

[12] Discrepancies are essentially due to cross-county commuting. The correlation between county-level WFH capacities calculated from both approaches is 0.81. For completeness, we publish our WFH capacity index based on both approaches in our online repository.

[13] In the aggregate, the discrepancy between WFH capacity calculated from the survey alone and calculated employing occupational employment counts is only about 1 percentage point (p.p.).

Figure 2.4 : Capacity to Work from Home by Sector



Notes: The figure displays WFH capacities and pre-pandemic WFH uptake by sector (NACE main sections) and in the overall economy. All values are reported in Appendix Table B.8. Data from the 2018 BIBB/BAuA Employment Survey, and Employment Statistics of the Federal Employment Agency (BA) 2019.

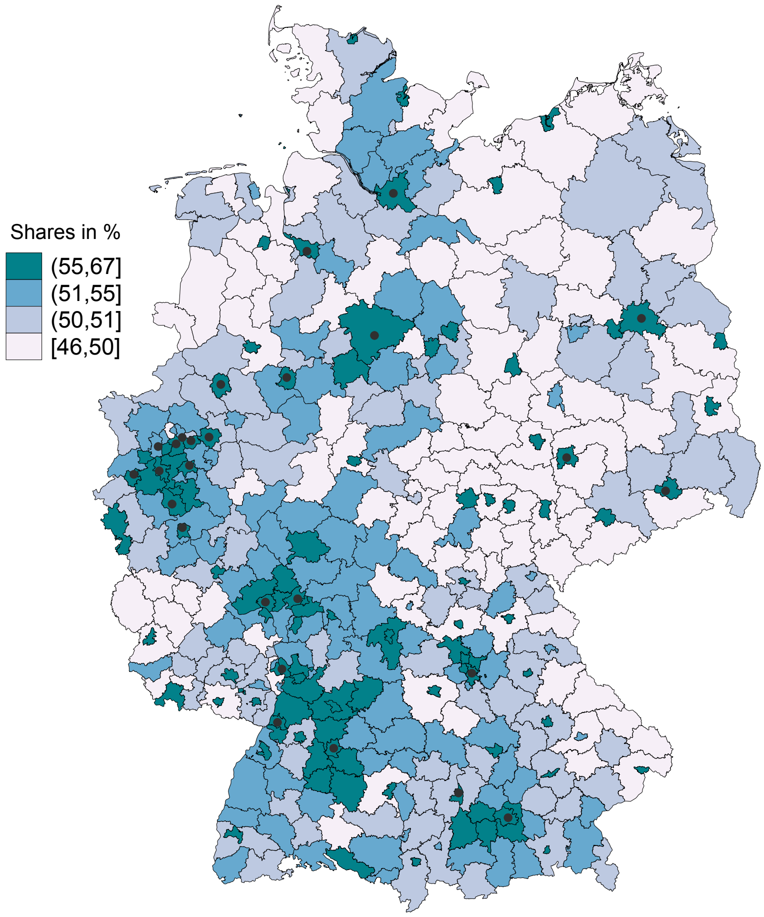
intensive industries.

2.4 WFH Capacity and the Covid-19 Pandemic

2.4.1 Predicting WFH Outcomes during the Covid-19 Pandemic

To assess whether our measure is a suitable predictor of actual WFH outcomes during the Covid-19 pandemic, we leverage WFH data at the industry, occupation, regional, and individual level. For an industry-level investigation, we use the ifo Business Survey (IBS), a monthly, nationally-representative survey of roughly $9,000$ German companies from all relevant industries (see Buchheim et al., 2020 and Sauer and Wohlrabe, 2020 for details). We use data from the April 2020 wave, in which companies were questioned about managerial

Figure 2.5 : Distribution of WFH Capacity in Germany



Notes: The map depicts the percentage of WFH feasible jobs across German counties by quartile of overall WFH capacity. Black dots represent cities with more than 250,000 inhabitants. Data from the 2018 BIBB/BAuA Employment Survey, and employment statistics of the Federal Employment Agency (BA) 2019.

responses to the Covid-19 crisis.[14] Nearly two-thirds of the firms indicated "relying more heavily on working from home" as part of their strategy to cope with the crisis. The measure thus captures efforts to expand WFH both at the intensive and the extensive margin. We compute industry-level shares of firms relying on WFH and plot these against our measure of WFH capacity at the 2-digit industry level in Figure 2.6a. The size of the bubbles is proportional to total employment in June 2019. The 45-degree line is highlighted in dashed grey. The plot shows that our measure of WFH capacity performs remarkably well in predicting WFH patterns across industries. The index explains about 58 percent of the variation in actual WFH during the pandemic. The correlation between industry-specific WFH capacity and WFH uptake is

[14] The first nationwide containment measures were implemented in Germany between late March and early May 2020 with the closure of restaurants and bars, as well as daycare facilities, schools, universities, and non-essential shops, followed by a gradual loosening of these measures.

0.76 and highly statistically significant.[15]

With respect to the occupation level, we compare our WFH measure to actual WFH rates surveyed in the IAB High-Frequency Online Personal Panel (HOPP), a monthly online panel survey developed by the Institute for Employment Research (IAB) (Sakshaug et al., 2020; Haas et al., 2021).[16] We use the May 2020 wave, in which about 7,500 employees report whether they worked from home in the previous week (mean $= 0.32$). We compute occupation-specific rates in actual WFH and plot these against our measure of WFH capacity at the 2-digit occupational level (Figure 2.6b). Observations are weighted with total employment in June 2019, assigning more importance to larger occupations. Essential occupations, such as "Medical and health care occupations", are highlighted in bold black.[17] The plot demonstrates that our measure of occupational WFH capacity is strongly associated with actual WFH during the pandemic. WFH feasibility constraints explain about 86 percent of the variation in actual WFH. The correlation between the two variables is 0.92 and highly statistically significant. Excluding essential occupations yields a marginally stronger correlation (0.93) and our WFH index explains a slightly higher share of the variation in WFH during the pandemic (87 percent). Overall, essential occupations do not appear to constitute outliers, i.e., we find a strong correlation between WFH feasibility and actual WFH during the pandemic also for these occupations.

To investigate the predictive power of our measure at the individual level, we use the HOPP data for an empirical exercise similar to that of Gottlieb et al. (2021) to assess the predictive power of our measure at the individual level. Since we do not observe both individual WFH feasibility and actual WFH in the same dataset, we regress individual WFH feasibility in the BIBB/BAuA data on employee characteristics (gender, migration background, children below age 11, age, academic degree) and occupations (2-digit KldB 2010) and use the resulting coefficients to impute individual WFH feasibility in the HOPP data. Figure B.2 in the Appendix plots predicted individual-level WFH feasibility, grouped into 20 equal-sized bins, against the share of workers in each bin that reported working from home in May 2020. The correlation between predicted WFH feasibility and individual WFH during the pandemic is positive and highly statistically significant.

[15] Excluding industries with over 50 percent employment in essential occupations (based on the classification at 3-digit KldB level in Koebe et al., 2020) yields a slightly stronger correlation (0.78) and our WFH index explains about 61 percent of the variation in pandemic WFH.
[16] The data and data documentation are provided internationally at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB): `https://fdz.iab.de/en.aspx`.
[17] We closely follow Koebe et al. (2020) to classify occupations into essential and non-essential.

Finally, we compare our regional measure of WFH capacity with county-level WFH data from the infas/infas360 survey, which documents the share of employees working "mostly or entirely" from home in February/March 2021.[18] According to the survey, 27 percent of employees spent most of their working hours at home.[19] Figure 2.6c demonstrates that our regional measure of WFH capacity is a strong predictor of regional differences in actual WFH during the crisis. WFH capacity alone explains 56 percent of the variation in actual WFH across counties.

2.4.2 Applications

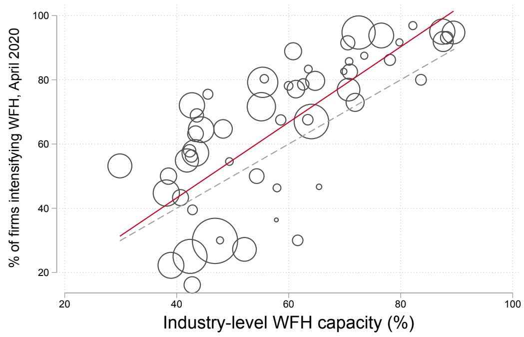
The fact that WFH feasibility is a good predictor of the observed variation in actual WFH during the crisis offers scope for broad applications of our measures. As the regional spread of Covid-19 crucially depends on the frequency of face-to-face contacts, county-level WFH capacity represents a useful proxy for the potential to socially distance employees from each other. For instance, using this measure, Alipour et al. (2021a) show that working from home significantly reduced SARS-CoV-2 infections and related deaths during the first wave in Germany. The analyses suggest that the effect of WFH appeared strongest in the weeks preceding the national lockdown measures, as workers and firms started to socially distance by transitioning to WFH. Once containment measures were imposed in late March 2020, millions of employees who could not work from home were registered for short-time work, thus reducing their working hours and physical presence at work. Hence, business closures and WFH appear to be substitute policies to some extent. Comparing actual WFH rates to WFH capacities can thus inform policymakers about unused WFH potential and support discussions about mandates or incentives to shift the economy toward its full WFH capacity. Using WFH capacity as a predictor of actual firm-level WFH, Alipour et al. (2021a) also demonstrate that businesses that could go remote more easily responded significantly better to the Covid-19 shock, reporting better business outcomes and filing fewer applications for short-time work.

Besides total WFH capacity, the level of untapped capacity also has valuable applications. For instance, it proves to be a useful predictor of where in the economy the Covid-19 shock triggered the strongest organizational adjustments toward WFH. Using online job vacancy posting data for Germany, Alipour et al. (2021c) show that the share of job postings with an explicit option to WFH in the job description more than tripled between 2019 and 2021. The strongest growth occurred in occupations that previously exhibited the largest untapped

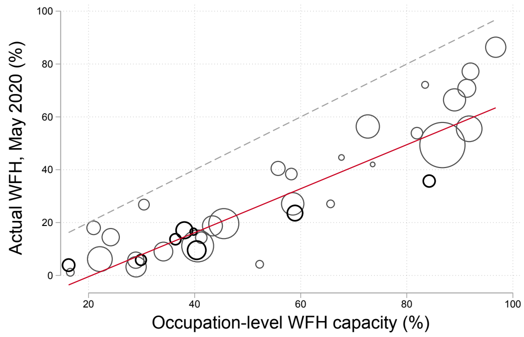
[18] See Alipour et al. (2021b) for details on the survey.

[19] This is notably lower than the 56 percent WFH capacity we estimate, most likely reflecting the fact that our measure also captures WFH at intensities below 50 percent of working hours.

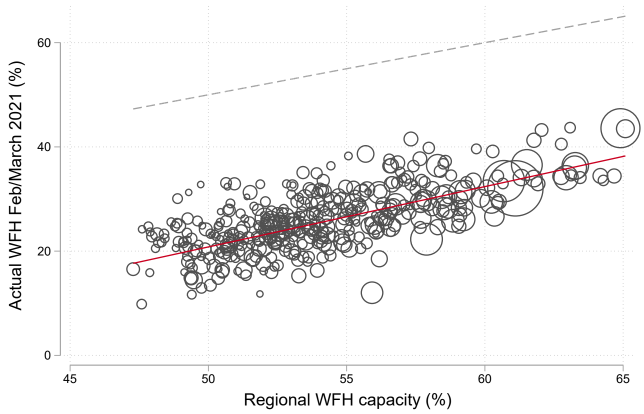
Figure 2.6 : Predicting Actual WFH during the Covid-19 Pandemic



(a) Industry-level WFH



(b) Occupation-level WFH



(c) Regional-level WFH

Notes: Figure (a) reports the linear fit between industry-specific shares of firms reporting intensified WFH in the April 2020 wave of the ifo Business Survey (IBS) and industry-level WFH capacity. 56 industry-level observations (2-digit NACE level) are computed from 7,227 firm-level responses (only industries with 10 or more respondents). Figure (b) reports the linear fit between the occupation-specific share of employees reporting WFH in the May 2020 wave of the IAB High-Frequency Online Personal Panel (HOPP) and occupational WFH capacity. 36 occupation-level observations (2-digit KldB 2010 level) are computed from 7,460 individual-level responses (only occupations with 10 or more respondents). Bold black markers are 2-digit occupations with more than 50 percent employment in essential 3-digit occupations. Figure (c) reports the linear fit between the regional share of employees reporting working from home mostly or entirely in the February/March 2021 wave of the infas/infas360 survey and county-level WFH capacity at the place of residence. The 45-degree lines are highlighted in dashed grey. All observations are weighted by total employment in June 2019 according to the Federal Employment Agency (BA).

capacity, suggesting that the Covid-19 shock prompted firms to increasingly exploit their untapped WFH potential by starting to advertise WFH feasible jobs with WFH options.

Our regional measure of WFH capacity is a useful input not only to models concerned with the geographic spread of SARS-CoV-2 (e.g., Felbermayr et al., 2021), but also to models addressing the changing spatial distribution of other variables, including the consumption of housing, goods, or services. Understanding the (post-)pandemic geography of consumption and its driving forces has attracted growing interest in the literature. For instance, the transition toward WFH not only shifts consumption of housing from dense urban centers with high WFH capacity to less densely populated suburban rings but also withdraws expenditure on consumer services from the centers of the metropolitan areas (e.g., Althoff et al., 2022; Barrero et al., 2021b; Brueckner et al., 2021; Davis et al., 2021; Delventhal and Parkhomenko, 2020; Ramani and Bloom, 2021). As a consequence, the new organization of work is likely to generate critical economic consequences for many lower-skilled individuals who depend on distance workers' expenditures. Thus, determining the magnitude, direction, and persistence of the shifts toward WFH remains of great importance for the post-Covid era. Accurate and detailed information on the distribution of WFH feasible jobs, differences in regional capacities, and potential for shifts toward WFH triggered by the Covid-19 shock are thus key to such endeavors.

2.5 Comparison of Task-Based and Survey-Based Measures

How does our survey-based measure of WFH capacity compare to popular task-based measures à la Dingel and Neiman (2020)? The rich data contained in the BIBB/BAuA Survey allows us to construct a task-based measure of WFH feasibility following the task-exclusion approach proposed by DN. Using the BIBB/BAuA Survey instead of O*NET data enables us to compute and compare WFH feasibility for Germany at the individual level.[20] The tasks and work conditions included in our data do not exactly match the tasks included in O*NET. We thus choose the relevant job characteristics that are most similar to those determined by DN. In particular, we assume that an employee's job is incompatible with *full-time* WFH if at least one of 11 conditions is met. These include, for instance, frequently carrying heavy loads, frequently handling microorganisms, working the majority of the time outdoors, or never using the Internet or email.[21] The full list of conditions is reported in Appendix Table B.10. Overall, the task-exclusion approach suggests that 34 percent of jobs can be performed entirely at home, a value that is remarkably close to the 37 percent calculated by DN for the German

[20] See e.g., Gottlieb et al. (2021) and Lewandowski et al. (2022) who demonstrate that cross-country differences in task content within the same occupations are sizeable.

[21] Specifically, if respondents rate any of the following as true, we code their job as not feasible for full-time WFH: Never using the Internet or E-Mail processing; Frequently lifting or carrying loads of more than 10 kg (women) or 20 kg (men); Frequent exposure to smoke, dust, gases, or vapor; Frequent exposure to cold, heat, moisture, humidity or draughts; Frequently handling microorganisms such as pathogens, bacteria, moulds or viruses; Frequently working with oil, grease or dirt; Works the majority of time outdoors; Frequently repairing or renovating; Frequently protecting, guarding, monitoring, or regulating traffic; Frequently cleaning, disposing of waste or recycling; Frequently monitoring or controlling machines, plants, or technical processes.

economy based on O*NET data. At the individual level, 29 percent of jobs are classified as WFH feasible according to both the replicated DN measure and our survey-based indicator (see Table 2.2). 28 percent of jobs are classified as WFH feasible according to the survey-based indicator but not according to the task-exclusion approach. Following the logic of DN, the task-exclusion approach aims at reflecting opportunities for working full-time from home. Thus, this portion can be interpreted as jobs that are only part-time WFH feasible. Only 5 percent of survey respondents rule out the possibility of WFH, while the task-exclusion measure suggests that WFH is feasible full-time. While this inconsistency may reflect the fact that the task-exclusion measure is too lax at identifying job characteristics that preclude WFH, we cannot reject the possibility of measurement error in the survey.

Table 2.2 : Individual-Level Comparison of Survey-Based and Task-Based Measure of WFH Feasibility

	Task-based WFH feasibility =1	Task-based WFH feasibility =0
Survey-based WFH feasibility = 1	28.9%	28.3%
Survey-based WFH feasibility = 0	5.2%	37.6%

Notes: The table compares our survey-based indicator with a task-based indicator of WFH feasibility at the individual level ($N =$ 17,160). The task-based indicator is computed using the task-exclusion approach proposed by Dingel and Neiman (2020) (see Appendix Table B.10 for details). Values of 1 indicate that WFH is feasible according to the corresponding measure. Data from the 2018 BIBB/BAuA Employment Survey.

Plotted at the occupational level, both measures show a remarkable similarity. Figure 2.7a reports the linear fit between the replicated DN measure and our survey-based measure. We find a strong correlation of 0.93 between the two approaches ($R^2 = 0.86$). The slope of the OLS line is statistically indistinguishable from one, and thus, effectively parallel to the 45-degree line. This suggests that the different measurement approaches primarily differ in terms of the estimated level of WFH capacity and much less with respect to the distribution across occupations. This discrepancy is consistent with part-time WFH feasible jobs that are captured in the survey but not in DN's index.

For further comparison, we compute two additional task-based measures inferred from our previous analysis of the determinants of WFH feasibility in Section 2.3.2. First, as working with a computer constitutes the strongest predictor of WFH feasibility, we compute the share of jobs that require frequent PC use as a simple proxy of WFH capacity. The second measure follows the task-exclusion approach by assigning zero WFH feasibility to jobs that require one or more of the tasks and work conditions that constitute negative and statistically significant predictors for WFH feasibility. These include frequently "nursing, caring, or healing", frequently "working standing up", frequently "working under noise", and frequently "performing manual work that requires a high degree of skill, fast sequences of movements, or greater force". We refer to this index as the estimation-implied measure.[22]

Figure 2.7b plots the two additional task-based measures against our survey-based measure at the occupational level. The results again show remarkable similarity with the survey-based approach. The slopes of the OLS lines of PC intensity and the estimation-implied measure are statistically indistinguishable from one (and thus parallel to the 45-degree line), suggesting that these measures differ, on average, only by a constant value. The correlation between PC intensity (the estimation-implied measure) and survey-based WFH is 0.80 (0.85). The regression lines of the estimation-implied measure and the replicated DN index are even statistically indistinguishable, despite using entirely different job characteristics as exclusion criteria for WFH feasibility.

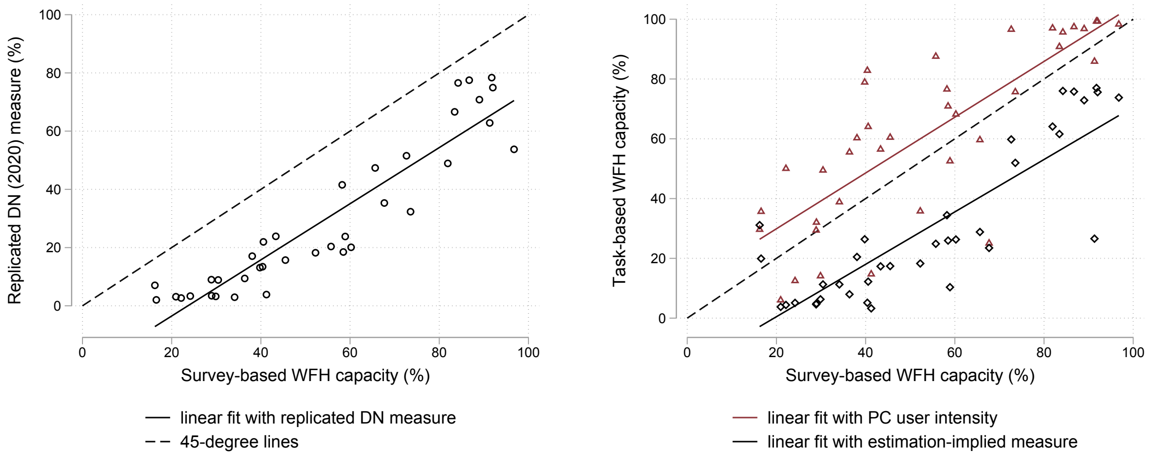
Overall, these results indicate that under reasonable assumptions, even very simple task-based measures of WFH capacity, such as the share of PC users, perform well at capturing differences across occupations. There is, however, greater sensitivity to the level of WFH capacity depending on the number and type of job characteristics deemed incompatible with WFH. This is consistent with the sizable variation in task-based estimates for the German WFH capacity discussed above. Still, for most applications, task-based measures will constitute suitable inputs that accurately capture relevant variation in WFH capacity.

2.6 Concluding Remarks

In a collective effort to reduce infection risk, the Covid-19 crisis has prompted a massive shift toward WFH. Evidence suggests that firms invested heavily to maintain business operations, while their employees were unable (or not allowed) to work from company premises (Barrero et al., 2021b). We shed light on the feasibility constraints of WFH during the pandemic by developing a measure of WFH capacity for the German economy, drawing on a rich employment survey and administrative employment data. Unlike most previous studies, our measure reflects the self-assessment of employees of their own job, includes jobs that are only suitable for part-time WFH, and uses information specific to the German economy. We find that 56 percent of jobs can be done at least partially from home. WFH feasible jobs are largely located in urban, densely populated areas, and in highly digitized industries. Using individual-level data on tasks and work conditions, we demonstrate that heterogeneity in WFH feasibility is mostly explained by differences in task content. OLS estimates suggest that WFH

[22] Notice that none of the features used to compute this measure correspond to the job characteristics used to replicate the DN index.

Figure 2.7 : Comparison of Survey-Based with Task-Based Measures of WFH Capacity



(a) Comparison with replicated DN measure **(b) Comparison with PC intensity and estimation-implied measure**

Notes: The figures report linear fits between the task-based measure of WFH capacity and our survey-based measure at the 2-digit occupation level. The replicated DN measure in (a) uses tasks and work conditions of the BIBB/BAuA that are most similar to the original conditions used in Dingel and Neiman (2020). The estimation-implied measure in (b) is computed based on the task-exclusion approach using tasks and work conditions that constitute negative and statistically significant predictors for WFH feasibility (see Section 2.3.2). PC use intensity in (b) is the share of employees who report frequently working with a computer. Data from the 2018 BIBB/BAuA Employment Survey.

feasible jobs are typically characterized by cognitive, non-manual tasks, and, in particular, by PC usage. By contrast, worker characteristics drive selection into actual WFH prior to the Covid-19 crisis. In particular, lower-wage and lower-educated workers were significantly less likely to WFH despite having a WFH feasible job.

We compare our survey-based measure with task-based measures of WFH capacity, which are very popular in the literature and typically rely on manually classifying the compatibility of tasks with WFH. The results reveal that task-based approaches capture differences in WFH capacity across occupations quite accurately on average, but vary in terms of the level of WFH capacity. We suggest that in settings with limited data availability, a simple measure of PC use intensity will constitute a suitable measure of WFH capacity.

We show that our WFH index constitutes a strong predictor of actual WFH outcomes during the crisis, at the occupation, industry, and county level, and discuss different applications in the context of Covid-19. As such, it is a useful measure to design targeted policies or evaluate social distancing mandates in the work context. It can provide a key element for models used in the burgeoning literature addressing the consequences of the Covid-19 shock for the organization of work and the spatial distribution of consumption.

3 My Home is My Castle – The Benefits of Working from Home during a Pandemic Crisis*

3.1 Introduction

The global Covid-19 pandemic is the most severe health crisis since the Spanish flu, costing millions of lives worldwide. In addition to the public health calamity, the spread of the virus has caused a harsh economic downturn. Most economists agree that there is little trade-off between fighting the pandemic and stabilizing the economy in the medium term (Kaplan et al., 2020): mitigating the economic impact of Covid-19 requires curbing the pandemic because individuals' behavioral responses to a large-scale outbreak have severe economic consequences. While voluntary behavioral changes can play an important role in reducing infections, these are generally too small and occur too late, as individuals do not fully take into account the infection externalities they have on others (Jones et al., 2020). Government-mandated behavioral changes via non-pharmaceutical interventions (NPIs) are thus necessary in order to keep the virus at bay (Eichenbaum et al., 2020). The short-run costs and benefits of different NPIs may vary substantially though: while strict lockdowns with mandated stay-at-home-orders and business closures are considered to be the most effective NPI to fight the pandemic (Flaxman et al., 2020), they are economically extremely costly (Fadinger and Schymik, 2020). By contrast, other NPIs that aim at reducing social interactions usually have a more moderate impact on infections and the economy (Brotherhood et al., 2020).

In this paper, we study the impact of one specific NPI: working from home (WFH, telework). Using data for Germany, we show that WFH is an effective measure to simultaneously maintain economic activity and mitigate the spread of SARS-CoV-2.[1] To quantify the economic and epidemiological effects of WFH, we compute an index of WFH potential, drawing on a pre-crisis employment survey. We collapse individual-level information about the teleworkablity of respondents' jobs to the occupational level and combine the resulting shares with

* This chapter is based on joint work with Harald Fadinger and Jan Schymik, and was published in the *Journal of Public Economics*, 2021.

[1] Compared to other NPIs, an important feature of WFH is the alignment of private and public incentives: WFH allows individuals to work efficiently, to preserve their jobs, and at the same time to reduce infection risks. By contrast, individuals may be reluctant to respect a government-imposed lockdown because of the associated economic costs that may outweigh personal health benefits. This makes it much easier to achieve a high level of compliance for WFH orders than for other NPIs, even in the absence of strict monitoring.

administrative data on the occupational composition of all 401 German counties.[2]

First, we investigate the impact of WFH on economic activity during the spring 2020 wave of the Covid-19 pandemic. The main instrument used to deal with the labor-market impact of the pandemic in Germany was the federal short-time work scheme (*Kurzarbeit*), which was substantially expanded in March 2020 and provided wage subsidies of around two-thirds of foregone earnings to companies in "inevitable" economic distress during the year 2020.[3] While unemployment hardly increased in Germany in the spring of 2020, firms filed short-time work (STW) applications for around 30 percent of the labor force.[4] Using administrative data and firm-level survey information, we show that regions and firms with a higher WFH potential experienced significantly fewer applications for STW.[5] A 1 p.p. increase in the share of teleworkable jobs at the county level reduces STW applications relative to total employment by between 0.8 and 2.6 p.p. At the firm level, we use industry-specific WFH potential as an instrumental variable for the actual uptake of telework in April 2020 to provide causal evidence for the employment- and output-preserving effect of telework. Firms that intensified telework during the crisis were 49 to 72 p.p. less likely to file for short-time work and up to 75 p.p. less likely to report adverse effects of the Covid-19 crisis. Overall, our results imply that telework helped strongly to mitigate the short-run negative effects of supply-side restrictions imposed by confinement rules on firms and workers. This is consistent with evidence for the US: Papanikolaou and Schmidt (2022) find that US industries with higher WFH potential experienced smaller declines in employment in spring 2020, while Koren and Peto (2020) show that US businesses that require face-to-face communication or close physical proximity were particularly vulnerable to confinement.

Second, we study the effect of WFH on SARS-CoV-2 infections before and after confinement rules were imposed in Germany. While the first cases of SARS-CoV-2 in Germany were recorded in late January, the pandemic really gained momentum in early March when people returned from skiing holidays in Austria (Felbermayr et al., 2021). In the meantime, authorities gradually ratcheted up restrictions on public life.[6] On March 22, all German states imposed strict lockdown measures in a coordinated manner.[7] We exploit detailed weekly panel data on

[2] This strategy is akin to Bartik (1991) and Blanchard and Katz (1992), who exploit exogenous variation in regional economic structure to assess labor-market impacts of economic shocks.
[3] In September 2020, the duration of the scheme was extended into 2021.
[4] This contrasts with the US, where due to the absence of a comprehensive furloughing scheme, the pandemic led to a steep increase in unemployment claims (Forsythe et al., 2020).
[5] By contrast, Kong and Prinz (2020), find no impact of stay-at-home orders on unemployment claims using high-frequency data for the US.
[6] See Weber (2020) and Appendix C.2 for details on the confinement measures in Germany.
[7] Exceptions were Bavaria and Saxony, which started confinement already a day earlier.

SARS-CoV-2 infections and deaths during the first wave of the pandemic from its outbreak until the end of the confinement (January 29 until May 06, 2020) for all 401 counties. Using cross-sectional variation, we find that a 1 p.p. increase in the share of teleworkable jobs is associated with a 4.5 to 8.1 percent reduction in the infection rate. Exploiting temporal variation within counties, we show that the infection-reducing effect of WFH was larger in the first weeks of the pandemic and faded after the implementation of lockdown measures.[8] This finding is in line with modeling studies from the epidemiological literature (Koo et al., 2020), which suggest that WFH is more effective in containing the virus at low levels of infections. Additionally, we use mobility data collected from a large German mobile phone provider to show that our results are consistent with mobility patterns. The level of work-related trips was systematically lower in high-WFH-ability regions before confinement, but this differential in mobility disappeared once the lockdown was in place and most people stayed at home. Overall, our results imply that WFH and lockdowns are to some extent substitutable policies. This has important implications for the reactivation period of the economy: to keep infection rates low while maximizing the level of economic activity, WFH should be a policy prescription as long as infection risks remain present.[9]

An arguable limitation of our study is that we primarily exploit cross-sectional variation in WFH opportunities instead of (quasi-)random variation in actual WFH uptake during the crisis. We address potential threats to validity in several ways: First, by employing WFH measures that proxy for WFH *feasibility* we reduce the risk that our estimates are confounded by other behavioral responses during the crisis that may be interdependent with *actual* WFH. In other words, we estimate the effect of the intention to treat rather than the treatment effect. Second, we account for a large set of potentially confounding factors. In our regional analysis, these include differences in population density, local economic conditions, regional healthcare capacities, the morbidity of the local population, and differences in social capital. Third, we corroborate our regional analysis with firm-level and industry-level data. Fourth, we also exploit time variation in short-time work and infections within counties using difference-in-differences estimators. Finally, we show that our results are robust to a battery of sensitivity checks reported in the Appendix.

Our study builds on the recent contributions quantifying the potential of jobs for telework. Dingel and Neiman (2020) determine the teleworkability of occupations by assessing the

8 Exploiting within-county variation, we find an around 2 to 5 percent larger reduction of infection rates before the confinement on average.

9 In line with this prescription, Kucharski et al. (2020) find strong complementarities between WFH and contact tracing in reducing effective reproduction numbers based on a modeling study.

importance of workers' presence at the workplace using task information. Instead, we draw on the approach of Alipour et al. (2023), who rely on an administrative employee survey that directly reports on workers' home-working practices before the Covid-19 outbreak and their own assessments of home-working opportunities to construct measures of WFH potential. In sensitivity checks, we show that our results are robust to using Dingel and Neiman's task-based measure.[10]

Furthermore, we contribute to the literature studying the costs and benefits of WFH by socio-economic status (SES). According to our survey, a key individual characteristic associated with having a job with high WFH potential is having a university degree. In line with this finding, Mongey et al. (2021) show that US workers with low WFH potential are less educated, have lower income, and fewer liquid assets. Using real-time survey data, Adams-Prassl et al. (2020) document a negative correlation between US and UK workers' self-reported share of teleworkable tasks and the probability of job loss during the Covid-19 pandemic. We complement their findings by showing a causal effect of WFH on reducing firms' short-time work applications. In this respect, WFH tends to exacerbate economic inequality during the pandemic. However, we also provide evidence for positive economic spillover effects of WFH: a one-percent increase in WFH potential is associated with a more than proportionate reduction in the probability of short-time work. Thus, when some employees start working from home, also jobs without WFH opportunities are preserved.

The association between SES and health is well documented: High-SES individuals tend to live longer, even though the precise channels of this finding remain unclear (Chetty et al., 2016; Stringhini et al., 2017). In the context of the Covid-19 pandemic, the correlation between a job's WFH potential and the individuals' SES is a specific mechanism contributing to this outcome: a larger WFH potential is associated with significantly fewer regional SARS-CoV-2 infections and deaths. This mostly benefits high-SES individuals, who can work from home and stay healthy. We also find that the impact of regional WFH potential on infections is stronger in high-income regions. This is in line with Chang et al. (2020), who find smaller reductions in mobility and, correspondingly, more SARS-CoV2 infections in low-income neighborhoods of US cities.[11] However, there are also indirect health benefits of higher regional WFH potential to workers who cannot engage in telework: lower contact rates while commuting and at the workplace also reduce the infection risk of workers who cannot work remotely.

[10] Other survey-based WFH studies are, for example, Papanikolaou and Schmidt (2022) or Von Gaudecker et al. (2020).

[11] Glaeser et al. (2020) – drawing on data for 5 US cities – show that higher mobility is associated with more SARS-CoV-2 infections.

Finally, we contribute to the literature investigating the impact of pandemic-related labor supply shocks. Karlsson et al. (2014) study the impact of the Spanish flu on economic outcomes in Sweden. Duarte et al. (2017) estimate the effect of work absence due to the 2009 flu pandemic on labor productivity in Chile.

In the next section, we examine the impact of WFH on regional and firm-level short-time work filings and firm distress. In Sections 3.3 and 3.4, we look at the relationship between WFH and SARS-CoV-2 infections at the county level, both before and after confinement, and study regional variation in mobility patterns during the first wave of the Covid-19 pandemic. Section 3.5 concludes.

3.2 WFH and Labor Market Adjustments during the Covid-19 Crisis

3.2.1 Measuring WFH in Germany

To measure the geographical distribution of jobs that can be performed at home, we follow Alipour et al. (2023) and combine representative employee-level information from the 2018 BIBB/BAuA Employment Survey with regional employment counts from the Federal Employment Agency. Specifically, we first aggregate individual-level information on WFH to the occupational level and use information on the composition of occupations in all 401 counties to further aggregate occupation-specific WFH shares to the county level. Thus, by construction, regional differences in WFH potential are determined by county-level variation in the occupational composition.

We compute three measures of WFH feasibility: First, the share of employees in a county who work from home “always” or “frequently” (*WFH freq*). Second, the share of employees working at home at least occasionally (*WFH occ*). And third, the share of employees who have ever worked from home or who do not exclude the possibility of home-based work provided the company grants the option (*WFH feas*). The last measure hence identifies jobs that can (at least partly) be done from home, independently of workers’ previous teleworking experience. Consequently, we interpret *WFH feas* as an upper bound for the share of employees who may work from home during the crisis. As switching to telework during the pandemic is arguably associated with transition costs, we conjecture that frequent and occasional teleworkers will be able to use telework earlier and to a greater extent than employees who have no previous teleworking experience. We thus interpret *WFH freq* as a lower-bound estimate for the share of employees actually working from home during the pandemic.

In the aggregate, before the pandemic about 9 percent of employees worked from home on a regular basis, 26 percent did so at least occasionally, and 56 percent have jobs that can be partly or completely performed at home. At the worker level, differences in WFH potential are mainly attributable to different task requirements of teleworkable and non-teleworkable jobs. Jobs that can be done from home are typically distinguished by a high content of cognitive, non-manual tasks, such as working with a computer, researching, developing, and gathering information (Alipour et al., 2023; Mergener, 2020).[12] Details on the variable construction and descriptive statistics are reported in Appendix C.1.

3.2.2 WFH and Short-Time Work: Regional Evidence

To contain the spread of the Coronavirus, the German government enforced drastic containment measures. Restrictions were gradually tightened starting in February 2020 and from March 22 to May 6 a strict lockdown was imposed (see Appendix C.2 for details). Many companies, especially in the hospitality, food services, and retail sector were subjected to mandatory shutdowns. Survey evidence suggests that during this period, nearly 40 percent of the workforce switched to telework to reduce infection risk (Eurofound, 2020). The consequences of the economic shock are reflected in a large number of filings for short-time work allowances. The federal STW scheme (*Kurzarbeit*) was substantially expanded from March 2020 until the end of the year.[13] It is normally used during heavy recessions and enables companies in “inevitable” economic distress to cut labor costs by temporarily reducing their employees’ regular working hours by up to 100 percent instead of laying them off. Up to 67 percent of employees’ foregone earnings are subsequently compensated by the Federal Employment Agency through the unemployment insurance fund.[14] In March and April 2020, STW applications for 10.7 million workers were filed, corresponding to 31 percent of total employment in September 2019. Note that in Germany, short-run labor market adjustments to the Covid-19 shock occurred primarily in terms of STW expansions and only very little happened via an increase in unemployment. In contrast to the unemployment surge in the US (see Coibion et al., 2020), the net number of unemployed in Germany increased by less than 250,000 in March and April 2020.[15]

[12] In Appendix C.3 we discuss correlations between employee characteristics and our WFH measures. Most of the variation in WFH across individuals is explained by occupational differences, while the skill level remains very significant even when accounting for workplace and demographic characteristics.
[13] In September 2020, it was extended until the end of 2021.
[14] Previous research indicates that STW schemes can be very effective in retaining employment and avoiding mass layoff during economic crises (see e.g., Balleer et al., 2016, Cooper et al., 2017, Boeri and Bruecker, 2011).
[15] In comparison, this number reached 3.3 million during the Great Recession in 2008/2009 (Bundesagentur für Arbeit, 2020).

In this section, we assess whether the possibility to work from home mitigates the Covid-19 shock by increasing the likelihood that workers can continue to perform their job instead of being put on short-time work. We examine this relationship by estimating the impact of WFH on STW applications at the regional level. To this end, we source administrative records on STW applications in March and April 2020 from the Federal Employment Agency. In Section 3.2.3, we provide corroborating evidence on the relationship between WFH and STW using firm-level data.

When interpreting the relationship between WFH and STW during the pandemic, one may be concerned about endogeneity for two reasons. First, regions with higher infection rates are likely to experience more STW applications, as a higher fraction of firms are forced to shut down, and more WFH because of greater safety concerns. We cannot directly control for differences in infection rates, however, as this would provoke a "bad control bias": WFH is likely to have a causal impact on both STW and local infection rates. We instead account for other county characteristics which determine the regional spread of SARS-CoV-2, such as infections in neighboring regions, the local age structure, population density, population health, healthcare infrastructure, and factors that have been shown to proxy for people's disposition to comply with public containment measures, among others. Second, there may be omitted regional characteristics that are correlated with the fraction of teleworkable jobs and also affect short-time work applications.

We thus account for a wide range of potential confounding factors at the county level. We will use the same sets of covariates in the regional infection analysis in the following Section 3.3. The first set of covariates comprises our *Baseline* controls, which we include in all specifications. Baseline controls include the number of days since the first detected infection to account for the non-linear dynamics of the pandemic. To deal with the transmission of infections from neighboring counties, we control for spatially weighted infection rates. These are defined as the log-weighted mean of infection rates in other counties, using inverse distances as weights. To account for differences in the density of human activity, baseline controls also include region-specific settled area, population, and GDP (all in logs). Second, we include a set of *Economy* controls to account for more detailed regional differences in economic activity beyond GDP, including the fraction of (in- and outward) commuters in the local workforce, an infrastructure index that captures the reachability of airports, the fraction of households with broadband internet access ($\geq$ 50 Mbps), the fraction of low-income households in the county ($\leq$ EUR 1,500 per month) and the employment shares in the aggregate services, manufacturing and wholesale/retail sectors. Third, we include *Health* covariates to account for regional differences in healthcare capacity and the morbidity of the local population. Health covariates include the fraction of male population, the fractions of the population in working age (15-64 yrs.) and elderly ($\geq$ 65 yrs.), remaining life expectancy at age 60, the death rate, the number of intensive-care-unit beds per 100,000 inhabitants and the number of hospitals per 100,000 inhabitants. Lastly, we account for differences in social capital, which have been shown to explain varying degrees of compliance with social distancing behavior and containment measures (Barrios et al., 2021; Borgonovi and Andrieu, 2020). Our *Social Capital* controls include crime rates, voter turnout and vote shares of populist parties in the 2017 federal election, and the number of registered non-profit associations per 100,000 inhabitants. Summary statistics and variable sources are reported in Appendix C.1.

Table 3.1 reports the OLS results from estimating the regional percentage share of employees for which STW was filed in March and April 2020 as a function of regional WFH potential and controls. The table is divided into three panels, one for each of our WFH measures. Regressions are weighted with pre-pandemic employment to give more importance to larger counties. This allows us to recover the conditional mean association between STW applications and telework at the individual level. Columns (1) to (5) report the OLS coefficients controlling for the different subsets of controls. Column (5) includes the full set of covariates.

The relationship between local WFH potential and STW applications is negative and significant at the one percent level for all three WFH measures and across all specifications. The estimates for *WFH feas* are consistently smaller than for *WFH occ* and *WFH freq*. This aligns with our interpretation that our measures reflect the upper and lower bounds of a county's actual WFH capacity, respectively. The estimates in Column (5) suggest that a 1 p.p. increase in local WFH capacity reduces the share of STW applications by 0.84 to 2.6 p.p. Increasing WFH by one standard deviation thus is associated with a 3.5 to 4.4 p.p. decrease in the local fraction of jobs registered for STW. A coefficient above one points to spillover effects from telework: to the extent that WFH allows firms to maintain business operations during the crisis, employees who continue to work on the company premises also benefit by experiencing a lower risk of STW.[16] Overall, the results strongly support the employment-preserving effect of WFH during the crisis.

Section C.4 in the Appendix discusses several robustness checks. First, we show that using realized STW instead of STW applications gives similar results. We also perform a placebo test and show that in January 2020 (the month before the Covid-19 crisis started), there

[16] Our analyses of the epidemiological effects in Section 3.3 suggest that these employees equally experience a lower exposure to infection risk.

was no statistically significant relation between WFH and STW. Finally, we use a difference-in-differences estimator to confirm that WFH reduced STW applications only during the pandemic. Section C.7.1 corroborates the regional analysis with estimations exploiting industry-level variation. We also show that our results are robust to using Dingel and Neiman's task-based WFH feasibility index instead of our survey-based measures.

3.2.3 WFH, Short-Time Work, and Covid-19 Distress: Firm-Level Evidence

Next, we move to the firm level to assess whether WFH had a mitigating effect on the economic shock of the Covid-19 pandemic. We draw on the ifo Business Survey, a representative survey of German firms, which elicits information on business expectations and conditions as well as various company parameters on a monthly basis.[17] In April 2020, roughly 6,000 firms were questioned about the business impact of and the managerial responses to the pandemic. Among a list of non-exclusive mitigation measures, the most frequently mentioned response was the intensified use of telework. Overall, nearly two-thirds of the companies stated greater reliance on telework as part of their strategy to cope with the crisis. Almost half of the surveyed companies filed for STW and 30 percent report a "very negative" impact of the pandemic on their business. In the following, we use these two indicators as our main outcome measures of the economic impact of the crisis on firms.

The firm-level analysis allows us to address several endogeneity concerns regarding the WFH estimates. In particular, there may be factors that simultaneously affect firms' disposition to use STW and WFH in their efforts to cope with the crisis. For instance, idiosyncratic infection risk might increase the likelihood of employing both STW and telework, leading us to underestimate the mitigating effect of WFH in an OLS regression. Mandatory business closures, on the other hand, are likely to increase the propensity of STW while reducing the likelihood of telework. Demand-side shocks may also correlate with STW and WFH and cause bias. We account for these potential confounding factors by controlling for observable covariates and by using our measure of industry-level WFH potential, which is plausibly orthogonal to firms' idiosyncratic Covid-19 shocks, as an instrument for intensified telework usage. Since firms expanded WFH both at the intensive and the extensive margin, we use *WFH feas*, which measures the overall share of teleworking jobs in a given industry, as our preferred instrument

[17] See Link (2020), Buchheim et al. (2020) and Sauer and Wohlrabe (2020) for a more detailed description of the survey.

and estimate the following 2SLS specification:

$$y_i = \beta_0 + \beta_1 \times \textit{telework}_i + \delta' X_i + \alpha_{c(i)} + \varepsilon_i \tag{3.1}$$

$$\textit{telework}_i = \pi_0 + \pi_1 \times \textit{WFHfeas}_{s(i)} + \lambda' X_i + \alpha_{c(i)} + v_i, \tag{3.2}$$

where y_i is either a dummy variable that indicates if firm i applied for STW or if the firm reports a very negative impact of the pandemic on business. Our variable of interest $\textit{telework}_i$ is a dummy indicator for firms that increased telework in April 2020. The instrument $\textit{WFHfeas}_{s(i)}$ is the WFH potential of firm i's industry s at the 2-digit level. The regressions also include county fixed effects ($\alpha_{c(i)}$) and a set of control variables (X_i). The baseline controls include firm size, firms' export share, survey fixed effects, and fixed effects for the survey completion date. Additional controls include self-reported business conditions and business expectations in Q4 2019 and an indicator for firms operating in an industry subject to mandatory business closure in April 2020.[18] In our sample, nearly 16 percent of businesses were affected by mandatory closures or severe restrictions.[19] In Table C.11 in Appendix C.5, we report results with demand controls by including the leave-one-out 2-digit industry average of firms reporting a drop in demand due to the Covid-19 crisis. We do not include the demand control in the main table as the information is only available for a reduced sample of firms. Summary statistics of the firm-level variables are reported in Appendix Table C.3.

Table 3.2 reports the results for our two outcomes, STW applications (Panel A) and Covid-19 distress (Panel B). We report the reduced-form (Columns 1 and 2), OLS (Columns 3 and 4), and IV (Columns 5 and 6) regression results and the first-stage coefficient $\hat{\pi}_1$.[20] Odd columns include baseline controls only; even columns add our additional controls. Standard errors are clustered at the 2-digit industry level. Our instrument *WFH feas* is negatively correlated with both outcomes and significant at the one percent level. The first-stage Kleibergen-Paap Wald F statistics are above 50, implying that the instrument is strong. The OLS estimates indicate that reliance on telework is associated with a statistically significant decrease in the likelihood of filing for STW (reporting an adverse Covid-19 shock) by 12.4 (14.7) p.p.; these estimates are reduced to 5.4 (6.5) once we include all covariates. Furthermore, firms reporting a weaker state of business before the pandemic are also more likely to file for STW and report

[18] Business conditions (expectations) are elicited on a trichotomous scale including negative (more unfavorable), neutral (roughly the same), and positive (more favorable).

[19] Mandatory closures of non-essential businesses and institutions were introduced by the end of March 2020 and were gradually lifted from April 19, onward. The shutdown primarily affected restaurants (only pick-up and delivery services allowed), retail stores, close-proximity services (e.g., barber shops), hotels, and cultural institutions (e.g., museums, nightclubs).

[20] Table C.10 in Appendix C.5 reports the full first-stage regressions.

a particularly negative impact of the crisis. Unsurprisingly, the outcomes for firms that were subject to mandatory business closures appear also significantly worse.

Columns (5) and (6) show that the IV estimates are negative and significant at the one percent level: relying on telework reduces the firm-level probability of filing for STW (report an adverse Covid-19 impact) by 49.2 (39.9) p.p. when accounting for all covariates. Notice that controlling for mandatory business shutdowns in Column (6) reduces the magnitude of the IV estimate considerably compared to Column (5). As closures were specifically mandated in industries characterized by high degrees of physical proximity among workers and customers and low teleworking potential (e.g., food services, retail trade, personal services), accounting for this variable is important for the reliability of the IV strategy. The IV estimates are substantially larger than the OLS estimates. A plausible explanation is that OLS estimates are biased towards zero due to unobserved idiosyncratic shocks. For instance, a confirmed Covid-19 case in the company will likely prompt an immediate managerial response by mandating telework and putting a fraction of the workforce on STW. In Appendix C.5, we replicate the estimations on our reduced sample, additionally controlling for the pandemic-induced demand shock. The likelihood of filing for STW and reporting an adverse effect of the crisis increases significantly when demand contracts. The WFH coefficient estimates remain statistically significant and their magnitude does not change substantially. Overall, the firm-level results corroborate the evidence from the regional analysis, showing that WFH has effectively mitigated the Covid-19 shock.

3.3 WFH and SARS-CoV-2 across Counties

We now turn to the impact of WFH on SARS-CoV-2 infections. WFH is expected to reduce infections for the following reasons. A higher county-level WFH share reduces the fraction of workers working on-site. This directly lowers the contact rate – defined as the average number of contacts of an infected individual, which is a key parameter in infectious disease models (Giesecke, 2002) – by reducing the number of personal contacts both at work and while commuting. In addition, a larger share of workers engaging in telework also allows co-workers who have to work on-site to keep more physical distance. We first study the effectiveness of WFH in reducing SARS-CoV-2 infections using cross-sectional variation before exploiting time variation within counties in Section 3.4.

To measure SARS-CoV-2 infections and fatality cases in Germany, we use administrative data provided by the Robert-Koch-Institute (RKI). To minimize measurement issues caused by reporting lags over weekends, we consider weekly data measured on Wednesdays. Our final dataset covers 15 weeks of the pandemic, from week 1 (January 23-29, 2020) to week 15 (April 30 - May 06, 2020). The sample covers the beginning of the pandemic in Germany and ends with the lifting of confinement after the first wave of the pandemic.[21]

To explore the cross-sectional association between regional variation in telework and the spread of Covid-19 across counties, we regress the log of regional SARS-CoV-2 infection rates, defined as the cumulative number of cases relative to the number of inhabitants, on our regional WFH measures, using disease data from the last sample week (Wednesday, May 06, 2020).[22] In all specifications, we weigh observations according to their population. Equivalently to the county-level results on STW in the previous section 3.2, we use our four distinct groups of covariates. All specifications include the set of *Baseline* covariates. Furthermore, we alternately include the *Economy*, *Health*, and *Social Capital* covariates. The most stringent specification includes the full set of controls.

Table 3.3 reports the estimation results. We find a robust negative association between WFH and infection rates across German counties throughout all specifications and WFH proxies. Our estimated coefficient of interest is significant at the one percent level for all WFH measures when including baseline controls in Column (1). Quantitatively, an increase in the WFH suitability (*WFH feas*) by 1 p.p. is associated with a 4.5 percent decrease in the local infection rate. An equivalent increase in *WFH freq* is associated with a 12 percent reduction in the infection rate. Consider the following thought experiment to illustrate the quantitative implication of the estimates: If Berlin, a county with a rather high share of *WFH freq* jobs (11.72 percent) had a one-standard-deviation lower share of such jobs, corresponding roughly to numbers for the county Bayreuth (Bavaria), this would imply 940 additional cases on top of the actual 5,992 cases that have been reported in Berlin as of May 06, 2020.

Note that we do not observe the actual fraction of workers WFH during the sample period. Instead, our WFH measures are proxies for this number. If there are adjustment costs for workers switching to telework due to Covid-19, *WFH freq* is plausibly most closely correlated with the actual WFH rate. We also observe the coefficient magnitudes of *WFH freq* to be larger compared to using *WFH occ*, which itself yields larger coefficient estimates than *WFH feas*. Importantly, because all three measures of telework are constructed with data collected before the Covid-19 crisis, the estimates are not subject to reverse causality. Instead, the coefficients on the WFH measures can be interpreted as reduced-form estimates, whose magnitude is

[21] See Appendix C.1 for a more detailed description and summary statistics of the RKI data.

[22] Results are robust to considering other weeks, see Appendix C.6.

plausibly downward biased relative to the true one due to mismeasurement.

When we add economy covariates in Column (2), the magnitude of WFH coefficients decreases slightly but remains significant at the one percent level for *WFH feas* and *WFH occ* and at the ten percent level for *WFH freq*. In Column (3), we use the set of health covariates instead and obtain very similar results compared to the baseline estimates from Column (1). Controlling for regional differences in social capital renders our WFH coefficients slightly larger compared to the baseline estimates and significant at the one percent level.[23] Lastly, we include the full set of controls in Column (5). The coefficients of interest remain significant at the one percent level for *WFH feas* and *WFH occ* and at the ten percent level for *WFH freq*.

We further assess the robustness and plausibility of the infection-reducing effect of WFH in Appendix C.6. Since systematic measurement error caused by regional variation in testing capacities might play a role in observing different infection rates, we show that our results are robust to considering fatality rates instead. We also show the robustness of the results in Table 3.3 based on a Poisson estimator, using either the number of infections or deaths as outcome variables to account for zero or few cases in some counties. To further assess whether the negative regional correlation between WFH and coronavirus infections indeed captures reduced workplace-related contagions, we interact WFH with regional working age population or employment shares. WFH shares have a stronger impact on SARS-CoV-2 infections in regions where a larger fraction of the population is in the labor force. In line with the literature studying the costs and benefits of WFH by SES (e.g., Chang et al., 2020), we also find health benefits of WFH to be larger in more affluent counties. We also replicate our results using infection data from other weeks. Lastly, we study the regional spillover effects of WFH in addition to the within-county effects stressed above. Our evidence suggests that commuting spillovers are important for commuting-intensive counties in both counties where many commuters have their workplace and counties where commuters reside.

3.4 WFH and SARS-CoV-2 Infections over Time

In this section, we further investigate how WFH affects the spread of Covid-19 using time variation within counties. A central policy question concerning confinement strategies is whether WFH has a complementary or a substitutive effect with respect to confinement. In other words, we ask if counties with a higher share of teleworkable jobs have lower infection rates because confinement can be implemented more effectively or if WFH instead allows for

[23] Bargain and Aminjonov (2020) and Barrios et al. (2021) show that compliance to containment policies depends on the level of social capital before the crisis.

more social distancing even in the absence of confinement.

3.4.1 Evidence from Infections before and after Confinement

To learn more about potentially time-varying effects of WFH on coronavirus infections, we now consider weekly panel data. We observe infection rates for each county over 15 weeks from January 29, 2020, to May 06, 2020. All German federal states simultaneously imposed confinement measures on March 23 in a coordinated way, except for Bavaria, which started the lockdown already on March 21. Thus, in our data, confinement is present during sample weeks 8-15.[24] We regress the weekly log infection rate on a set of terms interacting week dummies with *WFH freq*, controlling for a full set of county and week fixed effects and the log spatial infection rate. We also account for weekly precipitation, as rainfall might affect compliance with stay-at-home orders and local humidity conditions are likely to influence the transmission of the virus (Mecenas et al., 2020; Lowen and Steel, 2014).[25]

$$\log i_{it} = \sum_{t=1}^{T} \beta_t WFH_i \times t + \gamma' X_{it} + \delta_i + \delta_t + \varepsilon_{it}. \tag{3.3}$$

Here $i_{it} = I_{it}/L_i$ is the infection rate (cumulative infections divided by the number of individuals) in county i in period t, β_t captures the week-specific differential effect of *WFH freq* on infection rates, X_{it} is the vector of covariates and δ_i and δ_t are, respectively, county and period fixed effects. County fixed effects control for any unobserved county-specific factors correlated with infections and our WFH measures. We cluster standard errors at the county level. Figure 3.1 plots the estimated coefficients β_t and the 95-percent confidence band.

The weekly coefficient estimates in Figure 3.1 imply that WFH was particularly effective in reducing infection rates within counties at the earliest stage of the pandemic. Weekly coefficients of WFH are negative and significant at the one percent level for the first five sample weeks only; subsequently, the differential effect of WFH vanishes. Furthermore – presumably because there are fewer Covid-19 cases at the onset of the pandemic – confidence bands are substantially wider for the earlier weeks. The null hypothesis that the weekly WFH coefficients during pre-confinement weeks 1-7 are identical to those in weeks 8-14, after confinement rules were implemented by state governments, can be clearly rejected ($F = 28.80, p < 0.01$).

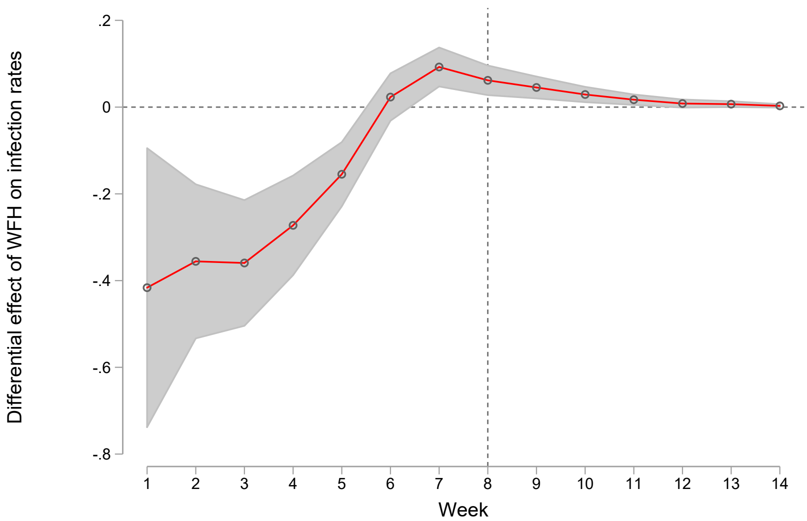
[24] See Appendix C.2 for a detailed description of confinement measures in Germany.

[25] To construct county-level rainfall, we use precipitation data from the Climate Data Center of the German Weather Service (*Deutscher Wetterdienst*). Daily observations of precipitation height are recorded at the station level. We interpolate the data to county centroids using inverse distance weighting from stations located within a radius of 30 kilometers. We compute weekly rainfall by averaging the daily values between consecutive Wednesdays.

Our finding that WFH is particularly effective at the beginning of the pandemic before the confinement lends empirical support to the epidemiological modeling studies that suggest a higher effectiveness of WFH in containing SARS-CoV-2 at low levels of infections (see Koo et al., 2020).

In the Appendices C.6 and C.7, we provide further robustness checks for the dynamic impact of WFH on infections. First, we estimate a simple difference-in-differences specification where we interact our WFH measures with a *pre confinement* dummy (weeks 1-7) and find a relatively larger effect of WFH on reducing infection rates before confinement rules came into effect. Second, we show the higher pre-confinement effectiveness of WFH is independent of local differences in confinement strictness. Lastly, we estimate a flexible dynamic spatial count model of disease transmission, based on a modeling approach from the epidemiological literature (Höhle, 2016). Compared to the panel estimates, this model has the following two advantages: *i.* it properly accounts for disease dynamics by including an autoregressive component of infections and *ii.* at the same time, it accounts for spatial correlation across counties. The estimates from this model confirm that WFH caused stronger health benefits before confinement was in place.

Figure 3.1 : The Effect of Working from Home on Infection Rates over Time



Notes: The figure plots coefficient estimates of $WFH_i \times t$ (using *WFH freq*, the percentage share of employees in the county with jobs that frequently do telework) on log infection rates by week (week 15 is absorbed by fixed effects). The dashed vertical line for week 8 indicates the week when the majority of confinement rules were set into force by federal states. The gray shaded area corresponds to 95-percent confidence intervals (with clustering at the county level).

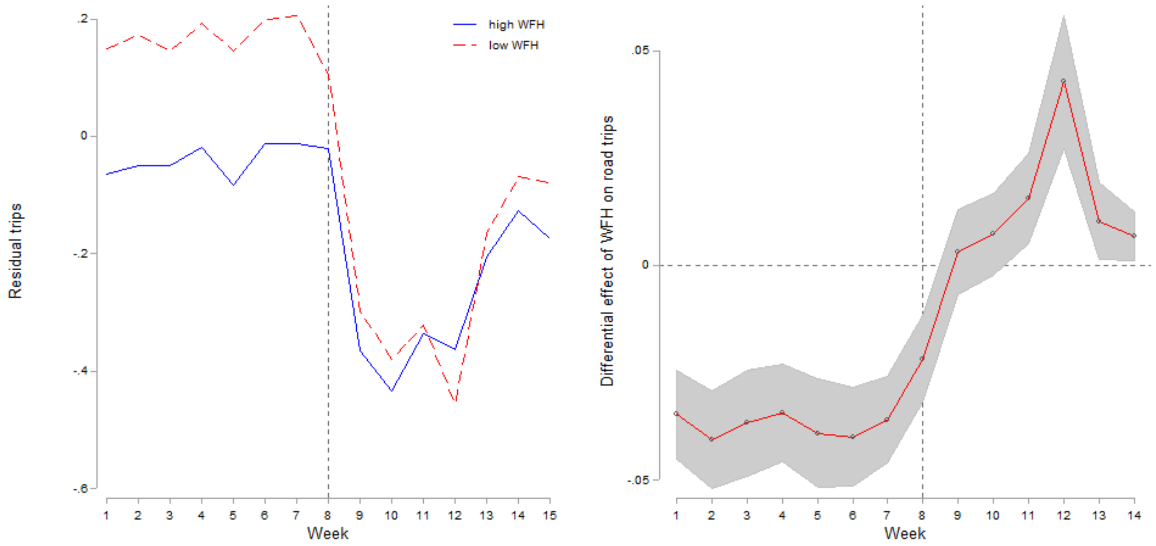
3.4.2 Evidence from Changes in Mobility Patterns

To explore the mechanism of why WFH was particularly effective in reducing infection rates during the early stages of the pandemic, we now consider adjustments in mobility patterns within counties over time. To study traffic movements, we use cell phone tracking data from Teralytics, a company that provides anonymized geo-location data of German cell phone users and identifies distinct trips by mode of transportation (motorized private transport, train, and plane).[26] Our measure of interest is the log of total weekly road trips by car within counties.[27] The data only report trips with a minimum length of 30 minutes and a minimum distance of 30 kilometers. Due to their nature, most of these trips are likely to be work-related and do not just capture recreational traffic. Between the end of January and the beginning of May, road mobility declined steeply in most counties (see Appendix C.7.2). To test for the role of WFH in reduced mobility, the left panel of Figure 3.2 plots the development of average residual road traffic within counties over time separately for regions with many and few teleworkable jobs. Average mobility is the mean residual log number of road trips within a county during a given week after controlling for GDP, population, and settled area (all in logs). High WFH (solid blue line) includes counties in the top 20 percentile of *WFH freq* and low WFH (dashed red line) includes counties in the bottom 20 percentile of *WFH freq*.[28]

The time series shows that regions with a higher share of teleworkable jobs experienced a lower level of traffic before the confinement after controlling for confounding factors.[29] Once confinement rules were implemented, there was a sharp decline in the level of road traffic in both groups of counties. While traffic was lower in high-WFH counties before confinement, counties experienced a convergence in traffic levels during the confinement, so that the drop in the number of road trips was larger in low-WFH regions. Towards the end of the confinement, traffic levels begin to move apart again. One explanation for this convergence in traffic patterns is the previously established association between WFH and STW. During the pandemic, 30 percent of employees in Germany were on short-time work. Once a large fraction of workers stayed home independently of whether they worked from there, the traffic-reducing effect of WFH became irrelevant. This interpretation is supported by the estimation results shown in the right panel of Figure 3.2. Similarly to the empirical infections model, we present weekly

[26] Teralytics is a Swiss company founded as a spin-off of the ETH Zurich and specialized in the collection and analysis of mobile network data. The company website is accessible at www.teralytics.net.
[27] We also consider commuting traffic by train in the Appendix.
[28] A similar pattern is visible when using different cutoff levels for *WFH freq* such as above/below the median or the top/bottom 10 percent.
[29] This is consistent with US evidence showing that local variation in the opportunity to do telework is a determinant for mobility levels (Brough et al., 2021).

Figure 3.2 : Working from Home and Decline in Regional Mobility



Notes: The left graph shows the development of average road mobility during the Covid-19 crisis. High WFH (solid blue line) includes counties within the top 20 percent of *WFH freq*, and low WFH (dashed red line) includes counties within the bottom 20 percent of *WFH freq*. Average mobility is the mean residual log number of road trips within a county during each week after controlling for log GDP, log population, and log area. The right graph plots coefficient estimates of $WFH_i \times t$ (using *WFH freq.*) on log number of road trips by week from week 1: Jan 23 - Jan 29, 2020, to week 15: Apr 29 - May 06, 2020 (week 15 is absorbed by fixed effects). The dashed vertical line for week 8 indicates the week when the majority of confinement rules were set into force by federal states. The gray shaded area corresponds to 95-percent confidence intervals (with clustering at the county level).

coefficient estimates of WFH based on the following specification:

$$\log T_{it} = \sum_{t=1}^{T} \beta_t WFH_i \times t + \gamma' X_{it} + \delta_i + \delta_t + \varepsilon_{it}. \tag{3.4}$$

Here T_{it} is the number of weekly road trips in county i during period t, β_t captures the week-specific effect of *WFH freq*, X_{it} is the vector of covariates and δ_i and δ_t are, respectively, county and period fixed effects. The vector of covariates includes weekly rainfall and interactions of week dummies with the share of commuters in the county. The right panel of Figure 3.2 plots the estimated coefficients β_t. The figure confirms that the differential effect of WFH on reducing mobility was particularly large before the confinement. Again, the null hypothesis that the weekly WFH coefficients during pre-confinement weeks are identical to those in weeks after confinement was implemented can be clearly rejected ($F = 51.40$, $p < 0.01$). Also here we see that the mobility-reducing effect of WFH over time increases again towards the end of the confinement period when businesses started to operate again. In Appendix C.7.2, we estimate the same model using commuter train traffic as an alternative outcome variable and obtain qualitatively similar results.

3.5 Conclusions

In the wake of the Covid-19 pandemic, much of the policy debate has been concerned with weighing the short-run economic and social costs of NPIs against their potential public health benefits. In this paper, we have argued that working from home is a particularly effective NPI because it allows for reducing infection risk while maintaining economic activity: all else equal, regions, industries, and firms with a higher WFH potential reported significantly fewer short-time work filings during the first wave of the pandemic in spring 2020. At the same time, counties with a higher share of teleworkable jobs also experienced significantly fewer Covid-19 cases. The effect magnitudes suggest that WFH also has positive spill-over effects on workers without the possibility to WFH, both in terms of labor-market effects and infection risks. Highly skilled workers currently have the greatest possibilities to engage in telework. This unequal access to WFH is likely to reinforce pre-existing inequality along socioeconomic dimensions. Moreover, we have shown that WFH was less important in reducing infections after confinement was imposed by authorities, in line with observed mobility patterns from cell phone tracking data. Thus, confinement and WFH are, to some extent, substitutable containment measures. This implies that WFH should be encouraged as long as significant infection risk remains.

Table 3.1 : The Effect of WFH on Short-Time Work Applications across Counties

	(1)	(2)	(3)	(4)	(5)
WFH feas	-1.22***	-0.70***	-1.28***	-1.24***	-0.84***
	(0.22)	(0.21)	(0.23)	(0.25)	(0.24)
R^2	0.23	0.33	0.27	0.28	0.36
NUTS-3 regions	401	399	391	401	389
WFH occ	-1.70***	-1.15***	-1.81***	-1.88***	-1.46***
	(0.24)	(0.23)	(0.25)	(0.27)	(0.29)
R^2	0.27	0.35	0.30	0.31	0.38
NUTS-3 regions	401	399	391	401	389
WFH freq	-3.34***	-2.20***	-3.48***	-3.69***	-2.60***
	(0.50)	(0.51)	(0.54)	(0.60)	(0.65)
R^2	0.27	0.34	0.29	0.29	0.37
NUTS-3 regions	401	399	391	401	389
Set of Controls					
Baseline	×	×	×	×	×
Economy		×			×
Health			×		×
Social Capital				×	×

Notes: Dependent variable is the percentage of the total number of persons mentioned in short-time work applications in March and April 2020 relative to employment in June 2019 based on data from the Federal Employment Agency. WFH is the percentage share of employees in the county with jobs that are suitable for telework (*WFH feas*) or who either at least occasionally (*WFH occ*) or frequently (*WFH freq*) worked from home in 2018. Observations correspond to NUTS-3 regions (counties) and estimates are weighted based on employment as of June 2019. *Baseline* controls include region-specific log population, log settled area, region-specific log GDP, the number of days since the first infection and log spatial infection rates (defined as a weighted mean of infection rates in other counties using inverse distances as weights) as of April 30th. *Economy* controls include the fraction of (in- and outward) commuters in the local workforce, an infrastructure index that captures the reachability of airports, the fraction of households with broadband internet access ($\geq$ 50 Mbps), the fraction of low-income households ($\leq$ EUR 1,500 per month), the share of workers employed in services, manufacturing, and wholesale/retail sectors, respectively. *Health* controls include the fraction of male population, the fractions of the population of working age (15-64 yrs.) and elderly ($\geq$ 65 yrs.), the expected remaining lifetime of people with age 60, the death rate, intensive-care-unit beds per 100,000 inhabitants and hospitals per 100,000 inhabitants. *Social Capital* controls include crime rates, voter turnout, vote shares of populist parties, and the number of all registered associations per capita. Heteroskedasticity-robust standard errors reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3.2 : Effect of WFH on Severity of Covid-19 Crisis – Firm-Level Evidence

	RF		OLS		IV	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Participated in Short-Time Work Scheme						
Intensified Telework			-12.41***	-5.40***	-71.55***	-49.42***
			(4.00)	(1.99)	(11.34)	(13.80)
WFH feas	-0.81***	-0.45***				
	(0.20)	(0.12)				
Mandatory Shutdown		29.58***		34.58***		20.64***
		(5.68)		(6.00)		(6.46)
State of Business 2019Q4						
negative		11.98***		12.08***		10.69***
		(1.74)		(1.81)		(1.91)
positive		-9.92***		-10.39***		-9.77***
		(1.71)		(1.79)		(1.72)
R^2	0.15	0.20	0.13	0.20		
Firms	6028	5796	6028	5796	6028	5796
First stage estimate ($\times 100$)					1.14***	0.92***
First stage KP F-stat					50.88	80.26
Panel B: Negative Corona Shock						
Intensified Telework			-14.74***	-6.57**	-74.72***	-39.13***
			(5.04)	(2.54)	(14.80)	(13.84)
WFH feas	-0.86***	-0.37***				
	(0.26)	(0.12)				
Mandatory Shutdown		40.58***		43.93***		33.94***
		(7.18)		(7.60)		(6.40)
State of Business 2019Q4						
negative		11.01***		11.00***		9.86***
		(2.66)		(2.77)		(2.98)
positive		-9.16***		-9.56***		-9.34***
		(1.99)		(2.00)		(1.89)
R^2	0.17	0.26	0.15	0.25		
Firms	5363	5156	5363	5156	5363	5156
First stage estimate ($\times 100$)					1.15***	0.94***
First stage KP F-stat					52.87	80.88
Baseline	×	×	×	×	×	×
Controls		×		×		×

Notes: The dependent variable is an indicator (rescaled by 100) identifying firms who participated in the short-time work scheme (Panel A) or who report a "very negative" impact of the Covid-19 crisis in April 2020 (Panel B). *Intensified telework* is a binary variable identifying firms who report intensified telework usage in response to the Covid-19 crisis. Baseline controls (not reported) include firm size in terms of employment (5 size categories), the share of sales generated abroad, fixed effects for the date of survey completion, survey fixed effects (Construction, Wholesale/Retail, Service and Manufacturing) and location fixed effects at the county level. Additional controls include a dummy for firms operating in an industry subject to mandatory business closures, pre-crisis business conditions in Q4 2019 (baseline: neutral), and business expectations in Q4 2019 (3 categories, not reported). Data are from the ifo Business Survey. Standard errors are clustered at the 2-digit NACE level and reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3.3 : The Effect of WFH on SARS-CoV-2 Infections across Counties

	(1)	(2)	(3)	(4)	(5)
WFH feas	-0.045***	-0.043***	-0.045***	-0.053***	-0.045***
	(0.011)	(0.014)	(0.011)	(0.011)	(0.014)
R^2	0.54	0.60	0.58	0.62	0.65
NUTS-3 regions	401	399	391	401	389
WFH occ	-0.061***	-0.054***	-0.060***	-0.069***	-0.060***
	(0.014)	(0.018)	(0.015)	(0.014)	(0.019)
R^2	0.55	0.60	0.59	0.62	0.66
NUTS-3 regions	401	399	391	401	389
WFH freq	-0.12***	-0.072*	-0.11***	-0.12***	-0.081*
	(0.032)	(0.041)	(0.034)	(0.035)	(0.045)
R^2	0.55	0.60	0.58	0.61	0.65
NUTS-3 regions	401	399	391	401	389
Set of Controls					
Baseline	×	×	×	×	×
Economy		×			×
Health			×		×
Social Capital				×	×

Notes: Dependent variable is the SARS-CoV-2 infection rate (in logs) up to May 06, 2020 (the alleviation date of the first confinement) based on data from the Robert-Koch-Institute. WFH is the percentage share of employees in the county with jobs that are suitable for telework (*WFH feas*) or who either at least occasionally (*WFH occ*) or frequently (*WFH freq*) worked from home in 2018. Observations correspond to NUTS-3 regions (counties) and estimates are weighted based on population size. *Baseline* controls include region-specific log population, log settled area, log GDP, the number of days since the first infection and log spatial infection rates defined as a weighted mean of infection rates in other counties using inverse distances as weights. *Economy* controls include the region-specific fraction of (in- and outward) commuters in the local workforce, an infrastructure index that captures the reachability of airports, the fraction of households with broadband internet access ($\geq$ 50 Mbps), the fraction of low-income households ($\leq$ EUR 1,500 per month), the share of workers employed in services, manufacturing, and wholesale/retail sectors, respectively. *Health* controls include the fraction of male population, the fractions of the population of working age (15-64 yrs.) and elderly ($\geq$ 65 yrs.), the expected remaining lifetime of people with age 60, the death rate, intensive-care-unit beds per 100,000 inhabitants and hospitals per 100,000 inhabitants. *Social Capital* controls include crime rates, voter turnout, vote shares of populist parties, and the number of all registered associations per capita. Heteroskedasticity-robust standard errors reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

4 The Future of Work and Consumption in Cities after the Pandemic: Evidence from Germany*

4.1 Introduction

The Covid-19 pandemic has disrupted traditional work organization, inducing a sudden and lasting shift towards working from home (WFH) (Barrero et al., 2021a,b; Aksoy et al., 2022).[1] The resulting transformation of the geography of work carries the potential to fundamentally alter the distribution of economic activity in cities and even to challenge their "survival" (Florida et al., 2021; Glaeser and Cutler, 2021). Recent research documents significant changes in consumption patterns in cities (Chetty et al., 2020a,b; Chen et al., 2021; Alcedo et al., 2022) as well as a declining premium on proximity to urban centers in real estate prices (Ramani and Bloom, 2021; Rosenthal et al., 2021; Althoff et al., 2022; Gupta et al., 2022). However, the existing literature lacks causal evidence on the link between the new geography of work and economic activity within urban agglomerations.[2]

We fill this gap by empirically studying the effect of WFH on the micro-geography of offline consumer spending in cities. We draw on novel card-transaction data supplied by *Mastercard* and survey evidence on the prevalence of WFH at the postcode level for five major German metropolitan areas between January 2019 and May 2022. Our empirical framework exploits the spatially differential exposure to the WFH shock induced by Covid-19 within cities. The granularity of the data allows us to trace differences in local spending trends from 2019 through the permanent lifting of pandemic restrictions and link these to the severity of the WFH shock. We organize the analysis into two parts.

In the first part, we analyze spatial consumption shifts within urban agglomerations. We explore differential spending trends across postcode areas with higher versus lower pre-crisis consumption intensity using a difference-in-differences (DiD) design. Consumption-intensive areas are typically located close to city centers, exhibit higher population and business density,

* This chapter is based on joint work with Oliver Falck, Simon Krause, Carla Krolage, and Sebastian Wichert.

[1] Additional evidence from job vacancy postings shows that job offerings are increasingly advertised with a WFH option (Alipour et al., 2021c; Bamieh and Ziegler, 2022). In the US, today's dominant work model for graduate employees is hybrid WFH with employees working some days at home and others in the office (Bloom et al., 2022).

[2] Other studies have assessed this question only implicitly (Chetty et al., 2020b), theoretically (Gokan et al., 2022; Kwon et al., 2022), or with a narrow spending definition (De Fraja et al., 2021, 2022).

and have more expensive housing. We find similar spending trends across all areas before the pandemic outbreak in March 2020, followed by a sudden spending drop in high relative to low consumption-intensity postcodes. The estimates imply that offline transaction volumes decline by 6-10 percent for every standard deviation increase in pre-Covid consumption intensity immediately after the outbreak. The gap increases to nearly 15 percent in subsequent months and had not recovered by May 2022. The pattern is similar across different spending categories, including eating places, grocery and food stores, and apparel stores. A closer look at the data reveals that the effects are partly driven by an *absolute* spending increase in lower consumption-intensity areas. In contrast, consumption-intensive areas lose revenue throughout the post-outbreak period. Notably, a distinguishing feature of lower consumption-intensity areas is stronger WFH growth during the pandemic. These observations motivate us to examine WFH as a key channel through which the pandemic shock altered the spatial distribution of offline consumption within cities.

In the second part, we investigate the causal link between regional changes in offline card transactions and differences in local WFH. The validity of our DiD design rests on the identifying assumptions that *i)* spending trends across postcode with high and low WFH growth are parallel except through the Covid-19 shock, and *ii)* that regional differences in WFH are exogenous. Since WFH uptake is unlikely to be orthogonal to other determinants of spending changes after the pandemic outbreak, the endogeneity of WFH poses a critical challenge to identification. We address this problem in two steps. First, we estimate intention-to-treat (ITT) effects based on a measure of "untapped WFH potential", defined as the local share of residents with a teleworkable job who *did not* work from home before the pandemic. The measure approximates the local scope to *expand* WFH after the outbreak relative to job-related feasibility (Alipour et al., 2023). Since untapped WFH potential is determined before the pandemic, it remains unaffected by other spending patterns disruptions, thus alleviating endogeneity concerns. The measure strongly predicts both observed WFH growth during the pandemic and projected growth rates based on employees' desires and employer plans for the post-Covid future. However, differences in untapped WFH potential may still be correlated with other determinants of spending changes. The fact that economic activity is unevenly distributed within cities may threaten identification (Redding, 2022). If, for instance, non-essential businesses are more concentrated in areas with lower untapped WFH potential, then our estimates may pick up supply-side disruptions due to business closures rather than WFH effects. Differences in behavioral adjustments to the Covid-19 shock may also bias our estimates to the extent that untapped WFH potential is correlated with differences in local population structure. Our second step to address these problems is thus to dynamically control for local area characteristics that may correlate with untapped WFH potential and time trends. The most demanding specification controls for measures of pre-Covid economic activity, local industry composition, socioeconomic status of the population, age composition, and building use, each separately interacted with a full set of time indicators.

Our DiD estimates suggest that spending trends across postcodes with higher and lower untapped WFH potential are parallel before March 2020, supporting the validity of our first identifying assumption. Postcodes with greater scope to expand WFH experience a sharp relative increase in consumer spending immediately after the outbreak. The effects are significant for spending on business days (Monday-Friday) but small and insignificant for spending on Saturdays, consistent with WFH as the driving mechanism. The unconditional estimates are positive and significant throughout the post-outbreak period. However, once we account for other potential sources of spending disruptions, the effects of WFH become insignificant during lockdown periods, remaining sizable and significant only in non-lockdown periods and after pandemic restrictions are permanently lifted. The estimates suggest that consumer spending increases 2–3 percent per one standard deviation increase in WFH potential, on average. We propose two explanations for this result. First, once we account for supply-side factors (e.g., local industry composition), WFH cannot generate regional spending shifts when most retail stores are closed across the economy; instead, we show that consumption shifts from offline to online commerce during lockdown periods. Second, as established by previous work, the ability to work from home is *negatively* correlated with job loss and short-time work during the pandemic (Adams-Prassl et al., 2020; Alipour et al., 2021a). This leads to a situation where WFH effects are attenuated as remote workers and employees on short-time work stay home during periods of heavy containment measures.

Our findings have important implications for the future of cities. There is growing consensus that WFH will stick in the post-pandemic economy. Our representative survey projects that 24 percent of workers will WFH at least partly in the future. Recent evidence from the United States and Germany suggests that WFH has already stabilized at this level (Bloom et al., 2022; ifo Institute for Economic Research, 2022a,b,c). Thus, we project that the spatial shifts in consumption induced by WFH and observed until May 2022 are here to stay.

4.2 Postcode-Level Data on Spending and WFH

Sample Our sample comprises postcode-level observations for the broadly-defined metropolitan areas of five major German cities: Berlin (5.2 million inhabitants), Hamburg

(3.1 million), Munich (2.6 million), Stuttgart (2.2 million), and Dresden (1.2 million), which together cover about 17 percent of Germany's total population. The metro areas are located in different parts of Germany and constitute the regional centers of their respective geographies. We observe daily consumer spending between January 2019 and May 2022, local area characteristics, as well as WFH uptake before and during the pandemic and expectations for the post-Covid future. Our observation period includes the outbreak of the Covid pandemic in Germany in March 2020 and two lockdowns (March–May 2020 and November 2020–May 2021).[3] Nearly all remaining Covid restrictions were lifted in March 2022.

Debit & Credit Card Transaction Data by Mastercard We measure local offline consumer spending using anonymized and aggregated data on debit and credit card transactions provided by *Mastercard Retail Location Insights*.[4] Offline spending refers to transactions at brick-and-mortar stores, spanning different sectors, including grocery and food stores, eating places, home improvement, apparel, hospitality, home furnishing, and consumer electronics. Transactions are aggregated from the point of sale (POS) to the postcode level and are available on a daily basis. We limit our sample to transactions with domestic cards to avoid distortions due to travel bans and international tourism. For confidentiality reasons, spending data for postcodes with few transactions and merchants in a given sector and day are missing. To ensure sufficient coverage over time, we limit the sample to postcodes with observations on at least five days per week in 2019 and focus our main analysis on *total* consumer spending. Our final sample includes 810 postcodes that we observe between 1 January 2019 and 31 May 2022.

WFH Survey & Local Characteristics by infas360 We complement the payment data with regional information on WFH patterns (measured at employees' place of residence) and area characteristics using representative survey data collected by *infas360*, a company specialized in micro-geographic survey and data-collection methods. We obtain postcode-level data from the spring 2022 wave of the infas360 CASA Monitor, a recurring online survey of roughly

[3] Lockdowns were characterized by mandatory closures of non-essential businesses and other severe containment measures, including school closures and contact restrictions. From January through June 2021 and November 2021 through March 2022, the containment measures required companies to offer WFH solutions to their employees conditional on the job profiles permitting remote work.

[4] In Germany, the volume share of all card payments – including debit and credit cards – represented about 48 percent of total consumer payments at points of sales (POS) in 2019 (ECB, 2020). In 2020, the share of card payments increased to 52 percent (ECB, 2021). Payments within the Mastercard network accounted for approximately 28 percent of total card payment volume (Statista, 2020).

11,000 individuals. We introduced a special set of questions about current and pre-Covid WFH frequency as well as employees' desires and their employers' plans for the post-pandemic future. An additional telephone survey was conducted with more than 1,000 participants to improve data quality. Furthermore, we include a broad range of information on socioeconomic characteristics, population characteristics, and area features compiled from surveys and administrative sources.

Summary statistics are reported in Appendix Table D.1. The mean postcode size in our sample is 16,300 inhabitants. Appendix Figure D.1 presents a map of Germany highlighting the postcodes included in our sample.

4.3 Drivers of Spatial Changes in Offline Spending

4.3.1 Spending Trends by Local Consumption Intensity

While the pandemic outbreak was a plausibly exogenous event, differences in area characteristics mediate the severity of the shock to the local economy. A natural dimension across which to explore the evolution of spending patterns is the pre-crisis consumption intensity. High consumption intensity areas offer a high density of stores, provide amenities that attract large numbers of consumers, and are often located close to city centers. Containment measures, including temporary business closures paired with behavioral responses to infection risk, are thus likely to disproportionately affect consumption hubs. We formally analyze the differential impact of the Covid shock across high and low consumption-intensity areas by estimating the following dynamic difference-in-differences (DiD) specification:

$$Spending_{ct} = \sum_{k \neq Feb\_2020} \beta^k [\mathbb{1}(k = t) \times \mathit{2019\_Consumption\_Intensity}_c] + \gamma_c + \delta_t + \epsilon_{ct}, \quad (4.1)$$

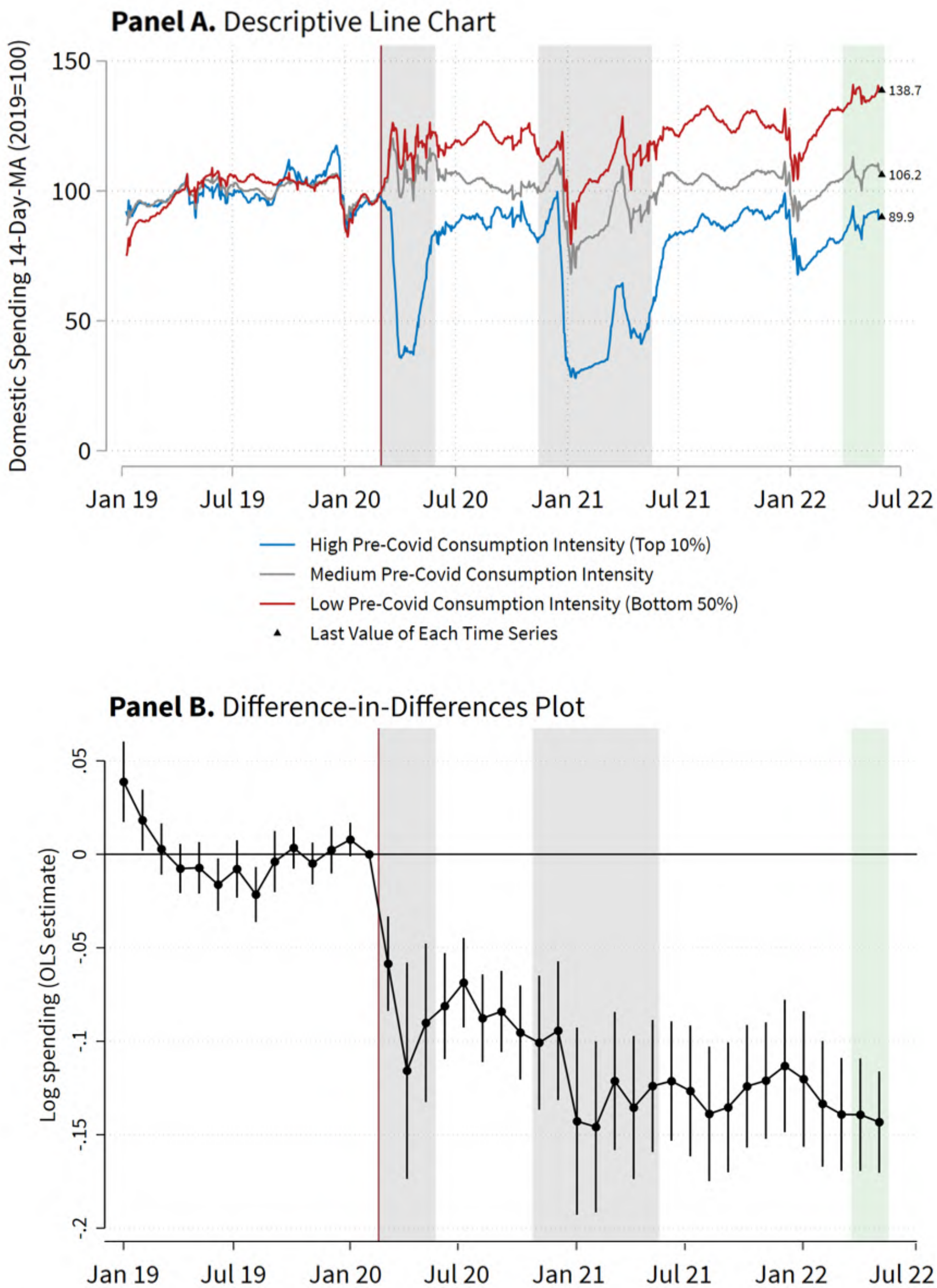
where $Spending$ is the log value of average daily offline consumer spending in postcode c and month t. $2019\_Consumption\_Intensity$ denotes postcode c's pre-Covid consumption intensity measured on a continuous scale. Specifically, consumption intensity refers to the local volume of consumer spending in 2019 relative to the national average and is thus time-invariant. The measure is standardized to have mean zero and unitary standard deviation. Postcode and year-month fixed effects γ_c and δ_t absorb time-invariant determinants of spending and common time shocks. Hence, the coefficients β^k trace spending differences associated with a one standard deviation higher pre-Covid consumption intensity over time. We use February 2020 as the reference period and cluster standard errors at the postcode level.[5]

Before turning to the DiD results, Panel A of Figure 4.1 draws raw spending trends for postcodes grouped by high (top 10 percent), medium, and low (bottom 50 percent) consumption intensity in 2019. The time series are normalized by the 2019 average in each category to reflect percentage changes relative to pre-pandemic levels. In 2019, high consumption-intensity areas attracted 75 percent of consumer spending, while medium consumption-intensity postcodes accounted for 18 percent. By contrast, only 7 percent of spending occurred in low consumption-intensity areas. While trends are similar in the year before the pandemic outbreak in Germany, regional spending diverges significantly after February 2020. Transaction volumes in high consumption-intensity areas decline by 60 percent in the first lockdown and by nearly 70 percent over the second lockdown (gray-shaded areas). Both lockdown periods were marked by mandatory closures of non-essential businesses and other strict containment measures. The trend recovers only partly between lockdown periods and reaches only 90 percent of the pre-crisis level after March 2022, when Covid restrictions were permanently lifted and nearly 80 percent of the population was vaccinated against Covid (green-shaded area). We find similar trends for pedestrian frequency in consumption-intense high streets in our five cities under inspection (see Appendix Figure D.2, showing the close co-evolution of consumer spending and pedestrian frequency). Trends in areas with a lower pre-crisis consumption intensity show a completely different picture. Transaction volumes *increase* in the first lockdown and remain above the pre-crisis level in nearly all periods after the outbreak. The most recent data point suggests that spending is 40 percent above the 2019 average. These spending trends are shared across sectors, as shown for the subcategories grocery and food stores, eating places, and apparel stores in Appendix Figure D.3.

The DiD coefficients $\hat{\beta}_k$ plotted in Panel B of Figure 4.1 complete the picture by giving insight into spending trends in more relative to less consumption-intensive areas. Pre-pandemic coefficients are small and largely statistically insignificant. The estimates imply that offline transaction volumes decline by about 12 percent for a one standard-deviation increase in pre-Covid consumption intensity in April 2020. The relative decline grows to nearly 15 percent in the second lockdown and does not recover by May 2022 (our latest data point). This shift is not merely driven by a change in the composition of spending across product segments

[5] Alternative clustering of standard errors, at the postcode-month level or at city district categories to account for spatial spillovers, does not meaningfully affect estimates.

Figure 4.1 : Regional Association of Pre-Covid Consumption Intensity and Offline Consumer Spending



Notes: Panel A shows 14-day moving averages of daily offline spending in three categories of postcodes: high (top 10%), medium, or low (bottom 50%) 2019 consumption intensity. In each category, time series are normalized by the 2019 average. Panel B plots DiD estimates $\hat{\beta}^k$ on the interaction terms between standardized 2019 consumption intensity and monthly dummies (Equation 4.1). 95-percent confidence intervals are drawn using standard errors clustered at the postcode level. The vertical red line marks the outbreak of the Covid-19 pandemic between February and March 2020. The shaded gray areas highlight "lockdown" periods, characterized by closures of non-essential businesses and other severe containment measures. The shaded green area marks the period after March 2022, when nearly all restrictions have been lifted. The consumer spending data comprise domestic debit and credit card payments.

or specific cities. Spending on different product segments declines in postcodes with high relative to low consumption intensity and shows no trend reversion in recent restriction-free months (see Appendix Figure D.4 for spending in the three product segments grocery and food stores, eating places, and apparel stores). In addition, the overall composition of consumer spending across all categories has remained stable over time, only with minor exceptions during lockdown periods (see Appendix Figure D.5). The spending effect is also similar across city size (Appendix Figure D.6). Still, a potential concern could be a behavioral change in consumers' preferred payment type from cash to cards. Since our empirical strategy yields estimates clean of such general time trends, only geographically heterogeneous shifts could be problematic. Reassuringly, estimates for the apparel industry, which already had a high share of card payments before the pandemic, are consistent with the overall results (Appendix Figure D.4), alleviating this concern. Our later estimations also control for differential time trends across local characteristics (e.g., business composition)to account for a possible heterogeneous take-up of card payments across different industries.

Taken together, the findings provide a first indication that the pandemic has permanently altered the micro-geography of consumption: offline spending gets withdrawn from previously popular destinations and relocated to less consumption-intensive areas. Simultaneously, a higher share of consumer spending is conducted online (see Appendix Figure D.7). Particularly during lockdown periods, when ubiquitous business closures preclude part of the usual offline spending, consumption shifted from offline to online commerce. The share of online spending spikes during lockdown periods, reaching between 35 percent in 2020 to 40 percent in 2021, before stabilizing at a level of about 24 percent in 2022. This means that consumption-intensive areas bear a double loss as offline spending is relocated to less consumption-intensive areas and to the Internet.

While we are confident in attributing changes in spending to consequences of the pandemic, our results are so far silent about the *mechanisms*. We characterize postcodes with a higher pre-Covid consumption intensity in Figure 4.2. Panel A estimates separate bivariate regressions of 2019 consumption intensity on postcode characteristics. Panel B presents OLS estimates from a multivariate regression using covariates selected by a first-stage Lasso regression. The results reveal that more consumption-intensive postcodes, on average, are less residential, have a greater share of working-age residents, higher cost of housing, higher population and business density, and a greater share of firms operating in finance and ICT. Thus, possible mediators of spending effects of the Covid-19 shock include supply-side factors, such as business closures and heterogeneous exposure to the pandemic due to different industry composition. Demand-side factors, such as regional differences in the adjustment of spending behavior due to heterogeneity in the composition of the local population may also play a role.

The correlates show that consumption-intensive areas are located closer to city centers. On average, moving away from the city center by 10 percent reduces local (pre-Covid) consumption intensity by 4 percent. The negative correlation between distance and consumption intensity is also significant when looking at each metro area separately (see Appendix Figure D.8). The erosion of city centers mirrored by gains in more remote areas is consistent with the "donut effect", previously documented for the real estate market in major US cities during the pandemic (Ramani and Bloom, 2021). However, an important difference is that land use in big German cities is less segregated than in the US. German inner cities have residential areas close to shopping streets and many mixed-use structures, often combining office space, stores, and housing units. While city centers are hubs of offline consumption, consumption-intensive areas are not limited solely to city centers (see Appendix Figure D.9). Overall, in open periods in summers 2020, 2021 and May 2022, the strongest declines in spending are concentrated in the city centers, while most suburbs and surrounding areas experience an increase in spending relative to pre-Covid levels. This is true, especially in bigger cities such as Berlin. At the same time, the heterogeneity in land use within the city centers explains why a "donut" is not as clearly discernible.[6]

Interestingly, pre-crisis consumption intensity is also negatively correlated with WFH growth in February 2022 relative to pre-Covid levels. Thus, the upsurge of WFH during the pandemic constitutes another potential driver of regional spending shifts after 2020. Motivated by the evidence suggesting that WFH not only constituted a "mass social experiment" (Barrero et al., 2021b) during the crisis, but is also expected to persist in the post-pandemic future, we subsequently focus on this channel.

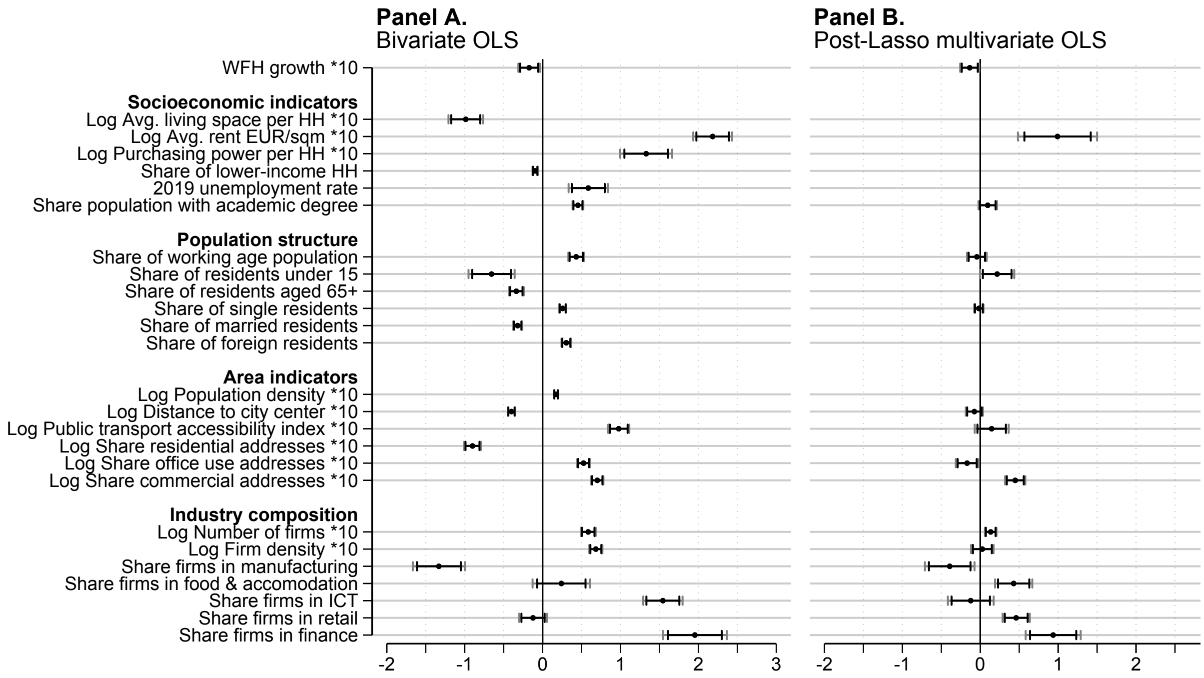
4.3.2 WFH and Changes in Offline Consumer Spending

To establish a causal link between WFH and regional shifts in consumer spending, we draw on the DiD framework introduced in the previous section. One major challenge to identifying the effect of WFH is that WFH uptake after February 2020 is likely correlated with other sources of spending disruptions. We address this problem in two steps.

First, we propose a measure of "untapped WFH potential", defined as the share of residents

[6] Appendix Figures D.10–D.14 map local changes in total offline spending for summers 2020 and 2021 as well as May 2022 compared to the same period in 2019 for each metro area. Note that during these periods, Covid restrictions were limited and stores could open as usual.

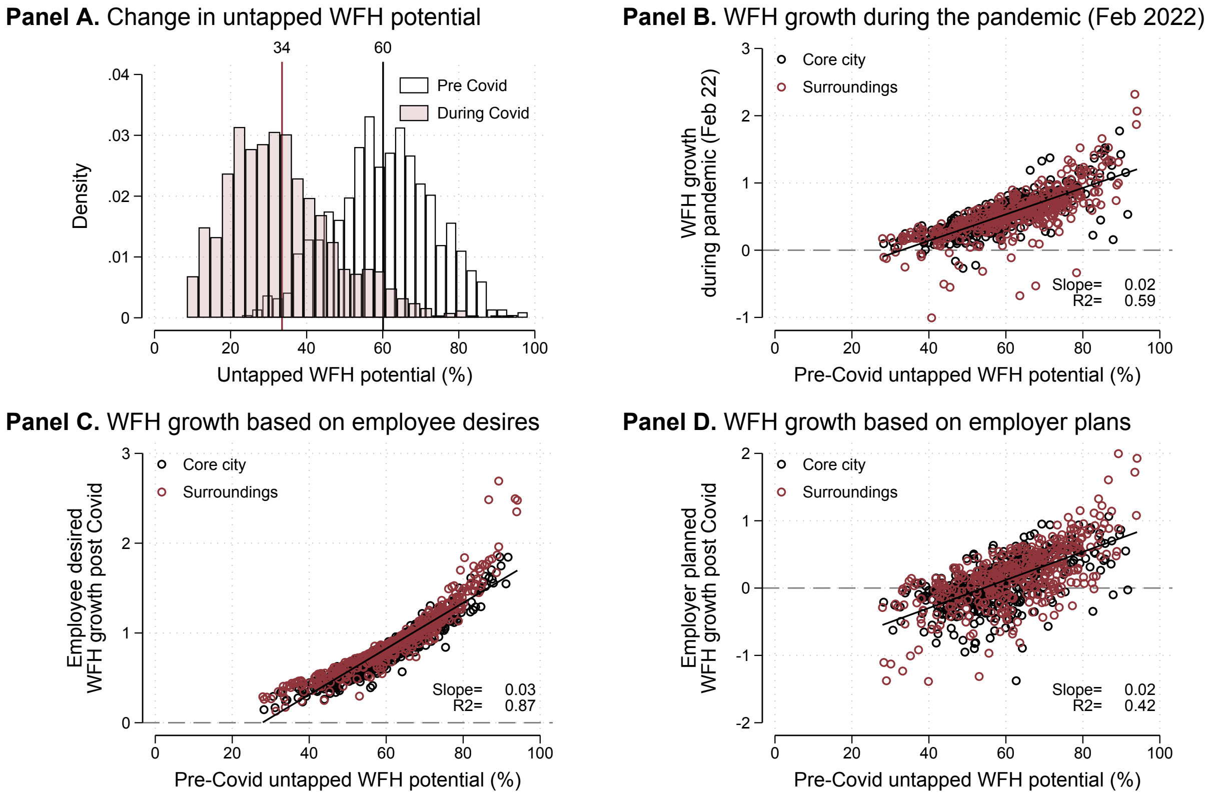
Figure 4.2 : Correlates of Log 2019 Consumption Intensity



Notes: Panel A reports estimates from bivariate OLS regressions of log 2019 consumption intensity on postcode characteristics after partialling out metro-area fixed effects. Panel B shows the results of a multivariate OLS regression in which the covariates are selected by a Lasso regression including all covariates and choosing the penalty with a 10-fold cross-validation to minimize the mean squared error. Confidence intervals are heteroskedasticity-robust and drawn at the 90 and 95 percent levels.

with a teleworkable job who *did not* work from home before the pandemic (Alipour et al., 2023). The idea is to approximate the local scope to *expand* WFH relative to maximum capacity after the pandemic outbreak. Since untapped WFH potential is measured pre-Covid, it is unaffected by other sources of spending disruptions. Using this measure instead of WFH uptake during the pandemic as our key explanatory variable thus alleviates some endogeneity concerns. Panel A of Figure 4.3 reports the distribution of untapped WFH potential across postcodes before the pandemic and in February 2022. The distribution shifted leftward as firms and employees went remote to reduce work-related contacts, exploiting their WFH potential. Panel B demonstrates that untapped WFH potential performs remarkably well in predicting observed WFH growth in February 2022 relative to pre-Covid levels. The result is similar when estimated for each metro area separately (see Appendix Figure D.15). Overall, the measure alone explains about 60 percent of the variation in WFH uptake during the pandemic. Panels C and D show that the strong relationship persists when using WFH growth rates based on employee desires and employer plans for the post-pandemic future. The results bolster the case that pre-Covid untapped WFH potential is an informative measure for local shifts to WFH.

Figure 4.3 : Untapped WFH Potential and WFH Growth



Notes: Panel A reports histograms of untapped WFH potential pre-Covid and during Covid (February 2022) at the postcode level. Panels B–D show linear fits between WFH growth rates and pre-Covid untapped WFH potential after partialling out five metro area fixed effects. WFH growth is the share of employees working at least one day per week from home relative to pre-Covid levels using self-reported WFH during Covid (February 2022) in Panel B, self-reported WFH desires for the post-Covid future in Panel C, and employee-reported plans of their employers for the post-Covid future in Panel D. Data are from *infas360*.

One may still be concerned that untapped WFH potential is not entirely orthogonal to other determinants of spending shifts. If, for instance, the measure is correlated with the local industry composition, then our estimates may pick up supply-side disruptions due to business closures rather than WFH effects. Differences in local population structure may also afflict our estimates if people react differently to the Covid shock, e.g., by adjusting the composition of their spending to varying degrees or because of differences in the propensity to shift from cash to card payment. In the aggregate, card payments in total consumer spending increased only moderately from 48 to 52 percent between 2019 and 2020. The same is true regarding the number of debit and credit cards issued and the number of POS terminals used by merchants for accepting card payments (see Appendix Figure D.16). Still, substitution rates may be heterogeneous and correlated with untapped WFH potential. Thus, our second step to alleviate endogeneity concerns involves comprehensively controlling for supply-side and structural factors that may correlate with untapped WFH potential and time trends. Formally, we include a vector of time-invariant controls $\mathbf{X}$ interacted with monthly dummies in our modified DiD specification:

$$Spending_{ct} = \sum_{k \neq Feb\_2020} [\mu^k \mathbb{1}(k=t) \times untap\_WFH\_pot_c + \mathbb{1}(k=t) \times \mathbf{X}_c' \pi^k] + \alpha_c + \gamma_t + \varepsilon_{ct}, \tag{4.2}$$

where $untap\_WFH\_pot$ is standardized (mean zero and unitary standard deviation) pre-Covid untapped WFH potential and α_c, γ_t are postcode and month-year fixed effects. The vector $\mathbf{X}$ comprises measures of the local commercial structure and industry composition (business density, 2019 consumption intensity, a dummy for the presence of a shopping center, as well as the share of businesses in retail, food & accommodation, arts & entertainment, other service activities, professional & technical activities, construction, and education respectively) and of the local population and settlement structure (population density, the share of addresses with residential use, the share of low-income households, the share of foreign residents, the share of married residents, as well as the share of residents under 15, between 15 and 29, and over 65, respectively). Thus, our estimates of interest $\hat{\mu}^k$ trace the differential time trend between high and low untapped WFH potential areas *clean* of trend differentials across any of the characteristics included in $\mathbf{X}$. We again use February 2020 as the reference period and cluster standard errors at the postcode level.[7]

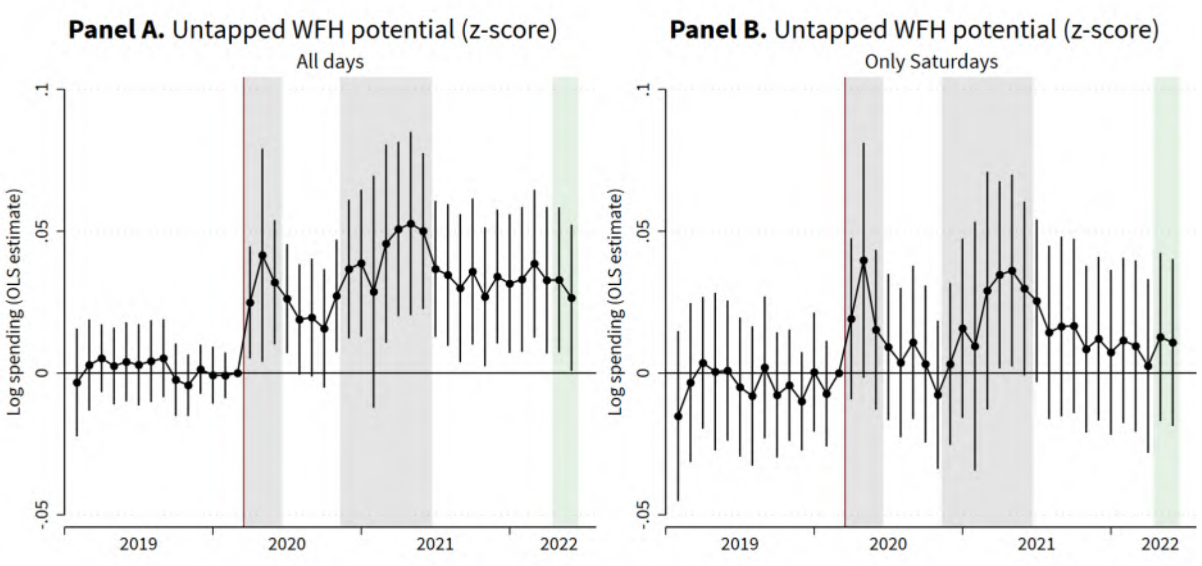
We start by presenting DiD coefficients conditional on time and postcode fixed effects only in Figure 4.4.[8] The outcome in Panel A is the log average daily spending over the whole week. The first feature that stands out is that pre-Covid coefficients appear close to zero and statistically insignificant, supporting the validity of our first identifying assumption; trends in outcomes across comparison groups evolve in parallel except through the Covid shock. With the beginning of the pandemic in March 2020, trends begin to diverge. Spending in postcodes with a higher untapped WFH increases significantly and remains different from zero thereafter. In contrast, postcode differences turn mostly insignificant when confining the outcome to spending on Saturdays in Panel B. These results are consistent with WFH as the driving mechanism, altering regional spending during regular working days by eliminating commutes and leaving weekend spending largely unaffected. We find no differences across business days, consistent with workplace mobility data from Google that indicates a general

[7] Alternative clustering of standard errors, e.g., at the postcode-month level or at city district categories to account for spatial spillovers, does not have a meaningful effect on the estimates.

[8] Appendix Figure D.21 show the descriptive line charts of spending by WFH growth and untapped WFH potential, analogously to Panel A of Figure 4.1.

reduction in workplace mobility but no significant differences across business days (Appendix Figure D.17).[9]

Figure 4.4 : DiD Results on the Association of Untapped WFH Potential and Log Spending



Notes: The figure plots DiD estimates $\hat{\beta}^k$ from separate regressions, in which the interaction terms are between monthly dummies and (standardized) untapped WFH potential. The dependent variable is average daily spending over all days in Panel A and average spending on Saturdays in Panel B. 95-percent confidence intervals are drawn using standard errors clustered at the postcode level. The vertical red line marks the outbreak of the Covid-19 pandemic between February and March 2020. The gray-shaded areas highlight “lockdown” periods, characterized by severe containment measures. The green-shaded area marks the period after March 2022, when nearly all restrictions have been lifted. Spending data comprise debit and credit card payments.

The full set of our DiD results is presented in Table 4.1. For better exposition, we group time indicators into six bins reflecting the different phases of the pandemic (and corresponding to the shaded areas in Figure 4.4); specifically, the pre-Covid period (reference group), the Spring 2020 lockdown, the open period in summer 2020, the winter lockdown 2020/21, the open period in 2021/22, and the out-of-Covid transition after March 2022.

Columns (1) and (2) report the estimates conditional on postcode fixed effects and time fixed effects. The coefficients are significant in all periods for spending over the whole week and mostly insignificant for spending on Saturdays, mirroring the DiD plots in Figure 4.4. The remaining columns use business day (Monday-Friday) spending as the dependent variable to focus on consumption during working days. Column (3) reports the baseline results without further controls. The association between untapped WFH potential and spending is positive

[9] The heterogeneity of the WFH effect on consumer spending is most evident when comparing business days versus weekends, whereas the estimates hardly vary within these two groups. In other words, our results do not imply the existence of peak WFH days, which some observers might have assumed to be Mondays and/or Fridays.

and significant in all periods. Column (4) controls for city-specific trends by including month fixed effects interacted with a metropolitan area indicator. The coefficients remain unchanged and significant. Column (5) includes commercial structure and industry composition controls, each separately interacted with a full set of month indicators. This attenuates the coefficients during lockdown periods and renders them statistically insignificant. The point estimates on open periods remain unchanged relative to Column (3). Column (6) replaces commercial controls $\times$ month fixed effects with interactions between population characteristics and time dummies. Finally, our most demanding specification in Column (7) absorbs all commercial and population controls, separately interacted with month fixed effects. The results remain essentially unchanged compared to Column (5). Once we account for other potential sources of spending disruptions, the impact of WFH becomes insignificant during lockdown periods and remains sizable and statistically different from zero in *non-lockdown periods*. On average, transaction volume increases by 2–3 percent for every standard deviation increase in untapped WFH potential during "open periods" and by 3 percent after restrictions are permanently lifted.

The lack of effects during periods with heavy containment measures and high infection risk is somewhat startling, given that social distancing provisions, including WFH rates, were exceptionally high during these months (Appendix Figure D.19). One possible explanation is that—after holding local industry structure fixed—ubiquitous business closures during these periods preclude most potential relocation of offline spending. Instead of shifting regionally, consumption shifted from offline to online commerce.[10] Another possible explanation is related to the observation that the likelihood of job loss and short-time work is *negatively* correlated with the ability to work from home (Adams-Prassl et al., 2020; Alipour et al., 2021a). If employees who cannot work remotely stay at home during lockdowns because they are put on short-time work, then the spatial correlation between untapped WFH potential and spending may vanish. By contrast, the reopening of the economy leads to a shift of offline consumption into areas where employees keep working from home relative to areas where employees leave the short-time work scheme.

Another potential concern might be that our estimates of the spatial spending shifts not only capture the WFH effect, but part of the effect may stem from migration from city centers to the suburbs and surrounding areas. This migration could be the result of increased WFH opportunities. Administrative population statistics from the metropolitan areas in our sample do not support this hypothesis. This mechanism may become more important in the long run,

[10] As shown in Appendix Figure D.7, the share of online spending reached conspicuous spikes during lockdown periods.

reinforcing the effects we document in this paper.

Table 4.1 : DiD Results on the Intention-to-Treat Effects of WFH on Log Spending

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pre-Covid Untapped WFH Potential (z-score)							
× Lockdown Spring 2020	0.03**	0.03**	0.03**	0.03**	0.00	0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
× Open Period Summer 2020	0.02**	0.01	0.02**	0.02**	0.02*	0.02*	0.02*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
× Lockdown Winter 2020/21	0.04***	0.03*	0.05***	0.05***	0.02	0.01	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
× Open Period Summer/Winter 2021/22	0.03***	0.02	0.04***	0.03***	0.03***	0.03***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
× Out-of-Covid Transition 2022	0.03**	0.02	0.03**	0.03**	0.03**	0.03**	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
R^2	0.87	0.87	0.87	0.87	0.90	0.89	0.90
Observations	33,191	33,113	33,190	33,190	33,190	33,190	33,190
Sample	All Days	Saturdays	Mo-Fr	Mo-Fr	Mo-Fr	Mo-Fr	Mo-Fr
Postcode FE	×	×	×	×	×	×	×
Month FE	×	×	×		×	×	×
Month FE × Metro Area FE				×			
Month FE × Commercial Structure					×		×
Month FE × Sociodemographic Structure						×	×

Notes: The table reports DiD estimates $\hat{\mu}^k$ based on Equation 4.2. Time dummies are grouped into six bins: the pre-Covid period (reference group), the Spring 2020 lockdown, the open period in summer 2020, the winter lockdown 2020/21, the open period in 2021/22, and the out-of-Covid transition after March 2022. The dependent variable is the log average monthly offline spending. Baseline estimates for all days in the specification with postcode and month fixed effects are displayed in column (1). In column (2), the outcome is the log average spending on Saturdays. Column (3) shows the results for spending restricted to business days (Mondays through Fridays). Column (4) controls for month times metro area fixed effects. Column (5) controls for month fixed effects separately interacted with measures of the local commercial structure (business density, 2019 consumption intensity, a dummy for the presence of a shopping center, as well as the share of businesses in retail, food & accommodation, arts & entertainment, other service activities, professional & technical activities, construction, and education respectively). Column (6) controls for month fixed effects separately interacted with measures of local population and settlement structure (population density, the share of addresses with residential use, the share of low-income households, the share of foreign residents, the share of married residents, as well as the share of residents under 15, between 15 and 29, and over 65, respectively). Column (7) includes the full set of controls interacted with month fixed effects. Standard errors are clustered at the postcode level and reported in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

4.4 Discussion and Outlook

Our study provides evidence that the pandemic has induced fundamental changes to the micro-geography of work and consumption in major cities. Analyzing detailed postcode-level data on offline consumer spending, we find spatial spending shifts from previously consumption-intensive urban centers towards less spending-intensive and more residential areas. We establish a causal relationship between the altered geography of work and consumer spending: A standard deviation increase in pre-Covid untapped WFH potential increases local offline spending by 2-3 percent after the end of pandemic restrictions. The effect is driven by spending during business days, rather than on Saturdays, and is only significant outside of lockdowns and once Covid restrictions are permanently lifted.

While our estimated consumption decline in city centers is roughly in line with the back-of-the-envelope calculations by Barrero et al. (2021b) of spending declines of 13 and 4.6 percent for Manhattan and San Francisco, our analysis is the first to provide a causal and micro-geographic estimate of such declines. Similar micro-geographical patterns have also been shown for the real estate market, with real estate prices declining most in city centers (Liu and Su, 2021; Bergeaud et al., 2023; Kwon et al., 2022).

What do our results imply for the future? WFH will most likely persist. Our survey data for the five metropolitan areas suggest that 30 percent of employees wish to work at least one day per week from home, up from 14 percent pre-Covid (Appendix Figure D.18). The result regarding employee desires fits well with the finding that employees highly value the option to WFH (Mas and Pallais, 2017). However, employer plans diverge from employee desires, as documented by previous research (Aksoy et al., 2022). Averaging employee desires and employer plans in our sample yields an expected post-pandemic WFH rate of about 24 percent. This value matches Germany's actual WFH rate in February 2022 and WFH rates elicited in a nationally representative firm survey in April, August, and November 2022 (ifo Institute for Economic Research, 2022a,b,c). Both actual WFH rates in Germany and workplace mobility trends by Google indicate a high persistence of WFH. The WFH rate jumped from 5 percent pre-Covid up to 34 percent, maintaining high levels throughout the crisis, and has been converging to the current level of roughly 25 percent. Similarly, workplace commutes have been stable at around 80 percent of pre-crisis levels since early 2022 (see Appendix Figure D.17 and Figure D.19). In combination, this underscores the persistence of the WFH shock on labor markets. It is hence reasonable to extrapolate the impact on the micro-geography of consumption in cities to the post-Covid future.

WFH contributes to the relocation of spending away from city centers. City suburbs and more outlying areas typically exhibit a higher pre-Covid untapped WFH potential, giving rise to a tentative "donut" (see Appendix Figure D.20 for the regional distribution of untapped WFH potential and WFH growth in February 2022 relative to pre-Covid). On average, moving from the 25th to the 75th percentile in the distribution of untapped WFH potential is associated with a 26 percent increase in distance to the city center ($p < 0.01$) and, based on our DiD estimates, causes a 15 percent increase in local spending.

The current shift in the micro-geography of work and consumption has significant implications for major cities and is likely to reshape them considerably. While suburbs are benefiting and online consumption is on the rise, city centers are facing challenges such as empty offices and less frequented stores. The survival of local businesses, city amenities, and the usage of buildings will depend on how many people regularly visit the city. Although the short-term effects on consumption are already observable, many long-term ramifications are yet to be realized, leaving avenues for future research.

5 Broadband Internet and the Pattern of Trade

5.1 Introduction

Comparative advantage in international trade is determined by cross-country differences in production capabilities. Classical trade theory à la David Ricardo and Heckscher-Ohlin attributes these differences to international differences in either production technology or relative factor endowments. However, recent evidence has shown that other country characteristics can confer comparative advantage. In particular, a new strand of research has focused on understanding the role of institutions as “new” sources of comparative advantage, including labor market institutions (Helpman and Itskhoki, 2010; Tang, 2012; Cuñat and Melitz, 2012; Egger et al., 2015), legal institutions (Nunn, 2007; Levchenko, 2007; Costinot, 2009; Rodet, 2017), financial institutions (Beck, 2002; Manova, 2008; Ju and Wei, 2011; Manova, 2013), environmental regulation (Broner et al., 2019), as well as informal institutions, such as social capital and trust (Tabellini, 2008), and attitudes toward obedience in the workplace (Campante and Chor, 2017). The mechanism at the core of these findings is similar: A change in the institutional environment affects the productivity of firms in the economy. Some industries, however, are affected to a greater extent than others by institutional inputs. This creates productivity disparities within the economy. Adding countries with different degrees of institutional development then produces a pattern of relative productivity across countries and industries, i.e., a pattern of comparative advantage.

Building on a similar mechanism, I argue that cross-country differences in broadband infrastructure can give way to comparative advantage in international trade. While some studies acknowledge the importance of infrastructural components in this context (e.g., by introducing them as control variables), only very few consider physical infrastructure in general (or broadband infrastructure in particular) as a source of comparative advantage *per se* (Yeaple and Golub, 2007). In this article, I contribute to understanding the role of broadband infrastructure for international trade by investigating whether and how first-generation (fixed-line) broadband Internet shaped international specialization patterns.[1]

[1] When not otherwise specified, broadband Internet refers to the International Telecommunication Union’s definition, i.e., fixed-line Internet at downstream speeds greater or equal to 256 kbit/s, including cable modem, DSL, fiber-to-the-home/building, other fixed (wired)-broadband subscriptions, satellite broadband, and terrestrial fixed wireless broadband. The definition excludes subscriptions that have access to data communications (including the Internet) via mobile-cellular networks. It should also include fixed WiMAX

To guide the empirical analysis, I formalize a simple theory of international trade that draws on Becker and Murphy (1992) and Costinot (2009). The model features an economy in which workers must perform a number of complementary tasks to produce output. Industries are characterized by their complexity, which refers to the importance of successful information transfer within the production process. Formally, complexity is defined as the number of tasks across which workers must coordinate to successfully produce output. More coordination implies higher communication costs. To mitigate these costs, firms devote a portion of their resources to improving the transmission of information among their workers. The productivity gains from investing in communication, however, crucially depend on the economy's broadband infrastructure. In the two-country general equilibrium framework featuring free trade, the model predicts that the country with a better "effective quality of communication", defined as the product of firm-level communication investments and country-level broadband infrastructure, specializes in more complex goods. In the model, this is the country that provides a more efficient broadband network and is populated by better-educated workers. Hence, human capital and broadband infrastructure jointly constitute sources of comparative advantage in more complex industries.

I test the theory by estimating a structural gravity model using harmonized trade flows from the CEPII-BACI database, which covers trade in 85 manufacturing industries among more than 100 countries over the period of 1998-2016 (Gaulier and Zignago, 2010). The complexity of industries is measured by an index that summarizes the degree of interdependence and codifiability of information in the production process based on task-level information from the Occupational Information Network (O*NET) database. I use cross-country data on the domestic broadband penetration rate provided by the International Telecommunication Union (ITU) to trace the diffusion of high-speed Internet over time and complement my gravity model with country-level characteristics (e.g., domestic factor endowments) and country-pair information (e.g., bilateral barriers to trade). Methodologically, I follow recent advances in the gravity literature and corroborate results from traditional OLS estimates (used in most of the existing literature) with Poisson Pseudo Maximum Likelihood (PPML) estimates, including appropriate fixed effects to account for potential inconsistency induced by heteroskedasticity, the presence of zero trade flows, and structural multilateral resistance terms (i.e., average trade barriers that each country faces with its trade partners) (Anderson and van Wincoop, 2003; Yotov et al., 2016; Larch et al., 2021). Estimating the gravity model on a panel of trade relationships covering the period since the introduction of broadband allows me to comprehensively control for time-invariant determinants of trade that may confound

and any other fixed wireless technologies.

the results. In other words, the identification comes from the *time variation* in broadband availability. This dynamic perspective is lacking in most existing studies testing for sources of comparative advantage; due to data limitation and because institutional features tend to change slowly over time.

To account for potential endogeneity of broadband deployment, I follow Czernich et al. (2011) and implement an IV approach in which the first stage corresponds to a nonlinear diffusion model of broadband technology. The rationale is to estimate the maximum broadband penetration rate at any point in time as determined by the pre-existing domestic fixed-line telephony and cable TV networks. The predicted values of the broadband penetration rate are then used to identify the effect of broadband Internet on trade patterns in the second stage.

The empirical results provide strong support for the theory. I find that broadband deployment increased trade both at the extensive and the intensive margin, based on OLS estimates. The PPML estimates and the IV approach support the OLS results. The estimates imply that closing the broadband gap between the 75th percentile (Czech Republic) and the 25th percentile (the Philippines) in 2016 increases exports in the industry at the 75th percentile of the complexity distribution relative to the 25th percentile by 4 to 16 percent. The estimates also confirm the positive association between increases in domestic human capital in increases in the complexity of exports suggested by the theory; however, I cannot definitively establish the causality of this channel. Traditional sources of comparative advantage and institutions typically evolve slowly or respond little to policy interventions. Infrastructure provision, on the other hand, is a key domain of industrial policy. The results thus emphasize the discretion of domestic policy to actively shape a country's specialization in the global economy.

This paper contributes new evidence to the limited research on non-traditional sources of comparative advantage in international trade. I join the strand of literature uncovering "new" sources of comparative advantage with the literature analyzing how the advent of broadband Internet influenced trade volumes and relationships.[2] For instance, Yeaple and Golub (2007) shed light on the effect of infrastructure provision on international specialization, by estimating its effect on industry-level productivity. The authors address potential endogeneity by implementing a three-stage least-squares estimation procedure, using lagged growth rates in infrastructure as instruments for contemporaneous growth. The results indicate that the availability of electrical generation capacity as well as a better road network confer comparative advantage. By contrast, there is no evidence that telecommunication

[2] See Nunn and Trefler (2014) for a review of institutional endowments as sources of comparative advantage.

infrastructure fosters specialization.

Ample evidence indicates that broadband Internet facilitated the international exchange of goods and services by reducing the cost of communication and access to information (Freund and Weinhold, 2002, 2004; Choi, 2010; Visser, 2019). However, the way in which broadband shapes specialization patterns in the sense of conferring comparative advantage is still little understood. To my best knowledge, there exists only one study that directly examines whether ICT infrastructure provision confers comparative advantage based on cross-country trade data. Wang and Li (2017) conjecture that R&D-intensive industries as well as industries with a higher level of specialization benefit relatively more than the rest of the economy from ICT. Using a cross section of trade among 152 countries in 86 industries, the authors use OLS to regress industry-level exports on the proxies for industry specialization and R&D intensity, respectively interacted with a proxy of country-level ICT development.[3] To address the potential endogeneity of ICT, they instrument ICT development in the year 2013 with development measures from the year 2000. Since historical ICT data is predictive of contemporaneous ICT development but itself is not affected by trade in 2013, it is considered a valid instrumental variable in this setting. The results yield positive and significant coefficients for both interaction terms, suggesting that ICT development does confer comparative advantage in R&D-intensive and more specialized industries. A limitation that this study shares with most previous literature on comparative advantage is the lack of panel data and the failure to corroborate potentially inconsistent OLS estimates with PPML estimates. This paper overcomes these limitations and provides a theoretical framework for the empirical exercise.

The next section presents the theoretical framework. Section 5.3 describes the data and the construction of key variables used in the empirical exercise. Section 5.4 outlines the empirical strategy and presents the instrumental variable approach. Section 5.5 provides descriptive evidence and presents the estimation results. Section 5.6 concludes.

5.2 Theoretical Framework

5.2.1 Production Technology and Market Structure

Consider an economy endowed with a continuum of industries, indexed by $i \in [0, 1]$, and one productive factor, labor (L), which is fully mobile across industries. Workers are endowed with

[3] The level of ICT development is proxied with measures provided by the International Telecommunications Union and the World Bank: the ICT Development Index, the ICT Subscription Index (i.e., broadband subscribers per 100 persons) and the ICT Usage Index (i.e., Internet users per 100 people).

$h > 0$ units of human capital and supply their work inelastically (for any positive wage). For simplicity, I assume that the parameter h does not vary within the population. In each industry, a large number of homogeneous, risk-neutral firms operate under perfect competition.[4] To produce a final good in a given industry i, a continuum of complementary tasks $t \in [0, z_i]$ needs to be performed. The number of tasks required in the production process, $z_i > 0$, is referred to as the *complexity* of industry i. Thus, more complex industries require a higher number of tasks to be performed. Formally, final output Q_i is produced according to the Leontief production function:

$$Q_i = \min_{t \in [0, z_i]} q(t), \tag{5.1}$$

where $q(t)$ denotes the quantity of task $t \in [0, z_i]$ that goes into the production of the final good. The production function implies that every task is indispensable in the production process. A worker who spends $l(t) \leq h$ units of their labor performing task t produces

$$q(t) = \max\{l(t), 0\} \tag{5.2}$$

units of task t. For practical purposes, let the industries be ordered on the interval $[0, 1]$ such that z_i is continuous and strictly increasing in $i \in [0, 1]$. Finally, it is assumed that within firms, workers fully specialize in the execution of one specific task, and thus cannot carry out different jobs simultaneously. At the same time, not more than one worker can be allocated to the same task.

5.2.2 Information and Communication Technology

In order to successfully perform an assigned task, a worker needs to communicate and coordinate their job with other workers in the firm. The central idea is that every worker generates information from the completion of their job which serves as an input to others. This kind of interdependence means that in every industry delays in information transmission, the loss of information or the breakdown of communication links impairs the final output's value. In the model, production success depends on *(i)* the number of tasks over which workers must coordinate their activities and *(ii)* the quality of information transmission. When complexity is higher or information transmission is poor, the likelihood that a task is not successfully performed increases. Formally, a worker's probability of success is $\pi_i \in [0, 1]$, which is given by:[5]

[4] Since, consequently, production in a given industry is symmetric, I refer to the output in industry i as good i.

[5] More generally, π_i could be thought of as the expected percentage of the maximum output level retained if a worker performs their tasks. For instance, a value of $\pi_i = 0.6$ could mean that a worker always reduces the potential output by 40%. Since firms are considered risk-neutral, these different interpretations are equivalent.

$$\pi_i \equiv \exp\left\{-\frac{f(z_i)}{\alpha\sigma_i}\right\}, \tag{5.3}$$

where the function $f : \mathbb{R}^+ \to \mathbb{R}^+$ is continuous and strictly increasing in industry-complexity z_i. Intuitively, higher complexity means greater coordination requirements and a higher risk at least one communication link is impaired. To keep the model tractable, I assume that $f(z_i) = z_i$ for all $i \in [0,1]$. Firms can reduce the likelihood of production failure by improving the quality of communication within their organization. The endogenous variable $\sigma_i \geq 0$ summarizes the level of firms' investments towards establishing a more efficient communication system. While investing in communication technology raises the quality of information transfer among workers, it cannot transform the parameter z_i, which is technologically fixed. The parameter $\alpha > 0$ captures the level of broadband infrastructure in the economy. α is exogenous and can be thought of as a public good that enhances the productivity of firms' investments into communication equipment. π_i is increasing in the industry's "effective quality of communication", i.e., the product of α and σ_i. If $\alpha\sigma_i \to 0$, i.e., if firms do not establish any basic communication systems and/or when the economy's infrastructure is very poor, then $\pi_i \to 0$ and workers certainly fail at their jobs as they are unable to successfully coordinate. Conversely, if $\alpha\sigma_i \to \infty$, then information transmission is perfectly efficient and workers are always successful at performing their task.

Every task is essential to production. In other words, as soon as at least one task is not performed, the entire project yields an output of zero. Final output is therefore given by:

$$Q_i = \begin{cases} \min\limits_{t\in[0,z_i]} l(t) & \text{with probability } \pi_i^{z_i} \\ 0 & \text{with probability } (1-\pi_i^{z_i}) \end{cases} \tag{5.4}$$

where $\pi^{z_i} = \exp\{-\frac{z_i^2}{\alpha\sigma_i}\}$. Equation 5.4 emphasizes that the probability of failure is i.i.d. across workers, as illustrated by the increase from π_i to $\pi_i^{z_i}$.

5.2.3 Optimal Investment

Firms maximize profits, taking final good price p_i and wages w as given. Investing in better communication is costly and produces a cost in terms of labor, $k(\sigma_i) = \sigma_i$. Hence, each worker has a total of $l(t) = (h - \sigma_i)$ units of labor to spend on production. Denoting l_i the number of workers employed, a firm operating in industry i will thus symmetrically allocate a total of $l_i(h - \sigma_i)$ units of labor across z_i tasks. As a result, the firm maximizes the following profit function by choosing the optimal level of investments in communication (per worker) and the number of workers:

$$\max_{l_i,\,\sigma_i} \Pi_i = p_i \frac{l_i(h-\sigma_i)}{z_i} \exp\left\{-\frac{z_i^2}{\alpha\sigma_i}\right\} - whl_i \tag{5.5}$$

The first-order condition of optimal investment requires that the marginal costs equal the marginal benefits:

$$1 = (h-\sigma_i)\frac{z_i^2}{\alpha\sigma_i^2} \tag{5.6}$$

Solving for σ_i yields the optimal level of investment in communication as a function of human capital, complexity, and the quality of broadband infrastructure:

$$\hat{\sigma}_i = \frac{1}{2\alpha}\left[z_i\sqrt{z_i^2 + 4\alpha h} - z_i^2\right] \tag{5.7}$$

Condition (5.7) implies that optimal investment in communication is strictly higher in more complex industries. Intuitively, when coordination is required across a larger set of tasks, there is a higher likelihood that at least one communication link fails, and the marginal benefit of improving communication is higher. Optimal investment also increases with the level of human capital: higher h implies a greater potential output when coordination is successful and thus a greater marginal benefit of investment in communication. By contrast, optimal investment is lower when the state provides a better broadband infrastructure. Intuitively, a given industry must compensate for a poorer communication infrastructure by devoting a larger amount of its own resources in order to maintain production.

Finally, note that in equilibrium marginal costs equal marginal revenue or, equivalently, real income in terms of final good i is equal to the expected output per worker:

$$\frac{hw}{p_i} = \frac{h-\hat{\sigma}_i}{z_i}\exp\left\{-\frac{z_i^2}{\alpha\hat{\sigma}_i}\right\} \tag{5.8}$$

Thus, when σ_i is chosen optimally and condition (5.8) holds, there are constant returns to scale in industry i and the demand for labor is indeterminate.

5.2.4 The Open Economy

Now, consider a world economy that comprises two countries, the 'North' and the 'South', indexed by $c \in \{N, S\}$. Both countries use the same production technology but might differ in terms of human capital endowment, population size, and the quality of broadband infrastructure. The two countries can exchange final goods at no trade costs but labor remains immobile across borders.

In the following, I derive the free trade equilibrium, defined as a continuum of prices $(p_i)_{i\in[0,1]}$, a set of wages $(w^c)_{c\in\{N,S\}}$, and a pattern of specialization such that all firms maximize their profits, consumers maximize their utility, and all final good and labor markets in the world economy clear.

The Pattern of Comparative Advantage To describe the free trade equilibrium in a *Ricardian* model of comparative advantage à la Dornbusch et al. (1977), I first compute industry i's productivity level ϑ_i^c, defined as the expected output per worker in efficiency units:

$$\vartheta_i^c \equiv \left(1 - \frac{\hat{\sigma}_i{}^c}{h^c}\right) \frac{1}{z_i} \exp\left\{-\frac{z_i^2}{\alpha^c \hat{\sigma}_i{}^c}\right\} \tag{5.9}$$

Then, the relative productivity of industry i in the two countries is given by:

$$A(z_i) \equiv \frac{\vartheta_i^S}{\vartheta_i^N} = \frac{h^N}{h^S} \frac{h^S - \hat{\sigma}_i{}^S}{h^N - \hat{\sigma}_i{}^N} \exp\left\{z_i^2 \left(\frac{1}{\alpha^N \hat{\sigma}_i{}^N} - \frac{1}{\alpha^S \hat{\sigma}_i{}^S}\right)\right\} \tag{5.10}$$

Proposition 1. *The North has a comparative advantage in complex industries ($\frac{\mathrm{d}A(z_i)}{\mathrm{d}z_i} < 0$) if and only if $h^N\alpha^N > h^S\alpha^S$.*

Proof. As firms chose $\hat{\sigma}_i$ optimally the envelope theorem guarantees that changes in the optimal level of investment in communication constitute negligible second-order effects. Thus, we can use the partial derivative of A with respect to z_i:

$$\frac{\mathrm{d}A(z_i)}{\mathrm{d}z_i} = \frac{\partial A(z_i)}{\partial z_i} = 2z_i \frac{h^S - \hat{\sigma}_i{}^S}{h^N - \hat{\sigma}_i{}^N} \frac{h^N}{h^S} \exp\left\{z_i^2 \left(\frac{1}{\alpha^N \hat{\sigma}_i{}^N} - \frac{1}{\alpha^S \hat{\sigma}_i{}^S}\right)\right\} \left(\frac{1}{\alpha^N \hat{\sigma}_i{}^N} - \frac{1}{\alpha^S \hat{\sigma}_i{}^S}\right) \tag{5.11}$$

Hence, A is strictly decreasing in z_i if and only if $\alpha^N \hat{\sigma}_i{}^N > \alpha^S \hat{\sigma}_i{}^S$, i.e., the North has a better effective quality of communication than the South. Substituting Equation 5.7 into the inequality yields:

$$\frac{1}{2}[\sqrt{z_i^4 + 4\alpha^N h^N z_i^2} - z_i^2] > \frac{1}{2}[\sqrt{z_i^4 + 4\alpha^S h^S z_i^2} - z_i^2] \tag{5.12}$$

From the last expression, one can easily see that the inequality is satisfied if and only if $h^N\alpha^N > h^S\alpha^S$. ■

Proposition 1 establishes that the relative productivity of the country with a higher value of $\alpha \times h$ is increasing with the complexity of the production process. In other words, better-educated workers and a better broadband infrastructure both constitute sources of comparative advantage in more complex industries.

Intuitively, an increase in complexity affects an industry's productivity by *i)* increasing the risk at that least one task is not successfully performed, $\pi_i^{z_i} \downarrow$, and *ii)* a change in the optimal level of investment in communication, $\hat{\sigma}_i$. The envelope theorem ensures that the latter channel can be neglected so that productivity decreases due to the first channel. How much productivity declines is essentially determined by the effective quality of communication of the industry. Higher $\alpha \times \hat{\sigma}_i$ implies a lower probability of failure, and thus, the increase in complexity decreases $\pi_i^{z_i}$ relatively less. Therefore, the drop in productivity is lower in the country where $\alpha\hat{\sigma}_i$ is higher. By Equation 5.7, this is the country where the product of human capital and broadband infrastructure is greater.

Note that while broadband infrastructure and human capital both confer comparative advantage, their individual effects unfold via two distinct channels. Human capital only determines comparative advantage through its impact on the level of optimal communication investment σ_i. Put differently, the monotonicity of A would be independent of countries' differences in h, if σ_i was exogenous. In contrast, broadband infrastructure has a primary and a secondary effect on the effective quality of communication ($\alpha \times \sigma_i$). However, changes in σ_i are always outweighed by the direct increase in α, so that $\alpha \times \sigma_i$ is increasing in α. In other words, α would still constitute a source of comparative advantage, even if firm-level communication investments were exogenous.

Free Trade Equilibrium Without loss of generality, suppose that $h^N\alpha^N > h^S\alpha^S$, i.e., the North is more developed and enjoys a comparative advantage in more complex industries relative to the South. As markets are competitive, prices equal marginal costs, i.e., a producing industry charges $p_i = w^c/\vartheta_i^c$. The monotonicity of A ensures that, for any given relative wage $\omega \equiv w^S/w^N$, there exists a cutoff industry of complexity $\tilde{z}$ such that

$$\omega = A(\tilde{z}), \tag{5.13}$$

where $A(z_i) < \omega$ if and only if $z_i > \tilde{z}$. Denote $H^c \subset [0,1]$ the subset of industries that produce in country c in the free trade equilibrium. Given $\tilde{z}$, every country produces the goods with the lower marginal cost of production. Accordingly, $H^N = \{i \in [0,1] : z_i \geq \tilde{z}\}$ and

$H^S = \{i \in [0,1] : z_i < \tilde{z}\}$. That is, the North produces in all industries that are more complex than $\tilde{z}$ as Northern firms are able to charge lower prices than their counterparts in the South. Similarly, less complex industries (below $\tilde{z}$) will relocate to the South, where the costs of production for these industries are lower than in the North.

Cobb-Douglas preferences imply that workers spend a constant share g_i of their income on every good i. Thus, world demand C_i for good i is given by:

$$p_i C_i = g_i(w^S h^S L^S + w^N h^N L^N), \tag{5.14}$$

where $\int_0^1 g_i \, \mathrm{d}i = 1$. Finally, a given country's national income is equal to the portion of world income spent on its goods, that is,

$$w^c h^c L^c = \int_{i \in H^c} g_i(w^S h^S L^S + w^N h^N L^N) \, \mathrm{d}i \tag{5.15}$$

Rearranging Equation 5.15 yields:

$$\omega = \frac{h^N L^N}{h^S L^S} \frac{\delta(\tilde{z})}{1 - \delta(\tilde{z})} \equiv B(\tilde{z}), \tag{5.16}$$

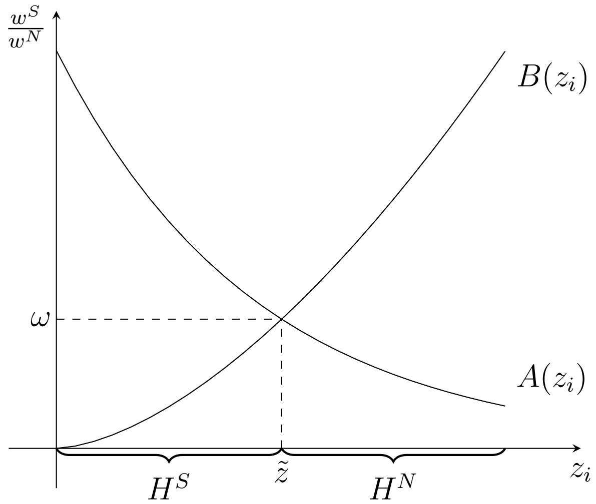
with $\delta(\tilde{z}) \equiv \int_{i \in H^S} g_i \, \mathrm{d}i$ reflecting the share of world income spent on Southern commodities. Note that $\frac{\partial \delta(\tilde{z})}{\partial z} > 0$, i.e, if the mass of industries located in the South increases, so does the share of world income spent on Southern goods. Equation 5.16 guarantees that trade will always be balanced in equilibrium. B is continuous and monotonically increasing in $\tilde{z}$: If more industries locate their production in the South, then $\tilde{z} \uparrow$, and—at constant prices—the South would encounter a trade deficit with respect to the North. To restore equilibrium, the relative wage must increase, $\omega \uparrow$. Together conditions (5.13) and (5.16) pin down the equilibrium relative wage and cutoff industry after the trade liberalization. The free trade equilibrium is illustrated graphically in Figure 5.1.

5.3 Data and Measurement

5.3.1 Trade Data

I draw on two trade databases for the empirical analysis. First, I use the World Database of International Trade (BACI) dataset, published by CEPII, which covers disaggregated and harmonized bilateral trade flows at the product level for more than 200 countries over the period 1994 to 2016 (Gaulier and Zignago, 2010). To aggregate trade flows to the industry level, I use concordance tables, which map products into NAICS 4-digit industries, provided by Pierce

Figure 5.1 : The Free Trade Equilibrium



Notes: The figure depicts the free trade equilibrium in the two-country world model in which $h^N \alpha^N > h^S \alpha^S$, i.e., the South has a comparative advantage in *less* complex industries (Proposition 1). ω is the equilibrium relative wage and $\tilde{z}$ the complexity of the equilibrium cutoff industry. The South produces goods of complexity below the cutoff; the North produces the goods above the cutoff.

and Schott (2012). This leaves me with a sample of yearly trade flows in 85 manufacturing industries among 109 exporting countries and 204 importing countries, after discarding countries with missing country-level data on broadband, human capital, or other relevant characteristics.

5.3.2 Exporter and Exporter-Importer Data

Exporter characteristics I measure the expansion of national broadband networks by the broadband penetration rate, defined as the number of subscriptions to fixed broadband Internet ($\geq$ 256 kbit/s downstream speed) per 100 inhabitants, included in the International Telecommunications Union's (ITU) World Telecommunication/ICT Indicators Database. The data cover more than 100 countries since the year 1997, in which broadband Internet is first recorded in Canada. The database also contains information on pre-existing infrastructure, specifically, fixed-line telephony and cable TV networks in 1997 and 1998. As suggested by Czernich et al. (2011), these existing networks can be used to predict the deployment of broadband Internet using a technology diffusion model, as the deployment of first-generation broadband heavily relied on the existing copper wire and coaxial cable grids. Other country characteristics such as GDP, population, and factor endowments (capital stock and human capital) come from the Penn World Table (version 9.1) database (Feenstra et al., 2015).

Bilateral variables I use standard gravity variables to approximate bilateral trade costs, including time-invariant factors (e.g., distance, colonial relationships, common language, contiguity) from the CEPII-GeoDist and Language database (Mayer and Zignago, 2011), and time-variant data on regional trade agreements (RTAs) from the Regional Trade Agreements Database (Egger and Larch, 2008).

5.3.3 Industry-Level Measures

Complexity I construct a measure of industry-level complexity using task-level data from the US O*NET database and employment shares provided by the US Bureau of Labor Statistics (BLS). Following the model's intuition that the number of tasks over which production must be coordinated determines the importance of efficient coordination, I build an industry-level index that captures interdependence among tasks and the difficulty of codifying information. Job characteristics in O*NET are classified into different categories (Knowledge, Skill, Values, etc.). I focus on "Work Contexts" and "Work Activities" as these classes match the notion of tasks in this context most closely. For each occupation, O*NET provides an average score on the "importance" and the "level" for required work activities (1–5) and an average score on the frequency of work contexts (0–7). After, rescaling all scores to a range between zero and one, the score of task t in industry i is given by the weighted sum of task-level scores in each occupation o:

$$M_{ti} = \sum_{o} \mu_{io} V_{to}, \tag{5.17}$$

where μ_{io} is the employment share of occupation o in industry i, and $V_{to} = 0.5 \times (importance_{to} + level_{to})$ if t is a Work Activity and $V_{to} = frequency_{to}$ if t is a Work condition. Then, the intensity of each task is obtained by dividing each score by the sum of scores in each industry:

$$I_{ti} = \frac{M_{ti}}{\sum_t M_{ti}} \tag{5.18}$$

In the next step, I compute a measure for an industry's complexity defined as the average task intensity of the following set of tasks, where tasks with an asterisk mark items that enter the measure with an opposite weight:[6]

Work Activities: *Getting Information, Coordinating the Work and Activities of Others, Interpreting the Meaning of Information for Others, Provide Consultation and Advice to Others, Thinking Creatively, Making Decisions and Solving Problems, Developing Objectives and Strategies,*

[6] Appendix Table E.1 lists a detailed description of each activity and work context.

Analyzing Data or Information, Processing Information, Handling and Moving Objects, Operating Vehicles, Mechanized Devices, or Equipment*, Updating and Using Relevant Knowledge.*
Work Contexts: *Contact With Others, Work With Work Group or Team, Coordinate or Lead Others, Importance of Repeating Same Tasks*.*

The results suggest that manufacturing computers and peripheral equipment and manufacturing communications equipment count among the most complex industries. "Sawmills and Wood Preservation" is the least complex industry. Appendix Table E.2 ranks the full set of NAICS 4-digit industries according to their complexity.

Skill and capital intensity I complement the complexity measure with industry-level measures of skill intensity and (physical) capital intensity. The measures allow controlling for traditional Heckscher-Ohlin sources of comparative advantage in the gravity model by including separate interaction terms with the capital and the human capital endowment of countries, respectively. Factor intensities are calculated from the NBER-CES database. I follow Chor (2010) and compute skill intensity as the log of the ratio of non-production workers to total employment and capital intensity as the log of the ratio of real capital stock to total employment. Both measures are averaged over the years 1987-1997.

5.4 Empirical Strategy

5.4.1 Main Specifications

The core of the analysis consists of a structural gravity model, relating bilateral trade flows to trade frictions and the size of trading partners. I build on recent developments and contributions in the gravity literature which provide theoretical foundations to standard gravity models and propose improvements to make sure that they align with theory.

First, I estimate the gravity model at the industry level, following a number of contributions that show that the structural gravity model satisfies the separability property, i.e., can be derived and estimated at any level of disaggregation (Eaton and Kortum, 2002; Anderson and van Wincoop, 2003, 2004; Costinot et al., 2012; Yotov et al., 2016; Donaldson, 2018). Second, I use the PPML estimator due to Santos Silva and Tenreyro (2006, 2011) to estimate the gravity equation. The PPML estimator has several advantages over the OLS estimator obtained from a traditional log-linear gravity model. For instance, PPML uses the information contained in zero trade flows (due to its multiplicative form) and is consistent in the presence of heteroskedasticity. Third, I account for multilateral resistances (Anderson and van Wincoop, 2003, 2004). Multilateral resistances acknowledges that trade between two countries is not only affected by bilateral frictions, but also by the average barriers each country faces with the rest of the world. In the case of panel data and industry-level trade flows, the presence of multilateral resistances motivates the inclusion of exporter-time and importer-time fixed effects in addition to exporter-industry and importer-industry fixed effects (Borchert et al., 2021; Larch et al., 2021; Baldwin and Taglioni, 2006). Since the interaction between industry-complexity and broadband penetration would be absorbed by including exporter-industry fixed effects, I instead add a time-varying measure of remoteness as an atheoretical proxy of multilateral resistance at the exporter-industry level (Helliwell, 1998). Forth, following the recommendation of Yotov et al. (2016) and Yotov (2021), I include domestic sales (in addition to international trade) to assure theoretical consistency. In sum, my preferred model to test the relevance of broadband deployment for trade flows through the channel of complexity, is given by the following model:

$$\begin{aligned} X^i_{cd,t} = &\exp[\beta_1(BB_{c,t} \times CMPLX^i) + \beta_2(HC_{c,t} \times CMPLX^i)] \times \\ &\exp[\beta_3(HC_{c,t} \times SKILLINT^i) + \beta_4(K_{c,t} \times CAPINT^i)] \times \\ &\exp[\mathbf{X}'_{cd,t}\gamma + \delta CLOSE^i_{c,t} + \pi_{c,t} + \mu_{d,t} + \alpha^i_d + \delta_{c,d}] \times \varepsilon^i_{cd,t}, \end{aligned} \tag{5.19}$$

where $X^i_{cd,t}$ is bilateral trade in levels between exporting country c and destination d in industry i and year t. The estimate of interest is β_1, which captures the impact of the interaction between the exporter's broadband penetration and industry complexity $(BB_{c,t} \times CMPLX^i)$. The inclusion of exporter fixed effects implies that the estimate is identified from the within-country broadband rollout. Similarly, β_2 captures the effect of human capital on trade in complex industries. The theory predicts that both β_1 and β_2 are positive, i.e., that increases in the level of human capital and expansions of the broadband network increase the level of exports in complex industries relative to other countries. Note that rather than explaining trade volumes, the coefficients capture differences in the composition of trade across time and countries. The specification also controls for traditional Heckscher-Ohlin channels of comparative advantage by including exporters' level of human capital interacted with industry skill intensity $(HC_{c,t} \times SKILLINT^i)$ and exporters' physical capital stock p.c. interacted with industry capital intensity $(K_{c,t} \times CAPINT^i)$. The vector $\mathbf{X}'_{cd,t}$ comprises a number of standard country-pair gravity measures of time-varying trade frictions, including the presence of regional trade agreements and a common currency. The terms $(CLOSE^i_{c,t} + \pi_{c,t} + \mu_{d,t} + \alpha^i_d)$ denote the time-varying exporter-industry remoteness index plus exporter-year, importer-year, and importer-industry fixed effects to control for inward and outward multilateral resistances. Remoteness is captured by how close an industry is to its trading partners and defined as importer size (i.e., the share of expenditure of the importing country relative to the world) weighted with inverse distance to the importing country. Finally, the full specification also includes exporter-importer fixed effects $\delta_{c,d}$, which control for any time-constant trade barriers. The inclusion of country-pair fixed effects also accounts for domestic trade flows, which have recently attracted attention in the Gravity literature (Yotov, 2021; Borchert et al., 2021).

5.4.2 Instrumental Variable Approach

The identifying assumption for interpreting the impact of broadband Internet on the pattern of trade as causal is

$$E[BB_{c,t} \times CMPLX^i \times \varepsilon^i_{cd,t}] = 0, \forall i, c, t, \tag{5.20}$$

i.e., the interaction term must be orthogonal to any unobserved exporting opportunities captured in the error term. By the law of iterated expectations, this is equivalent to

$$E[BB_{c,t} \times \varepsilon^i_{cd,t} \mid CMPLX^i] = 0, \forall i, c, t \tag{5.21}$$

The condition requires that for every industry, the exporting country's path of broadband deployment is uncorrelated with unobserved determinants of trade in $\varepsilon^i_{cd,t}$. The inclusion of comprehensive sets of exporter-year, importer-industry-year, and exporter-importer fixed effects, implies that to confound the effect of interest, omitted determinants of trade must occur at any other levels than those accounted for by the fixed effects. However, a more serious concern to the consistency of $\hat{\beta}_1$ is potential reverse causality, which occurs when the pattern of trade influences national broadband deployment. If, for instance, countries with a comparative advantage in complex industries put more effort into deploying high-speed Internet to support their exporting industries, this would cause broadband penetration to be endogenous and produce a spurious estimate.

To address endogeneity concerns, I borrow the IV strategy of Czernich et al. (2011). The authors, estimate the impact of broadband deployment on economic growth by instrumenting broadband penetration rates with the national copper wire and coaxial cable networks used to enable voice telephony and cable TV in the pre-broadband era. This approach exploits the fact that the deployment of fixed-line broadband relied heavily on these pre-existing networks to minimize the cost rollout. The authors propose a nonlinear technology diffusion model to approximate countries' broadband penetration over time:

$$BB_{c,t} = \frac{\sigma_c}{1 + \exp[-\lambda(t - \tau)]} + \vartheta_{c,t}, \tag{5.22}$$

where the parameter σ_c is the maximum broadband penetration level, λ determines the diffusion speed, τ corresponds to the inflection point, at which the diffusion curve reaches its maximum growth rate, and $\vartheta_{c,t}$ is the error term. Each country's maximum reach of the broadband network (i.e., the saturation level) σ_c is determined by the spread of cable TV and telephony networks before the advent of broadband Internet in the following form:

$$\sigma_c = \sigma_0 + \alpha_1 TELNET_{c,0} + \alpha_2 CABLENET_{c,0}, \tag{5.23}$$

where $TELNET_{c,0}$ is the number of telecommunication access lines per 100 inhabitants and $CABLENET_{c,0}$ is the number of cable TV subscribers per 100 inhabitants in 1996. Combining Equations 5.23 and 5.22 yields a first-stage equation that can be estimated using nonlinear least squares. Notice that while the maximum broadband penetration level is country-specific, the diffusion speed and the inflection point are constant across countries. The predicted annual broadband penetration rates obtained from the nonlinear first stage are subsequently used to replace actual values in Equation 5.19 in the second stage.

Table 5.1 show the results of estimating the diffusion model with nonlinear least squares. The diffusion curve is estimated for 71 countries that have information on their pre-existing cable TV and voice telephony networks. The results show that the spreads of both networks have a significant and positive effect on the maximum reach of the broadband diffusion curve (σ_c), corroborating the results of Czernich et al. (2011), who originally estimated the diffusion model on a sample of 25 developed countries. The F-test rejects the hypothesis that $\hat{\alpha_1} = \hat{\alpha_2} = 0$ at conventional levels of significance. On average, the inflection point is estimated around the year 2006. With an R^2 of 0.95, the model fits observed broadband diffusion remarkably well. Appendix Figure E.1 illustrates the model's fit by plotting observed and predicted broadband penetration for the period 1998-2017.

5.5 Results

5.5.1 Descriptive Evidence

Before turning to Gravity estimates, I examine whether there is evidence of the importance of broadband infrastructure for comparative advantage in the raw data. To this end, I group industries into complex and noncomplex using the top and bottom tercile of the complexity

Table 5.1 : First Stage Results

	(1)
Voice telephony network penetration rate, 1997 (α_1)	0.56***
	(0.03)
TV cable network penetration rate, 1997 (α_2)	0.22***
	(0.06)
Diffusion speed (λ)	0.44***
	(0.02)
Inflection point (τ)	2,005.91***
	(0.26)
Constant (σ_0)	2.13***
	(0.74)
R^2	0.95
Observations	1,420
Countries	71
F-test: $\alpha_1 = \alpha_2 = 0$	302.9

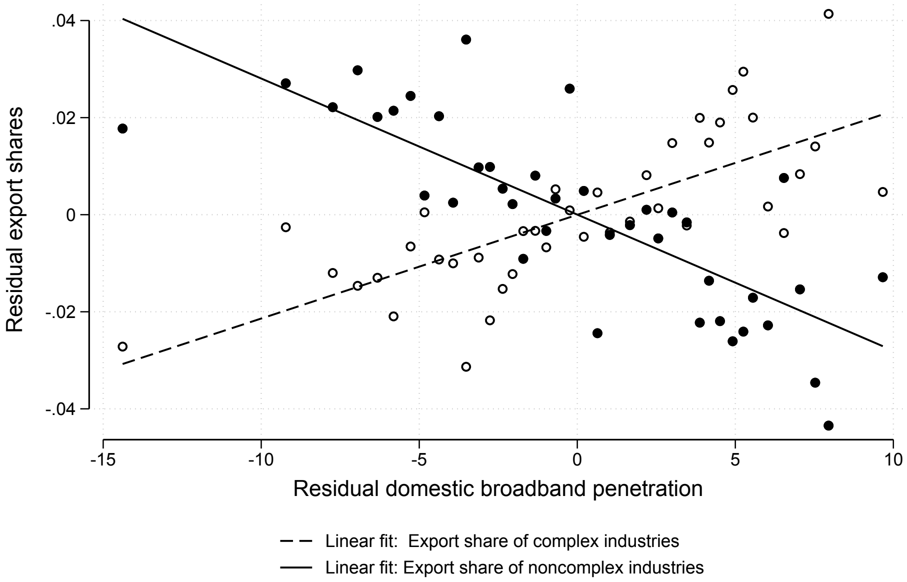
Notes: The table reports the results from a nonlinear least squares regression estimated on a sample of 71 countries over the period 1998-2017 (Equations 5.23 and 5.22). The dependent variable is the annual domestic broadband penetration rate, defined as the number of fixed-broadband subscriptions per 100 inhabitants. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

score as thresholds. Next, I compute each country's yearly value of exports in complex (noncomplex) industries relative to its total exports.

I first consider the correlation between a country's share of exports in complex (noncomplex) industries and domestic broadband diffusion pooled over 1998-2016. Figure 5.2 plots the linear fit between export shares and domestic broadband penetration rates after partialling out exporter and year fixed effects. Thus, the slopes reflect the effect of a *within-country* increase in broadband penetration rate. Observations are grouped into 40 equal size bins. The findings indeed show a conspicuous association between broadband deployment and the composition of exports: an expansion of broadband penetration by 10 points increases the share of exports in complex industries by 2 percentage points and reduces the share of noncomplex exports by approximately the same magnitude.

A second way to examine the raw data is to track the composition of exports over time, separately for countries that are ahead (frontier countries) and those that lag behind (laggards) in international broadband diffusion. To this end, I divide countries into two groups, those above and those below the median level of broadband penetration in 2006, the year around which the growth of broadband penetration is estimated to first slow (inflection point) based on the nonlinear diffusion model estimated in Section 5.4.2. Figure 5.3 plots the OLS estimates obtained from regressing the share of complex (noncomplex) exports on a dummy identifying

Figure 5.2 : Conditional Correlation between Export Composition and Broadband Penetration



Notes: The figure shows binned scatter plots with linear fits between export shares of complex (noncomplex) industries and domestic broadband penetration conditional on year and exporter fixed effects for the period 1998-2016 and 109 countries. Complex (noncomplex) industries correspond to the top (bottom) tercile of industries according to the complexity score (see Section 5.3.3). Estimated slopes are significantly different from zero at the 5 percent level (based on standard errors clustered at the country level).

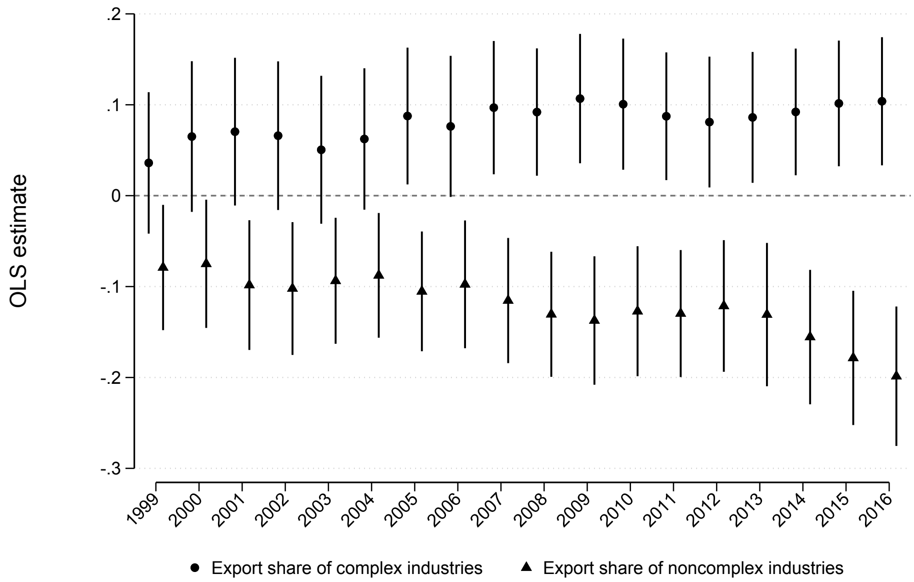
frontier countries in each year. The results show that the composition of exports clearly started diverging between frontiers and laggards over time. Before 2005 there is no statistically significant difference in the share of complex exports between the two groups; by 2009, the share of complex exports was about 10 percentage points higher for frontiers compared to laggards. While frontier countries already exported significantly fewer noncomplex goods in the early broadband years, this share continuously declined, in parallel with the diffusion of broadband.

Overall, the descriptive analysis shows that countries with a higher level of broadband diffusion specialize in complex industries. Of course, this correlation may be spurious. The next section presents Gravity estimates and results from the IV strategy to corroborate the correlational analysis.

5.5.2 Gravity Estimates: OLS Results

I start by estimating the Gravity model using OLS, as this has been the conventional approach in the comparative advantage literature. The results are presented in Table 5.2. Standard errors are clustered at the industry-country-pair level and bootstrapped in second-stage regressions

Figure 5.3 : Differences in Export Composition between Frontier and Laggard Countries



Notes: The figure plots OLS coefficients obtained by regressing the share of complex (noncomplex) exports on a dummy identifying countries above the median level of broadband diffusion in 2006 in each year. Complex (noncomplex) industries correspond to the top (bottom) tercile of industries according to the complexity score (see Section 5.3.3). The sample includes 109 countries. Confidence bands are drawn at the 90-percent level.

(Column 6). I consider different levels of clustering as robustness checks in Section 5.5.4. In Column (1), the dependent variable is a dummy equal to one for positive trade flows and zero otherwise. The coefficient of the interaction term between broadband and complexity is positive and statistically significant, suggesting that an increase in broadband penetration increases trade in complex industries at the extensive margin. Column (2) adds the interaction term between human capital and complexity as well as the traditional Heckscher-Ohlin sources of comparative advantage. The interaction between human capital and complexity as well as the Heckscher-Ohlin channels have positive and significant estimates, in line with the theory. Columns (3) and (4) estimate the traditional log-linear gravity equation, using the log of trade and positive trade flows only as the dependent variable. The estimate of the interaction with broadband is positive and statistically significant, even after controlling for Heckscher-Ohlin effects and human capital as a source of comparative advantage. To put the magnitude of the estimate in Column (4) into perspective, consider an increase in broadband penetration by 26 points, which corresponds to moving from the 25th to the 75th percentile in 2016 or closing the gap between the Philippines and the Czech Republic. Then, exports in the industry at the 75th percentile of the complexity distribution (Footwear Manufacturing) would increase by 25 percent relative to the industry at the 25th percentile of the complexity distribution (Leather and Hide Tanning and Finishing).[7]

Table 5.2 : OLS Results

	(1) OLS DUMMY	(2) OLS DUMMY	(3) OLS LOG_TRADE	(4) OLS LOG_TRADE	(5) OLS IV_SMPL	(6) IV IV_SMPL
CMPLX × BB penetration	0.03***	0.02***	0.21***	0.11***	0.09***	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
CMPLX × predicted BB penetration						0.06***
						(0.00)
CMPLX × human capital		0.57***		9.89***	9.25***	10.30***
		(0.01)		(0.16)	(0.21)	(0.08)
Skill-intensity × human capital		0.02***		0.52***	0.54***	0.54***
		(0.00)		(0.01)	(0.02)	(0.00)
Capital-intensity × capital p.c.		0.01***		0.11***	0.14***	0.14***
		(0.00)		(0.00)	(0.00)	(0.00)
Exporter-industry closeness	8.70	21.69	2,367.48***	2,442.39***	5,749.51***	5,758.67***
	(24.91)	(25.98)	(480.28)	(484.50)	(413.11)	(147.88)
Currency union	0.02***	0.02***	0.48***	0.49***	0.52***	0.51***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Free trade agreement	0.01***	0.01***	0.01***	0.01***	0.02***	0.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.62	0.62	0.62	0.63	0.65	0.65
Observations	35,735,105	35,735,105	9,912,530	9,912,530	8,595,077	8,595,077
# Exporters	109	109	109	109	71	71
# Importers	204	204	204	204	204	204
Period	1998-2016	1998-2016	1998-2016	1998-2016	1998-2016	1998-2016
Exporter-Year FE	×	×	×	×	×	×
Importer-Year FE	×	×	×	×	×	×
Importer-Industry	×	×	×	×	×	×
Exporter-Importer FE	×	×	×	×	×	×

Notes: The table reports OLS results based on logged Equation 5.19. In Columns (1) and (2), the dependent variable is a dummy equal to one for positive trade and zero otherwise; in Columns (3)–(6), the dependent variable is the log value of annual bilateral trade flows. Columns (1) and (2) are estimated on the whole sample, while Columns (2)–(6) use positive trade flows only. Columns (5) and (6) additionally restrict the sample to exporting countries with available data on their domestic voice telephony and TV cable network as of 1997. Standard errors (reported in parentheses) are clustered at the industry-country-pair level in all specifications and bootstrapped (100 repetitions) in Column (6). $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Column (5) re-estimates the full specification of Column (4) limiting the sample to exporters with information on pre-existing cable TV and voice telephony networks. This reduces the number of exporting countries from 109 to 71. The estimate of the broadband-complexity interaction is slightly smaller on the restricted sample. Column (6) reports the second stage results using predicted broadband penetration instead of actual rates obtained from the first

[7] The estimate is given by $100 \times [\exp(0.11 \times 26 \times 0.079) - 1] = 25.35$ percent, where 0.079 corresponds to the range between the 75th and 25th percentile of the log complexity distribution.

stage (Table 5.1). The second-stage estimate is positive and statistically significant and slightly smaller than OLS, implying a $100 \times [\exp(0.09 \times 26.1 \times 0.079) - 1] = 20$ percent increase of relative exports at the 75th complexity percentile when increasing broadband penetration from the 25th to the 75th percentile. For comparison, the human capital channel suggests that relative exports of the 75th percentile industry increase by 30 percent when moving from the 25th to the 75 percentile in the human capital distribution in 2016.[8]

In all specifications, the time-varying policy variables (presence of free trade agreements, currency union) have the expected positive signs and are mostly statistically significant, in line with established results of the vast gravity literature.

5.5.3 Gravity Estimates: PPML Results

Next, I turn to the results obtained when estimating the Gravity model using PPML. As noted above, the key advantages of the PPLM estimate compared to OLS is that it is consistent under heteroskdasticity and that it can take into account the information contained in zero trade flows rather than relying on positive trade flows only (Santos Silva and Tenreyro, 2006, 2011). Thus, the dependent variable corresponds to bilateral trade flows measured in levels instead of logs.

The first column of Table 5.3 estimates Equation 5.19 using positive trade flows only to allow direct comparison with the OLS results of Column (4), Table 5.2. The coefficient of broadband interacted with complexity is positive and significant. The estimate of 0.02 implies that increasing broadband penetration from the 25th to the 75th percentile increases exports in the 75th relative to the 25th percentile industry by $[\exp(0.02 \times 0.079 \times 26.1) - 1] \times 100 = 4.2$ percent (where 0.079 corresponds to the range between the 75th and 25th percentile of the log complexity distribution). This magnitude is substantially smaller than the 25 percent implied by the OLS estimate, bolstering previous research pointing out sizable differences between the OLS and PPML estimate (see e.g., Borchert et al., 2021). Column (2) shows the PPML results including zero trade flows in addition to positive trade flows; Column (3) reports the full specification including the Heckscher-Ohlin channels of comparative advantage and the interaction between human capital and complexity. The estimate of the broadband-complexity interaction remains positive and statistically significant in both specifications. Interestingly, including zero trade flows does not meaningfully affect any of the estimates in Column (3) (compared to Column 1). This is in line with previous findings, suggesting only

[8] This would be equivalent to closing the gap between Turkey and New Zealand. The estimate is computed as follows: $100 \times [\exp(10.30 \times 0.325 \times 0.079) - 1] = 31.76$ percent.

a marginal effect of including zero trade flows in PPML estimations on average (Borchert et al., 2021). This result is likely due to the fixed effects already accounting for most zero-trade relationships and to the fact that zero trade flows occur mostly in relationships with smaller countries, on which PPML places lower weight. Column (4) replicates Column (3) using the sample of 71 exporters with available data needed for the IV estimation. This does not affect the estimate of interest. Column (5) presents the IV results. The estimate of the interaction between predicted broadband penetration and complexity is positive and statistically significant, corroborating the previous results. The IV estimate of 0.07 is distinctly larger than in Column (4), implying a 16-percent increase in relative exports in the 75th percentile industry when moving from the 25th to the 75th percentile of the broadband penetration distribution. To put this figure into perspective, the estimate of the human capital channel in Column (5) suggests that increasing human capital from the level of Turkey (25th percentile) to New Zealand (75th percentile) increases relative exports in the 75th percentile industry (relative to the 25th percentile industry) by $100 \times [\exp(4.44 \times 0.325 \times 0.079) - 1] = 12$ percent. Again, this estimate appears substantially smaller when the Gravity equation is estimated with PPML than using OLS. Nonetheless, the OLS and PPML results are broadly consistent and provide evidence to support the theory.

5.5.4 Robustness

This section presents sensitivity analyses and robustness checks against alternative specifications, panel length, and assumptions about the variance-covariance matrix. The results are reported in Table 5.4. Panel A presents the results using actual domestic broadband penetration and Panel B reports the results of the IV approach based on predicted broadband penetration.

Balanced sample of countries First, some importers, in particular poorer countries, lack broadband data or other relevant domestic variables, so that the gravity model is estimated on an unbalanced sample of countries. To test whether the results are driven by this kind of selection, I re-estimate the model on a balanced sample of countries, i.e., excluding importers that have insufficient coverage as exporters. This reduces the number of importers to 109 in Panel A and 69 in Panel B. The results reported in Column (1) show that the estimates of interest are insensitive to the sample restriction.

Table 5.3 : PPML Results

	(1) PPML POS_TRADE	(2) PPML ALL_TRADE	(3) PPML ALL_TRADE	(4) PPML IV-SMPL	(5) IV-PPML IV-SMPL
CMPLX × BB penetration	0.02**	0.05***	0.02**	0.02***	
	(0.01)	(0.01)	(0.01)	(0.01)	
CMPLX × predicted BB penetration					0.07***
					(0.00)
CMPLX × human capital	5.38***		5.46***	6.90***	4.44***
	(1.16)		(1.16)	(1.15)	(0.03)
Skill-intensity × human capital	0.73***		0.69***	0.87***	0.86***
	(0.09)		(0.09)	(0.09)	(0.03)
Capital-intensity × capital p.c.	0.13***		0.13***	0.12***	0.12***
	(0.02)		(0.02)	(0.02)	(0.01)
Exporter-industry closeness	514.57	517.55	487.41	534.16	537.36***
	(622.17)	(700.57)	(626.74)	(638.40)	(116.61)
Currency union	0.12***	0.08**	0.08**	0.10***	0.10***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.00)
Free trade agreement	0.04*	0.04	0.04	0.04	0.04***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.01)
Observations	9,912,530	32,738,083	32,738,083	22,089,134	22,089,134
# Exporters	109	109	109	71	71
# Importers	204	204	204	204	204
Period	1998-2016	1998-2016	1998-2016	1998-2016	1998-2016
Exporter-Year FE	×	×	×	×	×
Importer-Year FE	×	×	×	×	×
Importer-Industry FE	×	×	×	×	×
Exporter-Importer FE	×	×	×	×	×

Notes: The table reports PPML results based on Equation 5.19. The dependent variable is the value of annual bilateral trade flows. Column (1) restricts the sample to positive trade flows. Columns (2)–(5) use all trade flows including zeros. Columns (4) and (5) restrict the sample to exporting countries with available data on their domestic voice telephony and TV cable network as of 1997. Standard errors (reported in parentheses) are clustered at the industry-country-pair level in all specifications and bootstrapped (100 repetitions) in Column (5). $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Only first-generation broadband As a second sensitivity exercise, I restrict the panel to the years 1998-2010 to focus on the impact of first-generation broadband internet. This avoids that the results are largely driven by the emergence of new broadband technologies, such as high-speed internet based on fiber optic cables after 2010. The results reported in Column (2) show that the point estimates are very robust to truncating the panel.

Other sources of comparative advantage Next, I test for robustness to another source of comparative advantage in complex industries. Specifically, Bombardini et al. (2012) argue that a lower domestic dispersion of human capital in the population constitutes a source of comparative advantage in industries with a higher degree of interdependence (or complementarity) across production tasks. The authors suggest that lower skill dispersion implies that workers with similar skill levels can be deployed across tasks, making the production of more interdependent industries relatively more productive. Conversely, industries in which skill is more easily substitutable benefit relatively more from a population with higher skill dispersion. The authors find empirical support for their hypothesis using a gravity model on a cross section of international trade flows estimated with OLS. To account for skill dispersion as a potential source of comparative advantage in my model, I compute a time-varying dispersion index of human capital based on different levels of educational attainment in a population, following Park (2006):

$$HC\_DISP_t^2 = \sum_{a=1}^{4} (m_{t,a} - \mu_t)^2 \times p_{t,a} \tag{5.24}$$

where a indicates the level of education, including no schooling, primary, secondary, and tertiary education. $p_{t,a}$ is a given country's share of the population aged 25 or older who have attained the level of education level a, $m_{t,a}$ is the average schooling years of those who have attained education level a, and μ_{t_a} is the average years of schooling in the population in year t. Column (3) of Table 5.4 introduces the interaction between domestic human capital dispersion and industry complexity. In addition, I cluster the standard errors more conservatively at the exporter-importer level to allow for correlation of errors within country pairs over time. In both Panels A and B, the estimate of complexity interacted with (predicted) broadband penetration remains robust and highly statistically significant. The impact of the interaction of human capital dispersion and complexity is positive and statistically significant in Panel B, suggesting that an increase in dispersion confers a comparative advantage in *more* complex industries. This finding is not consistent with Bombardini et al.'s results and points to the importance of using PPML as well as panel data to obtain reliable estimates.

Different fixed effects In Column (4), I use an alternative set of fixed effects, replacing importer-industry and exporter-industry with importer-exporter-industry fixed effects. This drops the interaction between human capital and complexity due to high colinearity with the fixed effects. However, the estimate of interest remains robust to the alternative specification.

Excluding USA Finally, Column (5) removes the United States from the sample. As the complexity measure is based on US data, this substantially reduces the risk that estimates are reversely driven by trade affecting the ranking of industries. Again, the estimates of the interactions between (predicted) broadband and complexity in Panels A and B remain robust to the procedure.

5.6 Conclusion

Uncovering the determinants of international trade patterns has occupied a rich theoretical and empirical literature. Previous research has primarily investigated the role of factor endowments and, more recently, institutions as potential sources of comparative advantage in trade. This paper provides novel evidence that the rollout of broadband Internet contributed to international specialization. I present a theoretical framework in which better broadband infrastructure enhances the productivity of firms' investment in communication systems. Better communication disproportionately benefits industries that are more complex, i.e., require coordination across a larger set of tasks. In a two-country world economy, the country with a higher level of human capital and a more developed broadband infrastructure specializes in more complex goods.

The model implications are consistent with the data. I estimate a state-of-the-art structural Gravity model using bilateral trade flows for 109 exporting and 204 importing countries between 1998 and 2016. The gravity estimates suggest that countries with a stronger increase in broadband penetration shifted their exports more toward complex goods. The estimates are robust to instrumenting actual broadband penetration with predicted broadband diffusion based on countries' pre-existing fixed-line telephony and cable TV networks (Czernich et al., 2011). PPML estimates suggest that a broadband expansion by 26 points (or closing the broadband gap between the Czech Republic and the Philippines in 2016) increases relative exports in complex industries (75th percentile vs. 25th percentile) by 4 to 16 percent. The estimates also consistently confirm the positive association between increases in domestic human capital and increases in the complexity of exports, as suggested by theory. However,

Table 5.4 : Robustness: PPML Estimator

	(1) '98-'16 EX=IM	(2) '98-'10 PNL	(3) '98-'10 CTRL	(4) '98-'10 FE	(5) '98-'10 NO_USA
Panel A: *PPML Results*					
CMPLX × BB penetration	0.02***	0.03***	0.03***	0.09***	0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
CMPLX × human capital	5.86***	3.47***	3.47*		
	(1.17)	(1.01)	(1.91)		
CMPLX × Skill dispersion			0.02	0.70***	0.33*
			(0.37)	(0.20)	(0.17)
Skill-intensity × human capital	0.71***	0.46***	0.46***	0.84***	0.99***
	(0.09)	(0.09)	(0.12)	(0.18)	(0.17)
Capital-intensity × capital p.c.	0.14***	0.18***	0.18***	0.10***	0.08***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
Observations	18,698,470	21,706,477	21,706,477	13,372,320	10,818,340
Panel B: *IV-PPML Results*					
CMPLX × predicted BB penetration	0.08***	0.07***	0.07***	0.10***	0.07***
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)
CMPLX × human capital	5.13***	3.10***	3.02***		
	(0.40)	(0.37)	(0.37)		
CMPLX × Skill dispersion			0.19**	0.95***	0.48***
			(0.09)	(0.06)	(0.11)
Skill-intensity × human capital	0.88***	0.58***	0.58***	0.99***	1.12***
	(0.02)	(0.03)	(0.03)	(0.06)	(0.13)
Capital-intensity × capital p.c.	0.12***	0.16***	0.16***	0.09***	0.08***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.02)
Observations	7,999,095	17,901,676	17,901,676	11,799,345	9,553,284
Exporter-Year FE	×	×	×	×	×
Importer-Year FE	×	×	×	×	×
Importer-Industry FE	×	×	×		
Exporter-Importer FE	×	×	×		
Exporter-Importer-Industry FE				×	×
SE cluster	Ex-Im-Ind	Ex-Im-Ind	Ex-Im	Ex-Im	Ex-Im

Notes: The table reports PPML results based on variations of Equation 5.19. The dependent variable is the value of annual bilateral trade flows. Panel A uses actual domestic broadband penetration rates as the explanatory variable of interest; Panel B uses predicted broadband penetration rates obtained from the nonlinear first stage described in Section 5.4.2. Column (1) restricts the sample of importers to countries with relevant data coverage as exporters. Column (2) restricts the sample to the period 1998-2010. Column (3) accounts for skill dispersion as a potential source of comparative advantage in complex industries. Column (4) uses exporter-importer-industry fixed effects, and Column (5) excludes the USA from the sample. All specifications additionally control for the presence of FTA, currency unions, and exporter-industry remoteness (output suppressed for brevity). Standard errors (reported in parentheses) are clustered at the industry-country-pair level in Columns (1)–(3) and clustered at the country-pair level in Columns (4)–(5). All standard errors in Panel B are bootstrapped (100 repetitions). Observations separated by fixed effects are subtracted from the total number of observations. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

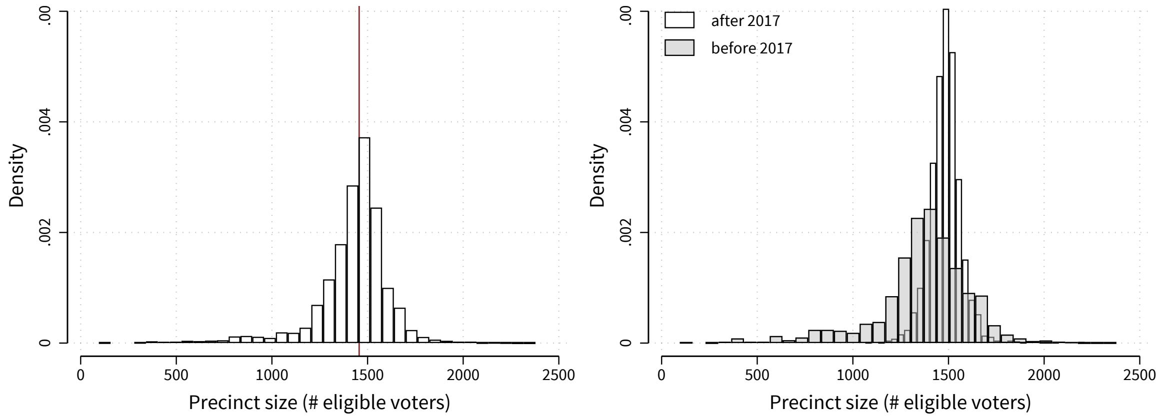
the empirical framework is limited in that it does not account for potential endogeneity of human capital. Overall, the study showcases the importance of non-traditional sources of comparative advantage in shaping international trade. Public goods in general, and broadband infrastructure in particular, can be significant determinants of the pattern of international trade. Unlike factor endowments, technology, or institutions, infrastructure provision is a key responsibility of industrial policy. Thus, the findings underscore the potential of domestic policy to actively shape a country's specialization.

Appendices

A Appendix to Chapter 1

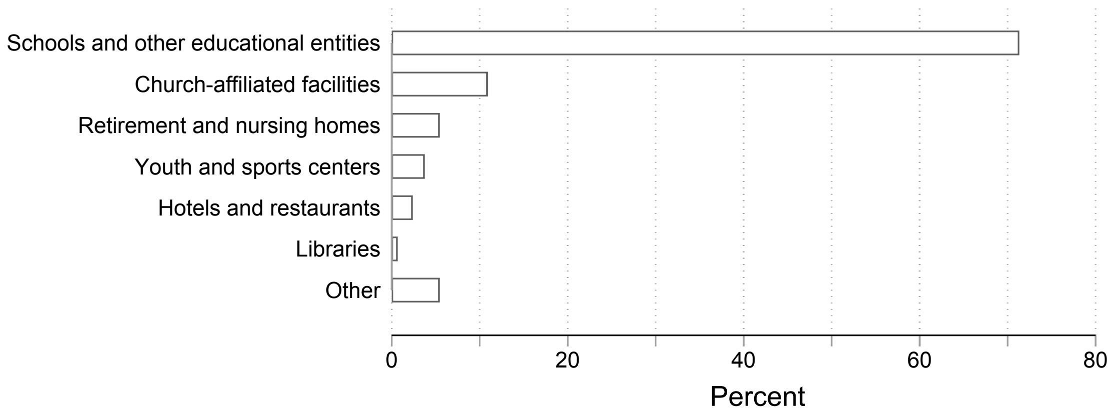
A.1 Figures

Figure A.1 : Distribution of Precinct Size



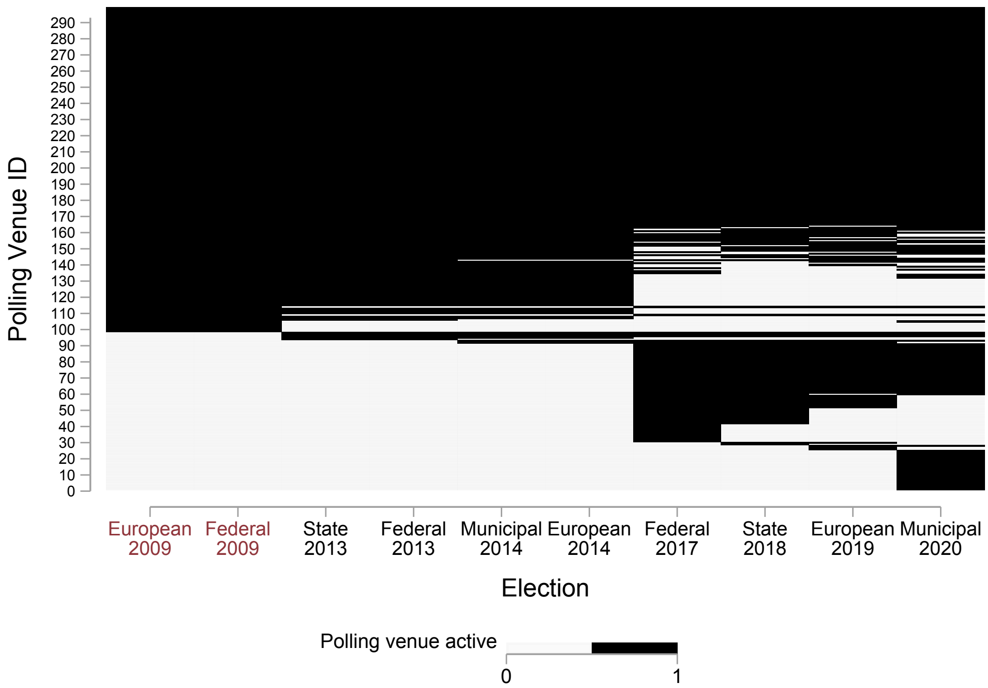
Notes: The figure plots the distribution of precinct of size (number of eligible voters) over all elections (left plot) and before and after 2017 when the Elections Office performed a major reconfiguration of precinct boundaries (right plot). Precincts are delineated according to their election-specific boundaries (i.e., before harmonization of precinct borders). The vertical line in the left plot highlights the median of the distribution.

Figure A.2 : Types of Polling Venues



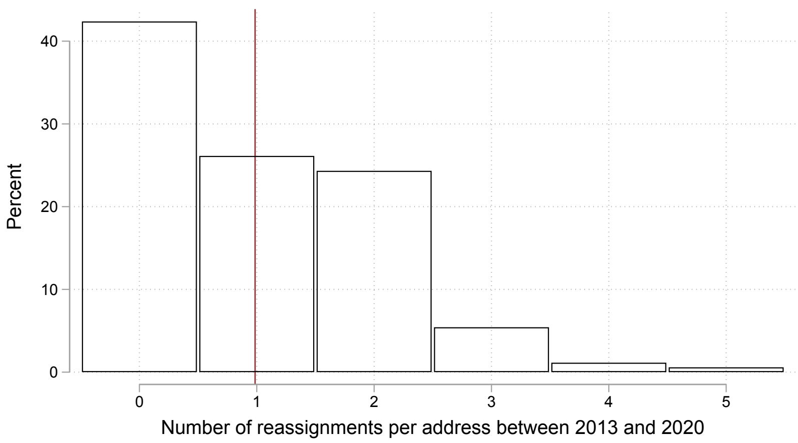
Notes: The figure shows the distribution polling venues over different categories in the eight elections held in Munich between 2013 and 2020 (293 distinct venues in total).

Figure A.3 : Activity Status of Polling Venues between 2009 and 2020



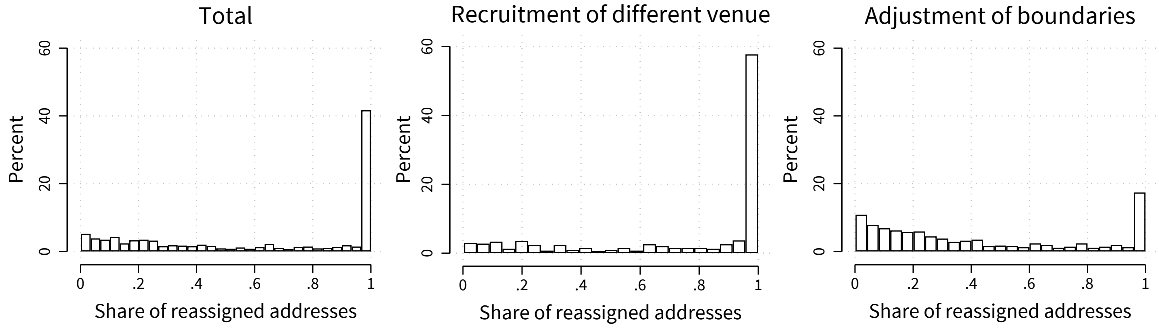
Notes: The figure illustrates the activity status of polling places in each election. We observe 293 distinct venues between 2013 and 2020. The 2009 European and Federal Elections are not part of our estimation sample (highlighted). Six venues were active only in 2009.

Figure A.4 : Frequency of Polling Place Reassignments per Residential Address



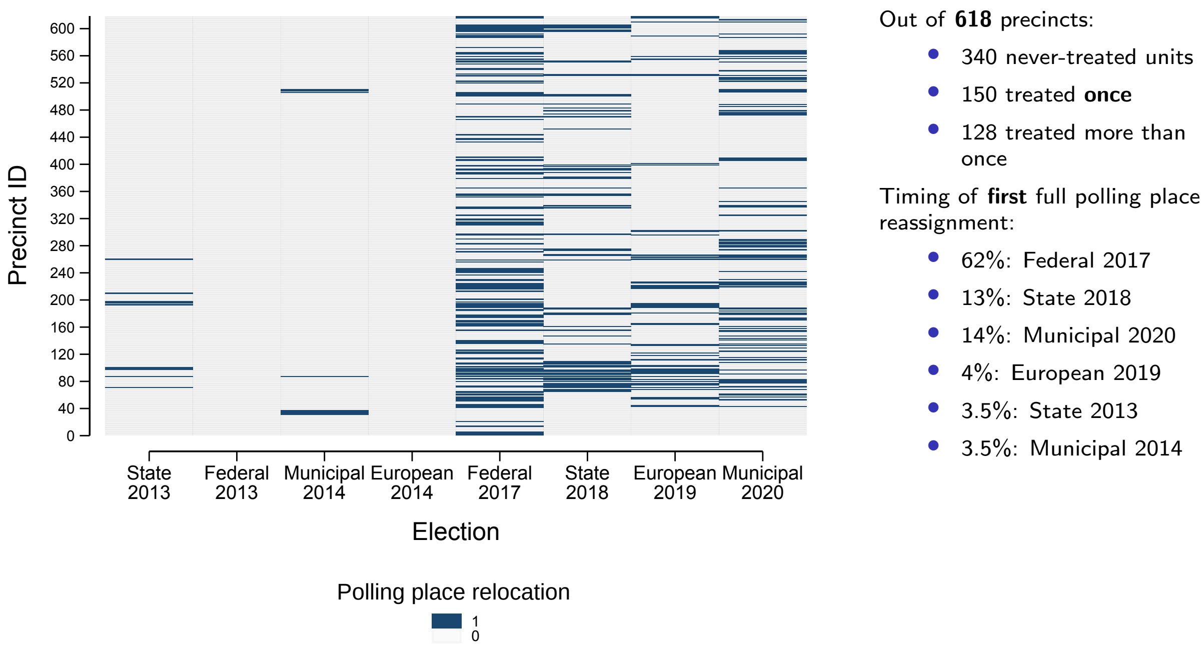
Notes: The figure plots the frequency of polling places reassignments (relative to the previous election) for residential addresses between 2013 and 2020. The vertical line highlights the mean.

Figure A.5 : Reassignment Intensity at the Precinct Level



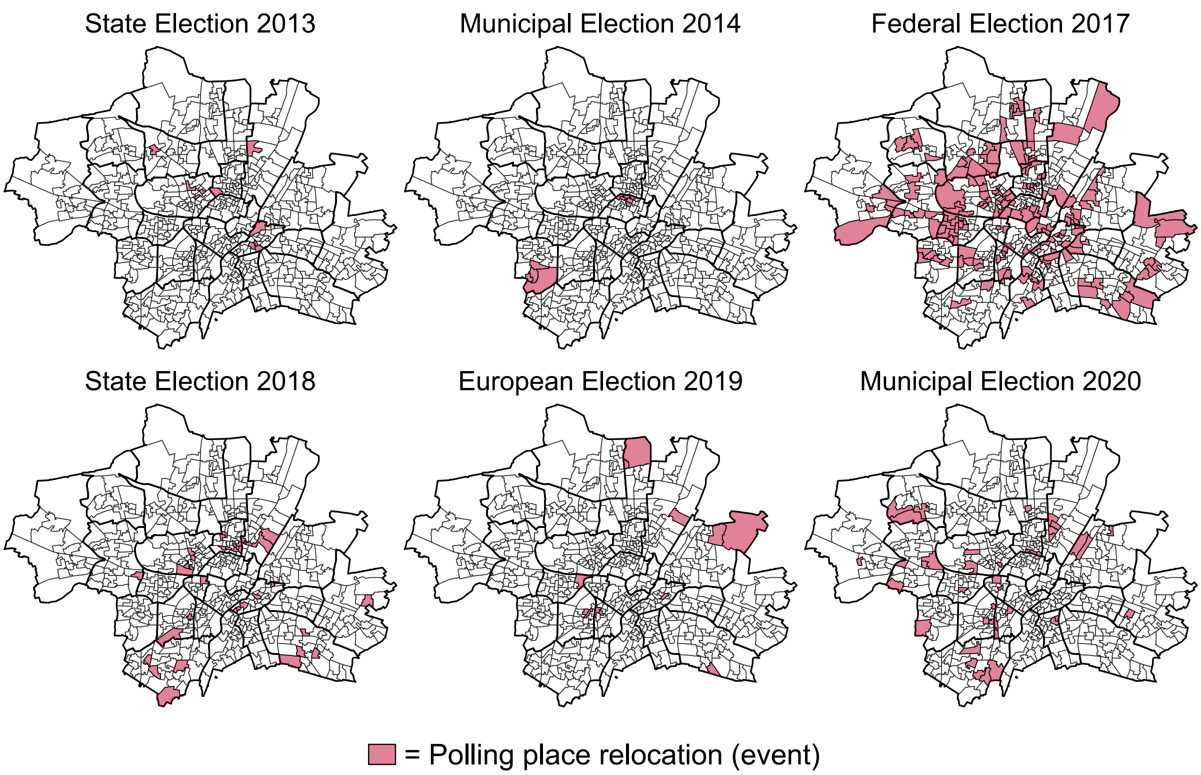
Notes: The figure shows the distribution of the share of residential addresses assigned to a different polling place relative to the preceding election at the precinct level overall (left plot) and by reason of reassignment, i.e., due to recruitment of a different polling venue (middle) or due to reconfiguration of precinct boundaries (right). Observations with zero reassignments are excluded.

Figure A.6 : Timing of Polling Place Reassignments



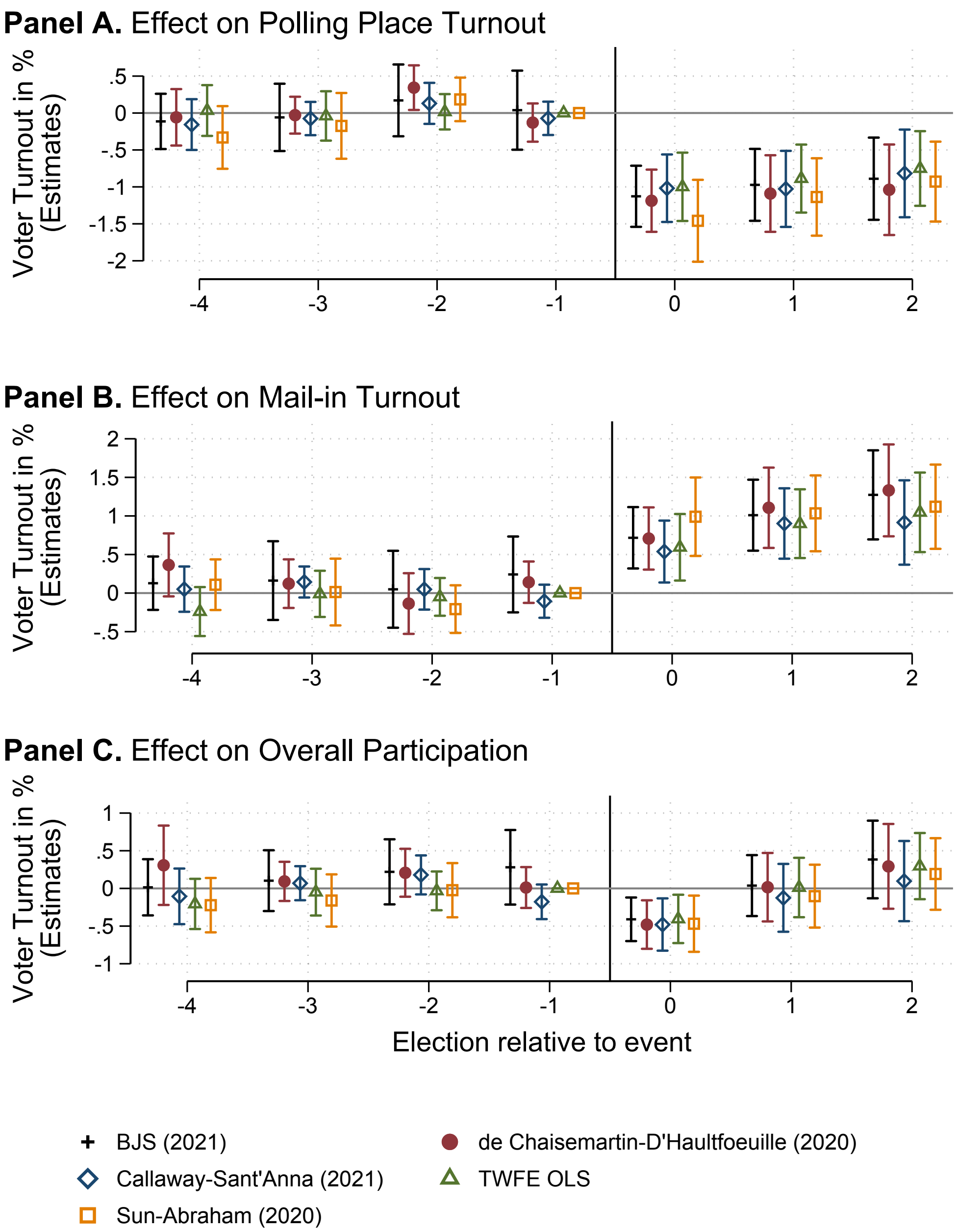
Notes: The figure illustrates the timing of polling place relocations (relative to the previous election) for the 618 precincts in our sample. Highlighted cells indicate that the entire precinct, i.e., 100% of home addresses, is assigned to a different polling place.

Figure A.7 : Spatial Distribution of Polling Place Reassignments



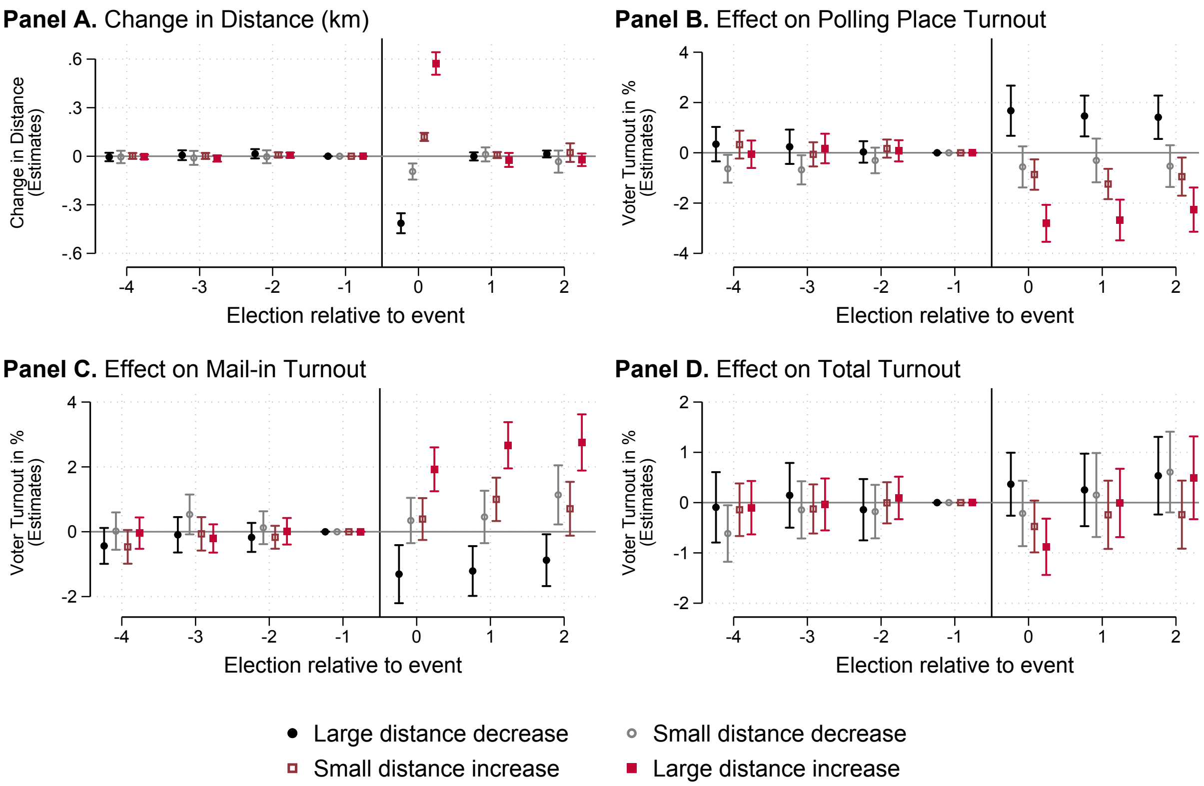
Notes: The maps illustrate the timing of polling place relocations (relative to the previous election) for the 618 precincts in our sample. Precinct boundaries are harmonized to the 2018 delineation to allow comparisons over time. Highlighted precincts indicate that the entire precinct, i.e., 100% of home addresses, is assigned to a different polling place for the first time in our panel. The were no relocations in the Federal Election 2013 and European Election 2014.

Figure A.8 : Robustness of Event Study Results to Novel Estimators



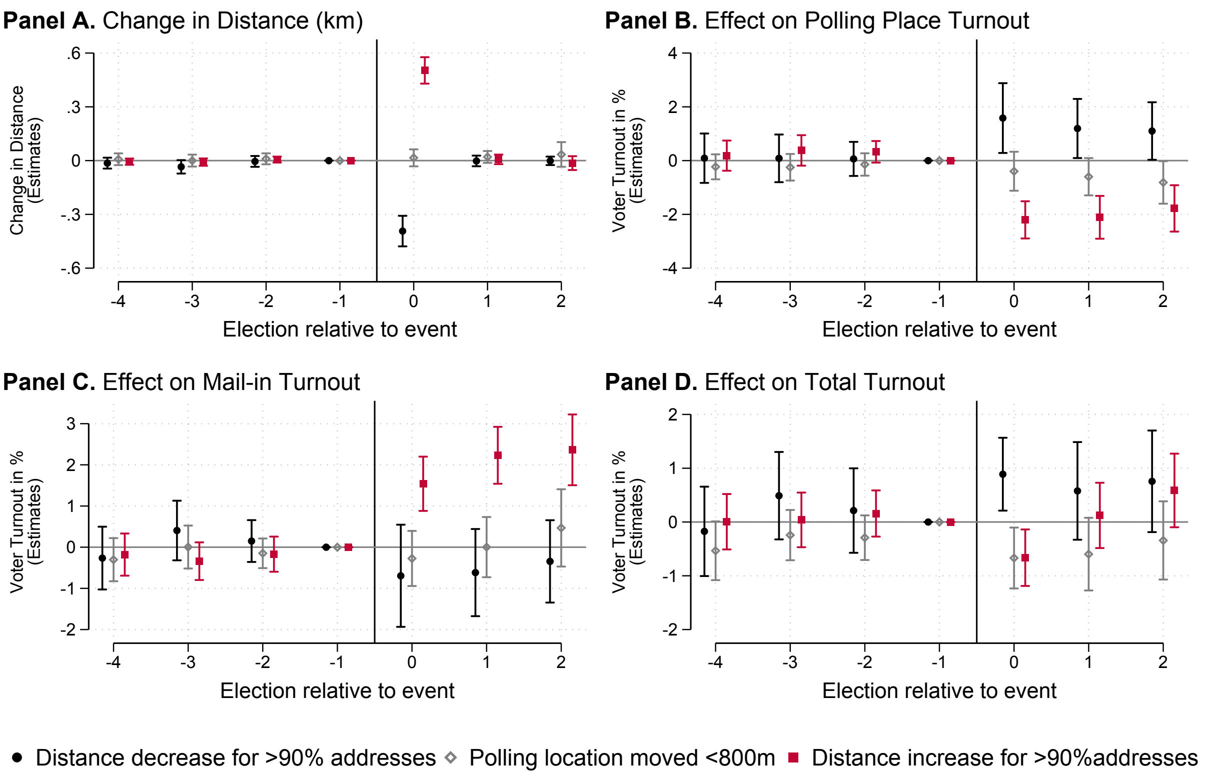
Notes: The figure presents event study results based on the specification presented in Column (4) of Table A.3 (i.e., Equation 1.8 using election fixed effects instead of election-district fixed effect). The model is estimated using TWFE-OLS as well as the estimators proposed by Borusyak et al. (2022), Callaway and Sant'Anna (2021), Sun and Abraham (2021), and de Chaisemartin and D'Haultfœuille (2020). The event is defined as the first time in which the entire precinct is reassigned to a different polling place. All specifications include time-varying covariates listed in Section 1.4.1. Regressions are weighted by the number of eligible voters. Confidence intervals are drawn at the 95 percent level using standard errors clustered at the precinct level.

Figure A.9 : Effect Heterogeneity by Change in Proximity to the Polling Location (4 bins)



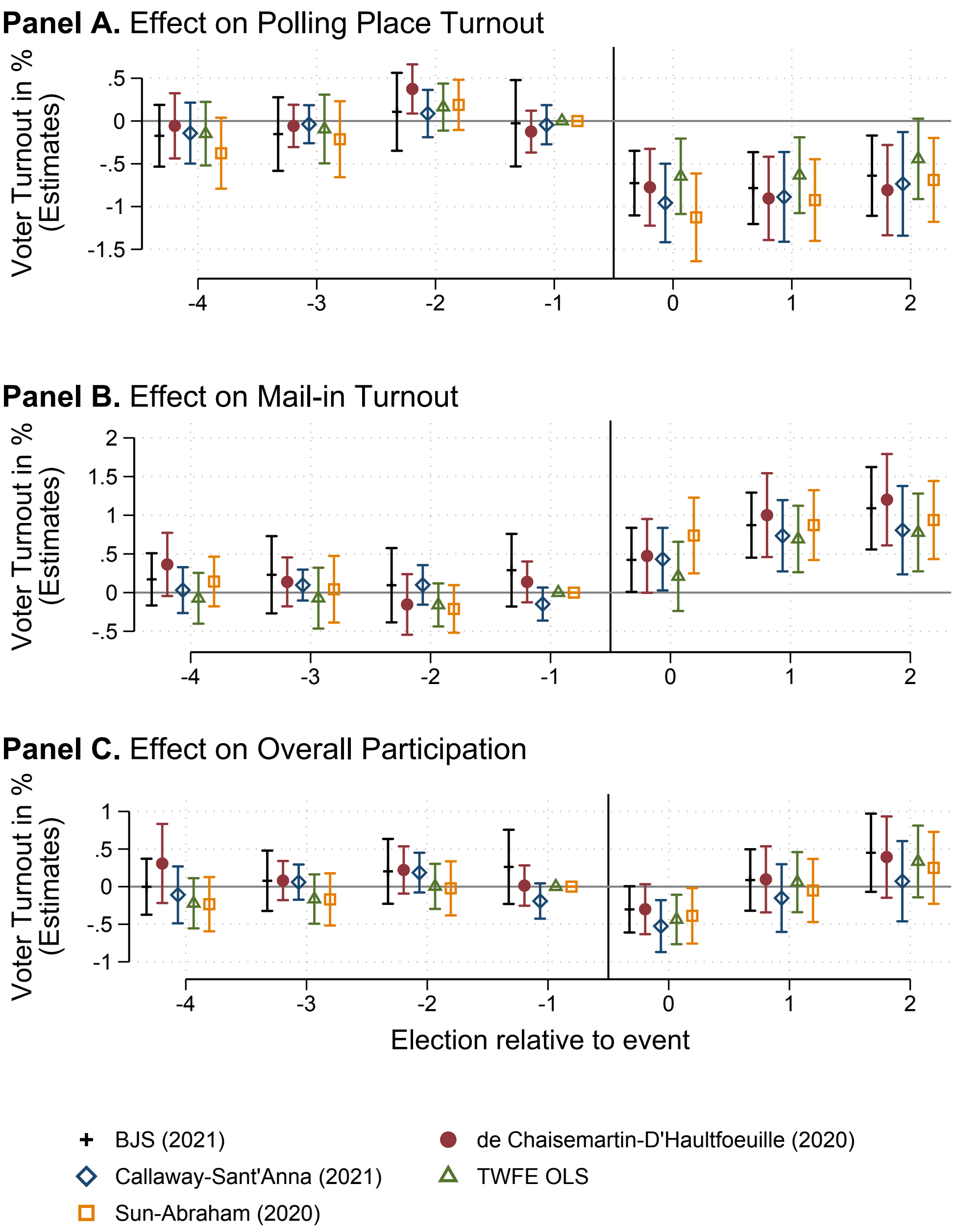
Notes: The figure presents event study results based on a version of Equation 1.9 in which event-time dummies are interacted separately with four mutually exclusive treatment indicators: two for distance increase and two for distance decrease due to reassignment. The event is defined as the first time in which the entire precinct is reassigned to a different polling place. Regressions are weighted by the number of eligible voters. Confidence intervals are drawn at the 95 percent level using standard errors clustered at the precinct level.

Figure A.10 : Effect Heterogeneity by Change in Proximity Restricted to Cases with Consistent Distance Changes



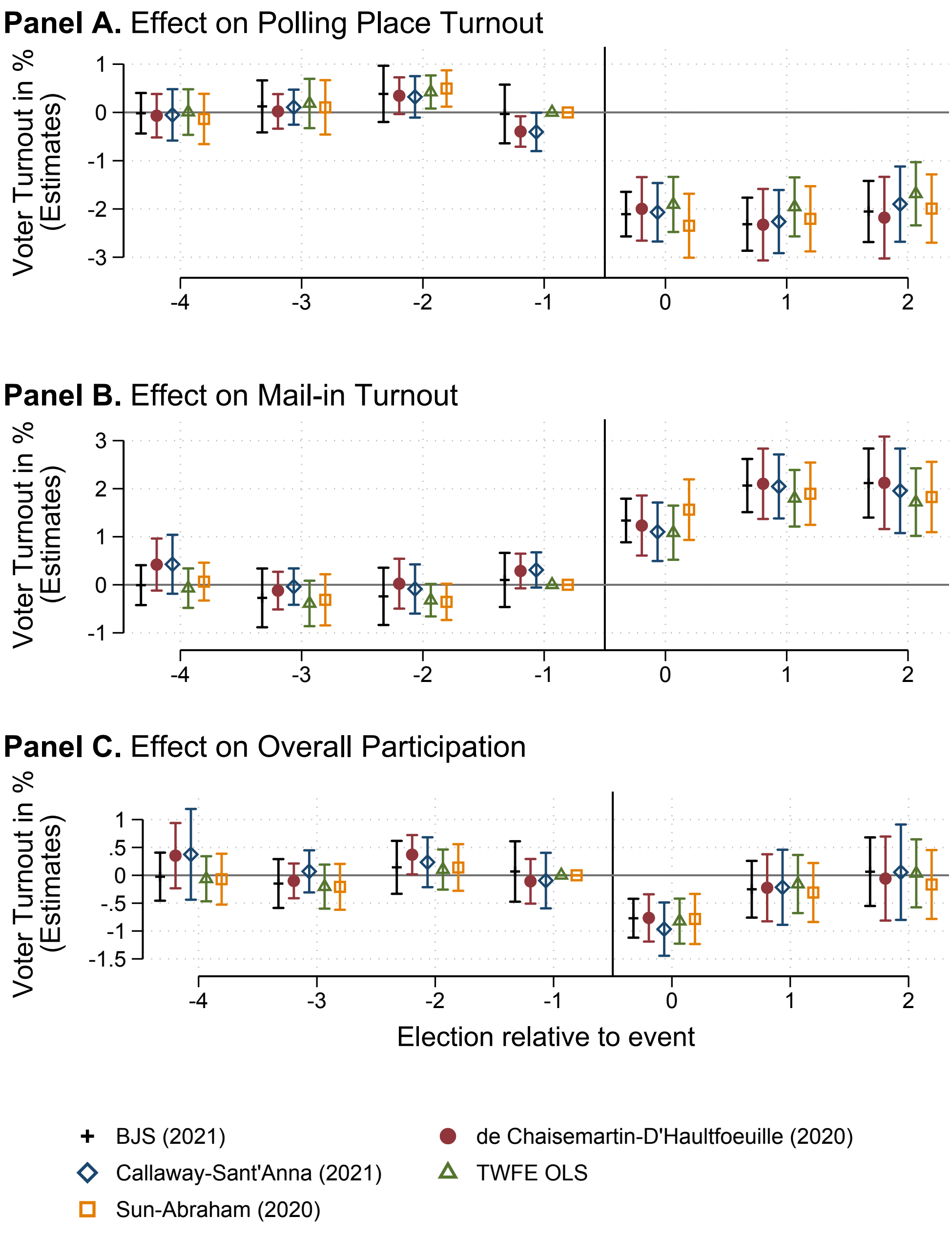
Notes: The figure presents event study results based on a version of Equation 1.9 in which event-time dummies are interacted separately with three mutually exclusive treatment indicators, identifying precincts where reassignments consistently increased (decreased) the distance for at least 90 percent of home addresses and where the polling place moved less than 800 meters from the old location. The event is defined as the first time in which the entire precinct is reassigned to a different polling place. Regressions are weighted by the number of eligible voters. Confidence intervals are drawn at the 95 percent level using standard errors clustered at the precinct level.

Figure A.11 : Event Study Results Absorbing the Distance Effect



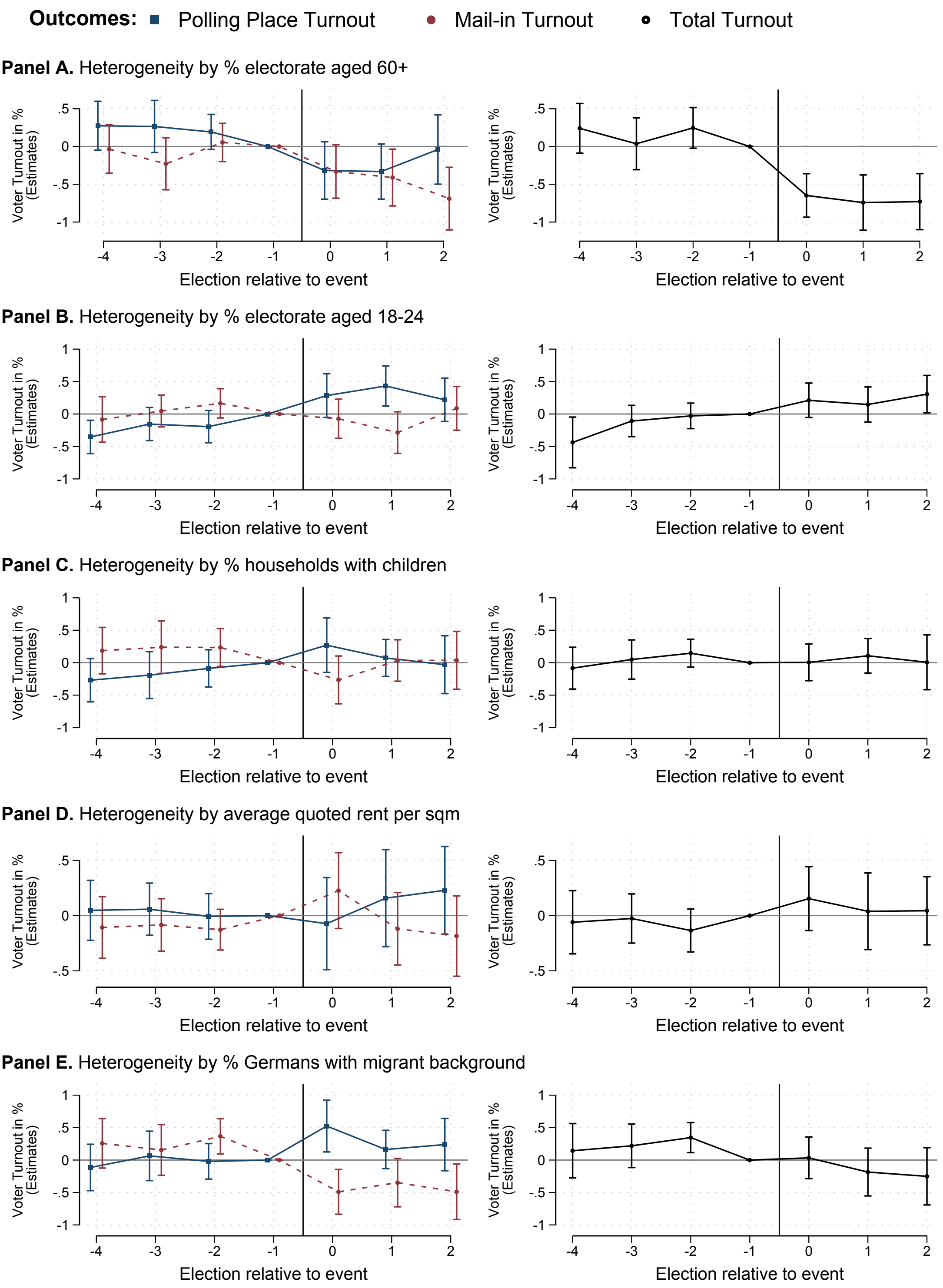
Notes: The figure presents event study results based on the specification presented in Column (4) of Table A.3 (i.e., Equation 1.8 using election fixed effects instead of election-district fixed effect). The model is estimated using TWFE-OLS as well as the estimators proposed by Borusyak et al. (2022), Callaway and Sant'Anna (2021), Sun and Abraham (2021), and de Chaisemartin and D'Haultfœuille (2020). The event is defined as the first time in which the entire precinct is reassigned to a different polling place. All specifications include time-varying covariates listed in Section 1.4.1. Regressions are weighted by the number of eligible voters. Confidence intervals are drawn at the 95 percent level using standard errors clustered at the precinct level.

Figure A.12 : Event Study Results Restricted to Units with Increased Distance



Notes: The figure presents event study results based on the specification presented in Column (4) of Table A.3 (i.e., Equation 1.8 using election fixed effects instead of election-district fixed effect). The model is estimated using TWFE-OLS as well as the estimators proposed by Borusyak et al. (2022), Callaway and Sant'Anna (2021), Sun and Abraham (2021), and de Chaisemartin and D'Haultfœuille (2020). The event is defined as the first time in which the entire precinct is reassigned to a different polling place. All specifications include time-varying covariates listed in Section 1.4.1. Regressions are weighted by the number of eligible voters. Confidence intervals are drawn at the 95 percent level using standard errors clustered at the precinct level.

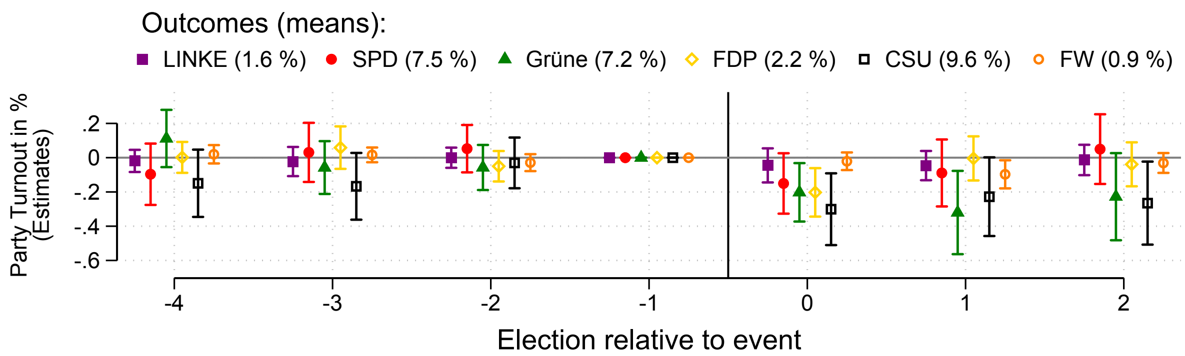
Figure A.13 : Effect Heterogeneity by Precinct Characteristics Conditional on Distance



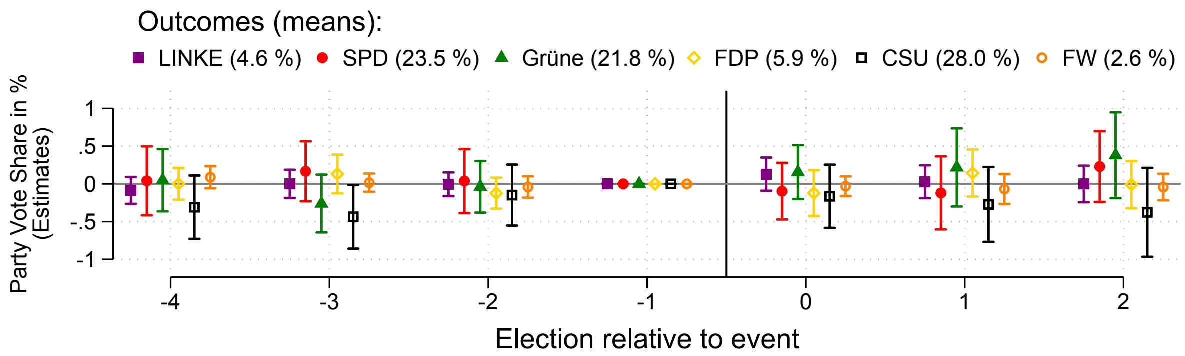
Notes: The figure presents event study results based on the triple difference estimator introduced in Equation 1.10 conditional on log street distance. Each panel uses a different heterogeneity dimension Z_p and plots the triple-difference coefficients $\hat{\gamma}^k$ for the three outcomes, polling place turnout, mail-in turnout, and overall turnout. The event is defined as the first time in which the entire precinct is reassigned to a different polling place. All specifications include time-varying covariates listed in Section 1.4.1. Regressions are weighted by the number of eligible voters. Confidence intervals are drawn at the 95 percent level using standard errors clustered at the precinct level.

Figure A.14 : Differential Effects of Reassignments on Party Outcomes

Panel A. Effect on Party Turnout



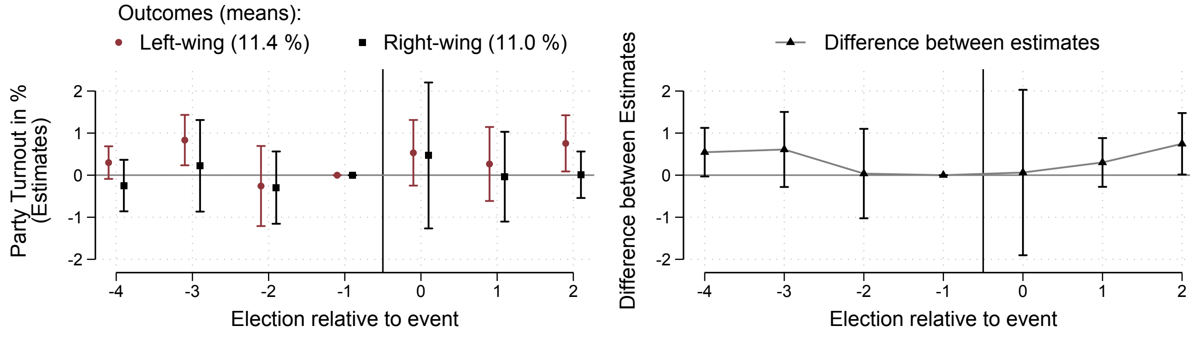
Panel B. Effect on Party Vote Shares



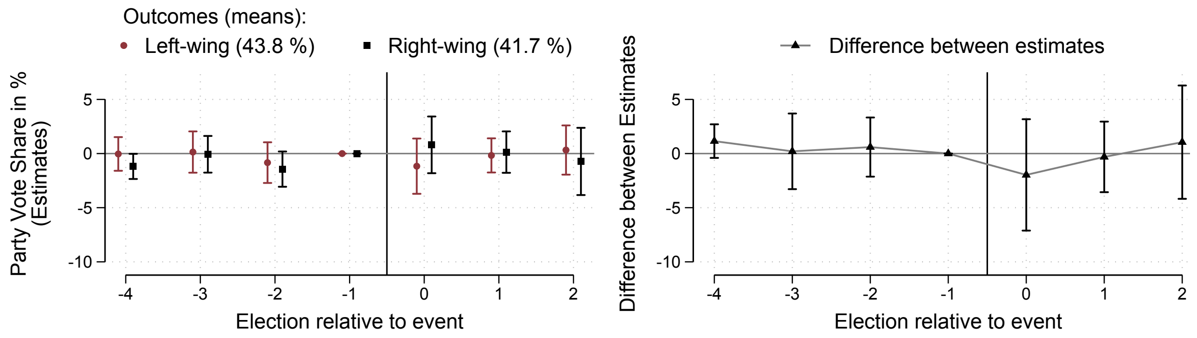
Notes: The figure presents event study results based on Equation 1.8. The outcomes in Panel A are party turnout defined as the number of votes relative to the number of eligible voters for the six largest parties that stood election in every election included in our panel, respectively. Dependent variables in Panel B are party vote shares, defined as the number of votes relative to total votes. Turnout and party shares capture only voting at the polling place. The event is defined as the first time in which the entire precinct is reassigned to a different polling place. All specifications include time-varying covariates listed in Section 1.4.1. Regressions are weighted by the number of eligible voters. Confidence intervals are drawn at the 95 percent level using standard errors clustered at the precinct level.

Figure A.15 : Effects of Reassignments on Party Outcomes by Mail

Panel A. Effect on Party Turnout



Panel B. Effect on Party Vote Shares



Notes: The figure presents event study results at the district level. The outcomes are party turnout (Panel A) and party vote shares (Panel B) by mail. Party turnout is defined as the number of votes relative to the number of eligible voters for left-wing and right-wing parties, respectively. Party vote share is defined as the number of votes relative to total votes for left-wing and right-wing parties, respectively. The right plot in each panel presents estimates and confidence bands for the difference between event-time indicators in each period. The event is defined as the first time in which the at least 70 percent of the district is reassigned to a different polling place. All specifications include time-varying covariates listed in Section 1.4.1. Regressions are weighted by the number of eligible voters. Confidence intervals are drawn at the 95 percent level using standard errors clustered at the district level.

A.2 Tables

Table A.1 : Summary Statistics of Precinct Characteristics

	Mean	Std. Dev.	Min	p25	Median	p75	Max
Outcome Variables							
Polling Place Turnout	34.24	9.04	9.94	26.18	35.54	41.70	55.86
Mail-in Turnout (Requested Polling Cards)	28.92	7.64	4.01	23.10	29.46	34.70	51.99
Overall Turnout	63.15	14.57	15.10	51.20	65.27	75.26	91.72
Variables of Interest							
Avg. Street Distance to the Polling Place (km)	0.71	0.34	0.16	0.47	0.63	0.87	2.83
Share of Reassigned Residential Addresses	0.14	0.32	0.00	0.00	0.00	0.00	1.00
Share Reassigned (Precinct Reconfiguration)	0.05	0.19	0.00	0.00	0.00	0.00	1.00
Share Reassigned (Recruitment of Polling Location)	0.08	0.26	0.00	0.00	0.00	0.00	1.00
Other Precinct Characteristics							
Number of Residents	2,428	403	758	2,169	2,325	2,591	6,272
% Residents Eligible to Vote	65.35	9.15	24.62	60.22	66.42	71.70	86.93
% Non-native German Residents	14.68	4.35	5.50	11.70	13.48	16.45	35.78
% Native German Residents	59.77	11.35	21.00	52.75	61.80	68.11	83.97
% EU Foreigners	12.90	3.97	4.00	10.13	12.38	14.99	36.05
% Non-EU Foreigners	12.66	6.18	1.91	7.97	11.49	16.06	50.82
% Single Residents	49.73	7.34	35.28	43.72	48.84	55.02	80.20
% Married Residents	37.29	6.49	15.50	32.28	37.43	42.77	51.84
% Electorate Aged 18–24	8.74	2.87	2.41	7.20	8.25	9.64	49.07
% Electorate Aged 25–34	21.15	6.57	7.40	15.73	20.83	26.01	42.30
% Electorate Aged 35–44	17.92	4.00	6.30	15.23	17.37	20.08	34.70
% Electorate Aged 45–59	24.62	3.97	4.85	21.97	24.40	27.25	45.32
% Electorate Aged 60+	27.57	8.39	2.61	21.30	27.57	33.29	63.80
% EU Foreigners in the Electorate	8.29	9.13	0.00	0.00	2.70	15.81	46.39
% Households with Children	17.53	6.08	5.31	13.35	16.69	20.43	58.75
Avg. Duration of Residence	21.69	4.45	6.80	18.53	21.72	24.51	45.11
Avg. Quoted Rent per sqm	17.42	4.54	6.69	13.67	16.45	20.30	43.92

Notes: The table reports summary statistics based on 4,944 observations (618 precincts with harmonized boundaries observed over eight elections held between 2013 and 2020). The statistics are *not* weighted and might therefore differ from values reported in the main text.

A.3 Elections in Munich

Federal Elections The German *Bundestag* is elected by German citizens aged eighteen and older for a four-year term. Elections are based on a mixed-member proportional representation system, in which half of the members of parliament are elected directly in 299 constituencies (*Wahlkreise*), four of which are located in Munich, and the other half is elected via (closed) party lists in the sixteen states. Accordingly, voters cast one vote for their local representative, who is elected by a plurality rule, and a second vote for a party list, drawn up

Table A.2 : Balancing Test on Precinct Characteristics

	(1) Indicator (Reassigned=100%)	(2) Indicator (Reassigned>0)	(3) Share Reassigned	(4) Share Reassigned (Precinct Reconfig.)	(5) Share Reassigned (Recruitment)	(6) Log Avg. Street Distance
#residents	0.009	-0.005	0.022	0.012	0.010	-0.002
	(0.013)	(0.018)	(0.014)	(0.011)	(0.013)	(0.012)
#single residents	0.010	0.005	0.030*	0.019	0.012	0.008
	(0.016)	(0.021)	(0.016)	(0.013)	(0.015)	(0.015)
#married residents	0.001	-0.022	0.015	0.000	0.014	-0.012
	(0.015)	(0.024)	(0.018)	(0.012)	(0.016)	(0.016)
#native German residents	0.005	-0.018	0.007	-0.005	0.012	-0.002
	(0.010)	(0.015)	(0.012)	(0.007)	(0.011)	(0.012)
#non-native German residents	0.015	-0.012	0.028	0.008	0.020	-0.029*
	(0.020)	(0.028)	(0.021)	(0.015)	(0.018)	(0.017)
#foreign residents	0.009	0.012	0.028	0.026	0.002	0.007
	(0.019)	(0.020)	(0.018)	(0.016)	(0.014)	(0.015)
#inhabitants eligible to vote	0.009	-0.004	0.008	-0.008	0.017	-0.005
	(0.013)	(0.016)	(0.012)	(0.008)	(0.011)	(0.012)
#eligible voters aged 18-24	0.009	-0.004	0.004	0.001	0.003	0.012
	(0.010)	(0.012)	(0.010)	(0.006)	(0.009)	(0.008)
#eligible voters aged 25-34	0.003	0.011	0.016	-0.007	0.023*	0.017
	(0.012)	(0.015)	(0.012)	(0.007)	(0.012)	(0.013)
#eligible voters aged 35-44	-0.005	-0.006	0.008	-0.002	0.010	-0.003
	(0.009)	(0.012)	(0.009)	(0.006)	(0.009)	(0.008)
#eligible voters aged 45-59	0.015	-0.017	0.013	-0.002	0.015	-0.008
	(0.010)	(0.013)	(0.010)	(0.007)	(0.009)	(0.009)
#eligible voters aged 60+	0.010	-0.006	-0.003	0.001	-0.004	-0.021*
	(0.013)	(0.015)	(0.013)	(0.010)	(0.011)	(0.011)
#German eligible voters	0.010	-0.006	0.011	-0.003	0.014	-0.009
	(0.009)	(0.012)	(0.009)	(0.005)	(0.009)	(0.010)
#EU-foreign eligible voters	0.003	-0.003	0.008	-0.002	0.010	0.009
	(0.010)	(0.015)	(0.010)	(0.007)	(0.010)	(0.008)
% households with children	-0.009	-0.007	0.019	0.016	0.004	0.026
	(0.020)	(0.026)	(0.022)	(0.013)	(0.020)	(0.020)
Avg. quoted rent per sqm	0.015	-0.003	0.005	-0.006	0.011	0.007
	(0.012)	(0.015)	(0.012)	(0.008)	(0.011)	(0.011)
Avg. duration of residence	0.002	-0.003	-0.004	0.001	-0.005	-0.011
	(0.011)	(0.014)	(0.011)	(0.007)	(0.010)	(0.012)
Observations	4,944	4,944	4,944	4,944	4,944	4,944
F-test	0.57 [0.91]	0.66 [0.84]	0.51 [0.95]	1.04 [0.42]	0.53 [0.94]	1.07 [0.38]
Precinct FE	×	×	×	×	×	×
Election FE	×	×	×	×	×	×

Notes: Each cell in Columns (1) through (6) reports an OLS estimate from a separate univariate regression on precinct characteristics (in rows), conditional an election and precinct fixed effects. All precinct characteristics are standardized to have mean zero and unitary standard deviation. The dependent variables are a dummy identifying reassignments that affected 100% of home addresses in a precinct (Column 1), a dummy identifying reassignments that affected a nonzero share of addresses (Column 2), the share of addresses assigned to a different polling place (Column 3), the share of addresses reassigned due to adjustment to precinct boundaries (Column 4), the share of addresses reassigned due to the recruitment of a different polling place (Column 5), and the log of average street distance to the polling location (Column 6), respectively. $F-$tests for the null that coefficients are jointly equal to zero are reported with p values in parentheses. Regressions are weighted by the number of eligible voters. Standard errors are clustered at the precinct level and reported in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table A.3 : Baseline Event Study Results

	(1)	(2)	(3)	(4)	(5)
Panel A: Effect on Turnout at the Polling Place [Mean outcome=33.7]					
Reassignment $(t-4)$	-0.02	0.03	0.02	-0.11	-0.16
	(0.19)	(0.18)	(0.18)	(0.20)	(0.16)
Reassignment $(t-3)$	-0.06	-0.04	-0.05	-0.03	-0.30*
	(0.18)	(0.17)	(0.17)	(0.21)	(0.16)
Reassignment $(t-2)$	-0.12	0.02	0.02	0.16	-0.07
	(0.14)	(0.12)	(0.12)	(0.14)	(0.11)
Reassignment $(t+0)$	-1.12***	-1.00***	-1.02***	-1.07***	-1.25***
	(0.25)	(0.24)	(0.23)	(0.24)	(0.20)
Reassignment $(t+1)$	-0.97***	-0.89***	-0.80***	-0.87***	-1.42***
	(0.25)	(0.23)	(0.21)	(0.25)	(0.21)
Reassignment $(t+2)$	-0.75***	-0.75***	-0.53**	-0.70***	-1.19***
	(0.28)	(0.26)	(0.22)	(0.27)	(0.23)
R^2	0.97	0.97	0.97	0.96	0.97
Panel B: Effect on Turnout via Mail [Mean outcome=28.7]					
Reassignment $(t-4)$	-0.21	-0.24	-0.22	-0.11	-0.06
	(0.18)	(0.16)	(0.16)	(0.17)	(0.15)
Reassignment $(t-3)$	0.08	-0.01	-0.00	-0.12	0.06
	(0.16)	(0.15)	(0.15)	(0.20)	(0.14)
Reassignment $(t-2)$	-0.17	-0.05	-0.04	-0.15	-0.07
	(0.13)	(0.12)	(0.12)	(0.14)	(0.11)
Reassignment $(t+0)$	0.52**	0.59***	0.60***	0.54**	0.68***
	(0.23)	(0.22)	(0.22)	(0.23)	(0.19)
Reassignment $(t+1)$	0.87***	0.90***	0.73***	0.87***	1.15***
	(0.24)	(0.23)	(0.21)	(0.24)	(0.21)
Reassignment $(t+2)$	0.90***	1.05***	0.72***	0.98***	1.34***
	(0.29)	(0.26)	(0.23)	(0.28)	(0.23)
R^2	0.95	0.96	0.96	0.95	0.96
Panel C: Effect on Total Turnout [Mean outcome=62.4]					
Reassignment $(t-4)$	-0.23	-0.21	-0.20	-0.21	-0.23
	(0.20)	(0.17)	(0.17)	(0.17)	(0.15)
Reassignment $(t-3)$	0.02	-0.05	-0.05	-0.15	-0.24*
	(0.19)	(0.16)	(0.16)	(0.17)	(0.14)
Reassignment $(t-2)$	-0.29	-0.03	-0.02	0.00	-0.14
	(0.18)	(0.13)	(0.13)	(0.15)	(0.12)
Reassignment $(t+0)$	-0.60***	-0.41**	-0.42**	-0.54***	-0.57***
	(0.20)	(0.16)	(0.16)	(0.17)	(0.16)
Reassignment $(t+1)$	-0.10	0.01	-0.07	0.00	-0.27
	(0.25)	(0.20)	(0.19)	(0.20)	(0.19)
Reassignment $(t+2)$	0.15	0.30	0.19	0.27	0.16
	(0.30)	(0.22)	(0.21)	(0.24)	(0.22)
R^2	0.98	0.99	0.99	0.99	0.99
Observations	4,672	4,672	4,944	4,672	4,528
Controls		×	×	×	×
Precinct FE	×	×	×	×	×
Election-District FE	×	×	×		×
Election FE				×	
Full sample			×		
Event: 100% reassigned	×	×	×	×	
Event: $>$50% reassigned					×

Notes: The table presents event study results based on Equation 1.8. The dependent variables are voter turnout (0–100) at the polling place (Panel A), by mail (Panel B), and overall (Panel C). In Columns (1)–(4), the event is defined as the first time in which the *entire* precinct is reassigned to a different polling place; in Column (5) the event occurs when at least 50 percent of addresses are reassigned. Columns (2)–(5) include time-varying covariates listed in Section 1.4.1. Except in Column (3), observations are dropped after a second reassignment (if any). Regressions are weighted by the number of eligible voters. Standard errors are clustered at the precinct level and reported in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table A.4 : Robustness of Event Study Results to Different Levels of Clustering

	(1) Cluster Precinct (baseline)	(2) TW Cluster Precinct+ Election-District	(3) Wild Cluster Bootstrap Precinct	(4) Wild Cluster Bootstrap District	(5) Wild Cluster Bootstrap District
Panel A: Effect on Turnout at the Polling Place					
Reassignment $(t-4)$	0.03	0.03	0.03	0.03	-0.11
	(0.18)	(0.19)	[0.865]	[0.870]	[0.561]
Reassignment $(t-3)$	-0.04	-0.04	-0.04	-0.04	-0.03
	(0.17)	(0.19)	[0.820]	[0.837]	[0.872]
Reassignment $(t-2)$	0.02	0.02	0.02	0.02	0.16
	(0.12)	(0.14)	[0.904]	[0.886]	[0.342]
Reassignment $(t+0)$	-1.00***	-1.00***	-1.00***	-1.00***	-1.07***
	(0.24)	(0.26)	[0.000]	[0.000]	[0.001]
Reassignment $(t+1)$	-0.89***	-0.89***	-0.89***	-0.89***	-0.87**
	(0.23)	(0.26)	[0.000]	[0.002]	[0.029]
Reassignment $(t+2)$	-0.75***	-0.75***	-0.75***	-0.75**	-0.70*
	(0.26)	(0.27)	[0.001]	[0.030]	[0.052]
Panel B: Effect on Turnout via Mail					
Reassignment $(t-4)$	-0.24	-0.24	-0.24	-0.24	-0.11
	(0.16)	(0.16)	[0.133]	[0.221]	[0.497]
Reassignment $(t-3)$	-0.01	-0.01	-0.01	-0.01	-0.12
	(0.15)	(0.16)	[0.957]	[0.949]	[0.604]
Reassignment $(t-2)$	-0.05	-0.05	-0.05	-0.05	-0.15
	(0.12)	(0.14)	[0.712]	[0.691]	[0.438]
Reassignment $(t+0)$	0.59***	0.59**	0.59**	0.59**	0.54*
	(0.22)	(0.23)	[0.013]	[0.020]	[0.065]
Reassignment $(t+1)$	0.90***	0.90***	0.90***	0.90***	0.87**
	(0.23)	(0.25)	[0.001]	[0.002]	[0.014]
Reassignment $(t+2)$	1.05***	1.05***	1.05***	1.05***	0.98**
	(0.26)	(0.27)	[0.000]	[0.000]	[0.012]
Panel C: Effect on Total Turnout					
Reassignment $(t-4)$	-0.21	-0.21	-0.21	-0.21	-0.21
	(0.17)	(0.17)	[0.214]	[0.256]	[0.229]
Reassignment $(t-3)$	-0.05	-0.05	-0.05	-0.05	-0.15
	(0.16)	(0.16)	[0.739]	[0.766]	[0.388]
Reassignment $(t-2)$	-0.03	-0.03	-0.03	-0.03	0.00
	(0.13)	(0.13)	[0.806]	[0.839]	[0.993]
Reassignment $(t+0)$	-0.41**	-0.41**	-0.41**	-0.41**	-0.54***
	(0.16)	(0.18)	[0.022]	[0.022]	[0.003]
Reassignment $(t+1)$	0.01	0.01	0.01	0.01	0.00
	(0.20)	(0.21)	[0.951]	[0.955]	[0.982]
Reassignment $(t+2)$	0.30	0.30	0.30	0.30*	0.27
	(0.22)	(0.21)	[0.187]	[0.094]	[0.399]
Observations	4,672	4,672	4,672	4,672	4,672
Number of Clusters	618	200+618	618	25	25
Precinct FE	×	×	×	×	×
Election-District FE	×	×	×	×	
Election FE					×

Notes: The table presents robustness checks to the level of clustering standard errors based on the event study specification in Equation 1.8. The event is defined as the first time in which the entire precinct is reassigned to a different polling place. Column (1) replicates the baseline results with standard errors (SE) clustered at the precinct level for comparison. Column (2) uses two-way clustered SE at the level of precincts and district-elections (reported in parentheses). Column (3) uses wild cluster bootstrap (WCB) at the precinct level. Column (4) uses WCB at the district level. Column (5) uses WCB at the district level and replaces election×district fixed effects with election fixed effects. p-values from wild bootstrap clustering are reported in square brackets. We use Rademacher weights and 1000 replications. All specifications include time-varying covariates listed in Section 1.4.1. Regressions are weighted by the number of eligible voters. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table A.5 : Effect Heterogeneity by Change in Proximity to the Polling Location

	(1) Polling Place Turnout	(2) Mail-in Turnout	(3) Total Turnout
$\mathbb{1}$(Distance decrease)$\times$			
Reassignment $(t-4)$	-0.19	-0.17	-0.36
	(0.24)	(0.22)	(0.24)
Reassignment $(t-3)$	-0.24	0.24	-0.00
	(0.24)	(0.22)	(0.23)
Reassignment $(t-2)$	-0.16	-0.02	-0.17
	(0.18)	(0.18)	(0.21)
Reassignment $(t+0)$	0.47	-0.40	0.07
	(0.35)	(0.31)	(0.24)
Reassignment $(t+1)$	0.55*	-0.35	0.20
	(0.32)	(0.31)	(0.28)
Reassignment $(t+2)$	0.47	0.07	0.54*
	(0.34)	(0.35)	(0.30)
$\mathbb{1}$(Distance increase)$\times$			
Reassignment $(t-4)$	0.14	-0.26	-0.12
	(0.21)	(0.20)	(0.20)
Reassignment $(t-3)$	0.07	-0.15	-0.08
	(0.20)	(0.18)	(0.19)
Reassignment $(t-2)$	0.13	-0.09	0.05
	(0.14)	(0.14)	(0.15)
Reassignment $(t+0)$	-1.87***	1.18***	-0.68***
	(0.27)	(0.26)	(0.20)
Reassignment $(t+1)$	-1.96***	1.83***	-0.14
	(0.27)	(0.27)	(0.25)
Reassignment $(t+2)$	-1.63***	1.76***	0.12
	(0.31)	(0.33)	(0.28)
R^2	0.97	0.96	0.99
Observations	4,672	4,672	4,672
Mean outcome	33.7	28.7	62.4

Notes: The table reports point estimates and standard errors underlying the plots presented in Figure 1.11. Estimations are based on Equation 1.9. The dependent variables are voter turnout (0–100) at the polling place (Column 1), by mail (Column 2), and overall (Column 3). The event is defined as the first time in which the entire precinct is reassigned to a different polling place. All specifications include precinct fixed effects, election$\times$district fixed effects, and time-varying covariates listed in Section 1.4.1. Regressions are weighted by the number of eligible voters. Standard errors are clustered at the precinct level and reported in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table A.6 : Effect Heterogeneity by Change in Proximity to the Polling Location (3 bins)

	(1) Polling Place Turnout	(2) Mail-in Turnout	(3) Total Turnout
$\mathbb{1}$(Distance decrease)×			
Reassignment ($t-4$)	-0.03	-0.31	-0.34
	(0.28)	(0.24)	(0.28)
Reassignment ($t-3$)	-0.21	0.23	0.02
	(0.29)	(0.25)	(0.26)
Reassignment ($t-2$)	-0.10	-0.11	-0.21
	(0.19)	(0.21)	(0.24)
Reassignment ($t+0$)	1.01**	-0.71**	0.29
	(0.40)	(0.36)	(0.27)
Reassignment ($t+1$)	0.97***	-0.58*	0.39
	(0.35)	(0.34)	(0.33)
Reassignment ($t+2$)	0.93**	-0.27	0.65*
	(0.37)	(0.38)	(0.33)
$\mathbb{1}$(Little change in distance)×			
Reassignment ($t-4$)	0.19	-0.50*	-0.31
	(0.27)	(0.26)	(0.25)
Reassignment ($t-3$)	-0.03	-0.02	-0.05
	(0.24)	(0.27)	(0.25)
Reassignment ($t-2$)	0.06	-0.15	-0.09
	(0.21)	(0.19)	(0.21)
Reassignment ($t+0$)	-0.60*	-0.02	-0.62**
	(0.31)	(0.30)	(0.25)
Reassignment ($t+1$)	-0.94***	0.56*	-0.38
	(0.32)	(0.33)	(0.34)
Reassignment ($t+2$)	-0.46	0.35	-0.11
	(0.34)	(0.39)	(0.33)
$\mathbb{1}$(Distance increase)×			
Reassignment ($t-4$)	-0.03	0.01	-0.01
	(0.25)	(0.23)	(0.24)
Reassignment ($t-3$)	0.08	-0.15	-0.07
	(0.27)	(0.21)	(0.23)
Reassignment ($t-2$)	0.13	0.02	0.15
	(0.18)	(0.18)	(0.19)
Reassignment ($t+0$)	-2.73***	2.00***	-0.73***
	(0.33)	(0.30)	(0.26)
Reassignment ($t+1$)	-2.55***	2.53***	-0.01
	(0.35)	(0.32)	(0.30)
Reassignment ($t+2$)	-2.46***	2.77***	0.31
	(0.39)	(0.39)	(0.37)
R^2	0.97	0.96	0.99
Observations	4,672	4,672	4,672
Mean outcome	33.7	28.7	62.4

Notes: The table presents event study results based on a version of Equation 1.9 in which event-time dummies are interacted separately with three mutually exclusive indicators for distance increase, little distance change, and distance decrease due to reassignment. The dependent variables are voter turnout (0–100) at the polling place (Column 1), by mail (Column 2), and overall (Column 3). The event is defined as the first time in which the entire precinct is reassigned to a different polling place. All specifications include precinct fixed effects, election×district fixed effects, and time-varying covariates listed in Section 1.4.1. Regressions are weighted by the number of eligible voters. Standard errors are clustered at the precinct level and reported in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table A.7 : Difference between Event-Time Indicators in Period 1 and Period 0

	(1) Mail-in turnout	(2) Polling place turnout	(3) Overall turnout
Panel A: Differences based on event study estimates restricted to precincts with increased distance			
BJS (2021)	0.73***	-0.21	0.52**
dChDH (2020)	0.87***	-0.33	0.54**
TWFE-OLS	0.72***	-0.05	0.67***
SA (2020)	0.33	0.14	0.48**
CS (2021)	0.98***	-0.31	0.67**
Panel B: Differences based on event study estimates after absorbing transportation effect			
BJS (2021)	0.45**	-0.06	0.39**
dChDH (2020)	0.53***	-0.13	0.40**
TWFE-OLS	0.48***	0.01	0.50***
SA (2020)	0.13	0.20	0.34**
CS (2021)	0.32*	0.06	0.38*

Notes: The table reports the difference between the event study estimates in period 1 and period 0 relative to reassignment ($\hat{\mu}_1 - \hat{\mu}_0$) for mail-in, in-person, and overall turnout according to the TWFE-OLS estimator and the four novel estimators proposed by Borusyak et al. (2022) (BJS, 2021), Callaway and Sant'Anna (2021) (CS, 2020), Sun and Abraham (2021) (SA, 2020), and de Chaisemartin and D'Haultfœuille (2020) (dChDH, 2020), respectively. Event study estimates in Panel A are obtained on a sample restricted to never-treated precincts and precincts in which reassignments resulted in an increase in average distance. Estimates in Panel B are obtained controlling for the log of street distance to absorb the distance effect. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

by the respective party caucus. Each constituency is represented by one seat in the *Bundestag*, with the remaining seats being allocated based on the second votes to achieve proportionality.

Bavarian State Elections Similar to the federal parliament, the Bavarian *Landtag* is elected for a five-year term on the basis of mixed-member proportional representation. German citizens aged eighteen and older with residence in Bavaria elect the representatives of their constituencies (*Stimmkreise*) and vote for an (open) party list. In contrast to the federal parliament, the allocation of seats in the state parliament takes into account the parties' aggregate first (constituency) votes as well as their second (party-list) votes. The number of single-member constituencies in Munich increased from eight to nine in 2018 due to stronger population growth in Munich compared to the rest of the state.

Munich City Council Elections Municipal elections in Munich comprise three distinct elections which are held on the same day every six years: the election of the local district committees (*Bezirksausschuss)*, charged with representing the interests of citizens living in 25 distinct city districts in Munich, the mayor's race, which is decided based on an absolute

Table A.8 : Effect Heterogeneity by Precinct Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Effect on Turnout at the Polling Place							
$Z_p =$	% electorate aged 60+	% electorate aged 18-24	% households with children	Average quoted rent per sqm	% non-native German residents	Average duration of residence	Polling place turnout
$Z_p \times$							
Reassignment $(t-4)$	0.26	-0.31**	-0.23	0.04	-0.03	0.29*	0.49***
	(0.17)	(0.13)	(0.16)	(0.15)	(0.19)	(0.16)	(0.17)
Reassignment $(t-3)$	0.24	-0.13	-0.17	0.05	0.12	0.23	0.23
	(0.18)	(0.12)	(0.18)	(0.12)	(0.19)	(0.16)	(0.15)
Reassignment $(t-2)$	0.18	-0.20	-0.11	-0.01	-0.00	0.15	0.13
	(0.12)	(0.13)	(0.15)	(0.11)	(0.14)	(0.12)	(0.12)
Reassignment $(t+0)$	-0.45*	0.37**	0.37	-0.17	0.74***	-0.30	-0.66***
	(0.23)	(0.19)	(0.26)	(0.26)	(0.26)	(0.23)	(0.23)
Reassignment $(t+1)$	-0.49**	0.60***	0.26	-0.02	0.55***	-0.59***	-0.76***
	(0.21)	(0.19)	(0.21)	(0.26)	(0.20)	(0.20)	(0.23)
Reassignment $(t+2)$	-0.17	0.46**	0.16	-0.05	0.70***	-0.48**	-1.05***
	(0.26)	(0.22)	(0.36)	(0.24)	(0.25)	(0.23)	(0.22)
R^2	0.97	0.97	0.97	0.97	0.97	0.97	0.97
Panel B: Effect on Turnout via Mail							
$Z_p =$	% electorate aged 60+	% electorate aged 18-24	% households with children	Average quoted rent per sqm	% non-native German residents	Average duration of residence	Polling place turnout
$Z_p \times$							
Reassignment $(t-4)$	-0.02	-0.12	0.16	-0.10	0.20	0.08	0.06
	(0.16)	(0.17)	(0.18)	(0.14)	(0.19)	(0.15)	(0.15)
Reassignment $(t-3)$	-0.21	0.03	0.23	-0.08	0.11	-0.05	0.02
	(0.17)	(0.13)	(0.20)	(0.12)	(0.20)	(0.15)	(0.15)
Reassignment $(t-2)$	0.06	0.17	0.25*	-0.12	0.35***	0.34***	-0.00
	(0.13)	(0.12)	(0.15)	(0.09)	(0.14)	(0.10)	(0.12)
Reassignment $(t+0)$	-0.22	-0.14	-0.34*	0.30	-0.65***	-0.12	0.52**
	(0.20)	(0.18)	(0.21)	(0.21)	(0.19)	(0.20)	(0.21)
Reassignment $(t+1)$	-0.28	-0.42**	-0.11	0.02	-0.64***	0.15	0.99***
	(0.22)	(0.19)	(0.20)	(0.21)	(0.21)	(0.22)	(0.23)
Reassignment $(t+2)$	-0.58**	-0.10	-0.11	0.03	-0.83***	-0.25	1.10***
	(0.23)	(0.19)	(0.28)	(0.21)	(0.20)	(0.24)	(0.24)
R^2	0.96	0.96	0.96	0.96	0.96	0.96	0.96
Panel C: Effect on Total Turnout							
$Z_p =$	% electorate aged 60+	% electorate aged 18-24	% households with children	Average quoted rent per sqm	% non-native German residents	Average duration of residence	Polling place turnout
$Z_p \times$							
Reassignment $(t-4)$	0.24	-0.43**	-0.08	-0.06	0.16	0.38*	0.55***
	(0.17)	(0.20)	(0.16)	(0.15)	(0.21)	(0.19)	(0.17)
Reassignment $(t-3)$	0.03	-0.10	0.05	-0.03	0.24	0.18	0.25*
	(0.18)	(0.12)	(0.15)	(0.11)	(0.17)	(0.15)	(0.14)
Reassignment $(t-2)$	0.24*	-0.03	0.14	-0.14	0.35***	0.49***	0.13
	(0.14)	(0.10)	(0.11)	(0.10)	(0.12)	(0.13)	(0.14)
Reassignment $(t+0)$	-0.68***	0.23*	0.03	0.13	0.09	-0.42**	-0.13
	(0.15)	(0.13)	(0.16)	(0.15)	(0.18)	(0.16)	(0.16)
Reassignment $(t+1)$	-0.78***	0.18	0.15	-0.00	-0.09	-0.44**	0.23
	(0.18)	(0.14)	(0.14)	(0.17)	(0.20)	(0.19)	(0.21)
Reassignment $(t+2)$	-0.76***	0.36**	0.05	-0.02	-0.13	-0.73***	0.04
	(0.19)	(0.15)	(0.24)	(0.16)	(0.25)	(0.21)	(0.24)
R^2	0.99	0.99	0.99	0.99	0.99	0.99	0.99
Observations	4,672	4,672	4,672	4,672	4,672	4,672	4,672

Notes: The table reports point estimates and standard errors underlying the plots presented in Figure 1.13. Results are based on the triple-difference estimator presented in Equation 1.10. Each column in each panel represents a separate specification using a different heterogeneity dimension Z_p, which corresponds to a standardized (mean zero and unitary standard deviation) precinct characteristic measured in 2013. The dependent variables are voter turnout (0–100) at the polling place (Panel A), by mail (Panel B), and overall (Panel C). The event is defined as the first time in which the entire precinct is reassigned to a different polling place. All specifications include precinct fixed effects, election×district fixed effects, and time-varying covariates listed in Section 1.4.1. Regressions are weighted by the number of eligible voters. Standard errors are clustered at the precinct level and reported in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

majority rule in a direct election, and the election of the city council (*Stadtrat*), which consists of 80 members elected based on (open) party lists and the mayor as the chairperson. In addition to German citizens with residence in Munich, EU foreigners are also eligible to vote in municipal elections.

European Elections The European Parliament is elected for a five-year term based on proportional representation. In Germany, each voter casts a single vote for a (closed) list of candidates nominated by a party. All Germans aged eighteen and older are eligible to vote in European elections. It is also possible for non-German EU citizens living in Munich to vote in the city but they have to lodge a request for registration on the electoral roll before each election.

A.4 Effect Heterogeneity by Reassignment Reason

In this section, we investigate effect heterogeneity by reason of reassignment using the event study framework introduced in Section 1.4.1. Precinct reconfigurations are less likely to lead to *entire* precincts being reassigned (see Appendix Figure A.5). To ensure enough precision of our point estimates, we define the event as the first time that 50 percent or more residential addresses of a precinct are reassigned. Formally, let R_p be an indicator equal to 1 for precincts where reassignment occurred because of recruitment of a new polling venue and let B_p denotes an analogous indicator for cases in which reassignments are due to reconfiguration of precincts. Then, the modified event study specification takes the following form:

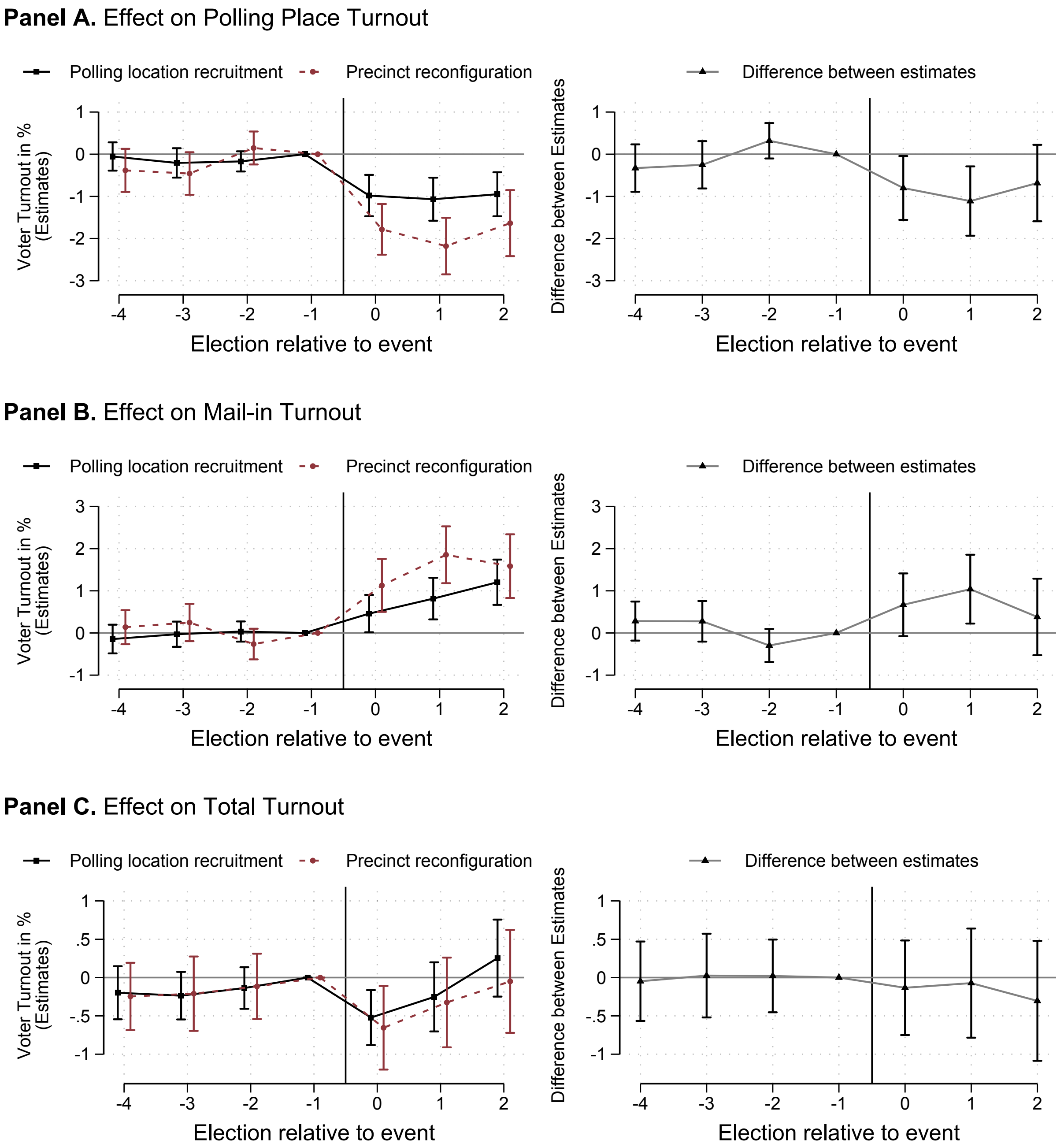
$$Y_{pt} = R_p \times \sum_{k \neq -1} \beta^k \mathbb{1}(\tau = k) + B_p \times \sum_{k \neq -1} \alpha^k \mathbb{1}(\tau = k) + \mathbf{X}'_{pt}\phi + \delta_p + \delta_{d(p)t} + \varepsilon_{pt}, \tag{A.1}$$

where the coefficients $\hat{\beta}^k$ and $\hat{\alpha}^k$ trace the differential time path of turnout separately for the two groups defined by R_p and B_p. As in our main specification, we include election$\times$district fixed effects, a vector of precinct indicators, and time-varying controls.

The results are presented in Figure A.16. The outcome in Panel A is turnout at the polling place; Panels B and C show the results for mail-in and total turnout, respectively. The left plot in each panel reports estimated coefficients $\hat{\alpha}^k$ and $\hat{\beta}^k$ for $k \in \{-4, ..., 2\}$; the right plot reports estimates and 95 percent confidence bands of the *difference* between the pair of estimates in each period.

Reassuringly, pre-event estimates for both reassignment types are insignificant for all outcomes. Post-reassignment estimates follow a very similar trajectory. Treatment effects after a precinct reconfiguration seem slightly more pronounced; yet out of nine pairs of point estimates, only three are statistically different from each other. Thus overall, the results do not suggest that reassignments for different reasons carry different consequences.

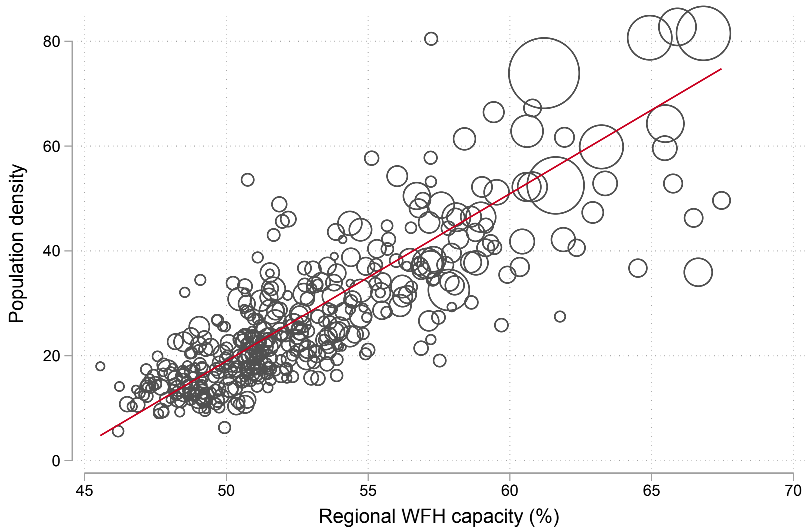
Figure A.16 : Effect Heterogeneity by Reassignment Reason



Notes: The figure presents event study results based on Equation A.1. The left plot in each panel report estimates on interaction terms between event-time indicators and a dummy identifying reassignments due to recruitment of a new polling place and precinct reconfiguration, respectively. The right plot in each panel presents estimates and confidence bands for the difference between estimates in each period. The event is defined as the first time in which more than 50 percent of residential addresses in a precinct is reassigned to a different polling place. Regressions are weighted by the number of eligible voters. Confidence intervals are drawn at the 95 percent level using standard errors clustered at the precinct level.

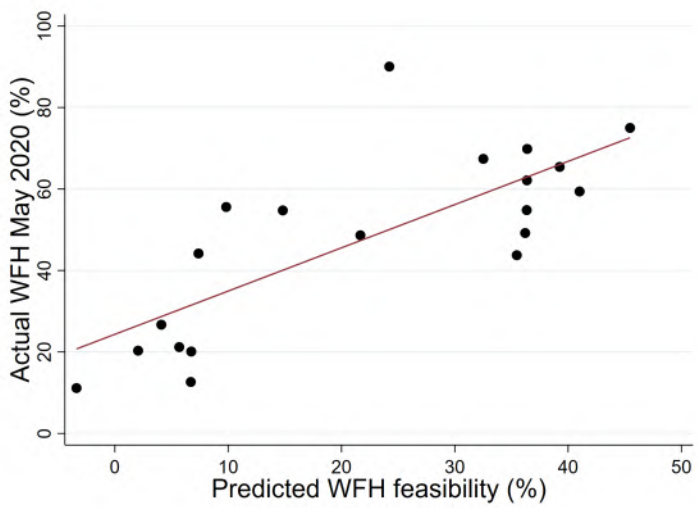
B Appendix to Chapter 2

Figure B.1 : Correlation between Population Density and WFH Capacity



Notes: The figure shows the linear fit between county-level population density (total population relative to settled area in hectares) and county-level WFH capacity. The size of the bubbles is proportional to total employment. Data from Destatis, Employment Statistics of the Federal Employment Agency (BA) 2019.

Figure B.2 : Predicting Actual Individual-Level WFH during the Covid-19 Pandemic



Notes: The figure shows the linear fit between individual-level actual WFH reported in May 2020 and predicted WFH feasibility. Individual WFH feasibility has been predicted in the BIBB/BAuA data based on employee characteristics (gender, migration background, child below age 11, age, academic degree) and occupations (2-digit KldB 2010) and subsequently imputed in the HOPP data. The binned scatterplot groups predicted WFH feasibility into 20 equal-sized bins and plots them against the share of workers in each bin that reported to actually WFH in May 2020. Data from the IAB High-Frequency Online Personal Panel (HOPP) May 2020, and the 2018 BIBB/BAuA Employment Survey.

Table B.1 : Capacity to Work from Home by Occupation (KldB-10 2-digit)

KldB-10 2-digit Occupations	frequent WFH	occasional WFH	untapped WFH (employer)	untapped WFH (employee)	WFH capacity
11 Occupations in agriculture, forestry, and farming	7.591	6.928	10.32	5.601	30.44
12 Occupations in gardening and floristry	3.026	6.105	17.13	14.91	41.25
21 Occupations in production and processing of raw materials, glass- and ceramic-making and -processing	0	6.851	9.709	0	16.56
22 Occupations in plastic-making and -processing, and wood-working and -processing	1.210	3.779	10.44	13.48	28.91
23 Occupations in paper-making and -processing, printing, and in technical media design	2.978	14.62	29.97	10.67	58.23
24 Occupations in metal-making and -working, and in metal construction	0.618	2.806	13.84	4.863	22.13
25 Technical occupations in machine-building and automotive industry	4.126	9.940	20.36	11.04	45.50
26 Occupations in mechatronics, energy electronics and electrical engineering	8.770	19.66	22.12	7.939	58.49
27 Occupations in technical research and development, construction, and production planning and scheduling	6.899	25.59	28.29	11.86	72.65
28 Occupations in textile- and leather-making and -processing	3.026	13.23	25.50	10.38	52.26
29 Occupations in food-production and -processing	4.929	7.605	10.63	5.806	28.97
31 Occupations in construction scheduling, architecture and surveying	10.49	28.07	32.34	11.01	81.92
32 Occupations in building construction above and below ground	0.800	4.930	13.59	4.854	24.17
33 Occupations in interior construction	1.081	5.154	9.733	4.988	20.96
34 Occupations in building services engineering and technical building services	3.090	11.32	15.47	4.121	34.12
41 Occupations in mathematics, biology, chemistry and physics	4.621	18.31	23.64	9.161	55.74
42 Occupations in geology, geography and environmental protection	20.75	25.43	18.85	8.524	73.57
43 Occupations in computer science, information and communication technology	23.78	52.17	14.05	6.666	96.77
51 Occupations in traffic and logistics (without vehicle driving)	5.122	6.843	18.00	8.056	38.06
52 Drivers and operators of vehicles and transport equipment	1.200	3.058	7.772	4.187	16.24
53 Occupations in safety and health protection, security and surveillance	4.936	10.47	21.26	3.131	39.79
54 Occupations in cleaning services	5.681	2.936	6.740	14.52	29.88
61 Occupations in purchasing, sales and trading	28.14	27.41	25.81	7.645	89.00
62 Sales occupations in retail trade	3.346	8.229	20.43	8.569	40.58
63 Occupations in tourism, hotels and restaurants	11.68	9.773	12.10	9.804	43.36
71 Occupations in business management and organisation	14.48	29.70	29.73	12.77	86.72
72 Occupations in financial services, accounting and tax consultancy	9.992	24.36	40.87	16.42	91.76
73 Occupations in law and public administration	8.975	19.12	36.71	19.06	84.23
81 Medical and health care occupations	2.915	10.82	17.86	8.832	40.39
82 Occupations in non-medical healthcare, body care, wellness and medical technicians	3.635	9.327	13.07	10.28	36.38
83 Occupations in education and social work, housekeeping, and theology	12.79	20.92	15.22	9.975	58.92
84 Occupations in teaching and training	64.61	20.63	4.756	1.526	91.32
91 Occupations in in philology, literature, humanities, social sciences, and economics	23.47	43.60	12.52	3.857	83.45
92 Occupations in advertising and marketing, in commercial and editorial media design	20.12	32.60	28.86	10.43	92.02
93 Occupations in product design, artisan craftwork, fine arts and the making of musical instruments	28.64	4.545	29.86	4.637	67.68
94 Occupations in the performing arts and entertainment	21.21	32.60	10.03	1.791	65.63

Notes: The table reports WFH capacities and pre-pandemic WFH uptake by occupation (2-digit KldB 2010). Data from the 2018 BIBB/BAuA Employment Survey.

Table B.2 : Capacity to Work from Home by Occupation (ISCO-08 1-digit)

ISCO-08 1-digit Occupations	frequent WFH	occasional WFH	untapped WFH (employer)	untapped WFH (employee)	WFH capacity
0 Armed forces occupations	1.542	6.064	29.89	23.16	60.66
1 Managers	29.02	39.94	13.08	6.368	88.43
2 Professionals	32.89	35.74	16.01	5.906	90.55
3 Technicians and associate professionals	9.374	19.36	26.25	11.50	66.49
4 Clerical support workers	6.440	12.95	34.60	15.59	69.72
5 Services and sales workers	4.276	8.101	15.06	9.104	36.56
6 Skilled agricultural, forestry and fishery workers	2.185	6.090	11.95	11.79	32.02
7 Craft and related trades workers	1.845	5.104	15.83	5.876	28.67
8 Plant and machine operators and assemblers	1.085	1.638	11.19	7.279	21.20
9 Elementary occupations	1.592	2.523	12.17	8.656	24.94

Notes: The table reports WFH capacities and pre-pandemic WFH uptake by occupation (1-digit ISCO 2008). Data from the 2018 BIBB/BAuA Employment Survey.

Table B.3 : Capacity to Work from Home by Occupation (ISCO-08 2-digit)

ISCO-08 2-digit Occupations	frequent WFH	occasional WFH	untapped WFH (employer)	untapped WFH (employee)	WFH capacity
11 Chief executives, senior officials and legislators	39.77	40.26	6.758	9.398	96.19
12 Administrative and commercial managers	30.72	42.55	16.67	3.165	93.17
13 Production and specialized services managers	25.82	41.02	13.16	8.352	88.35
14 Hospitality, retail and other services managers	29.23	26.59	8.634	2.730	67.19
21 Science and engineering professionals	12.83	41.60	26.85	12.26	93.63
22 Health professionals	7.341	15.87	22.84	6.720	52.75
23 Teaching professionals	66.00	20.41	4.685	0.781	91.68
24 Business and administration professionals	25.33	47.30	18.81	5.658	97.18
25 Information and communications technology professionals	23.50	52.75	14.46	6.930	97.73
26 Legal, social and cultural professionals	23.54	39.83	20.00	7.105	90.47
31 Science and engineering associate professionals	7.632	18.95	27.04	9.418	63.03
32 Health associate professionals	1.994	10.92	17.36	8.197	38.44
33 Business and administration associate professionals	13.29	21.85	35.99	16.04	87.25
34 Legal, social, cultural and related associate professionals	11.54	20.72	16.21	9.468	57.94
35 Information and communications technicians	19.09	48.27	15.56	4.635	87.69
41 General and keyboard clerks	9.768	15.34	37.09	17.93	80.50
42 Customer services clerks	4.958	11.44	41.09	19.01	76.56
43 Numerical and material recording clerks	5.926	11.96	31.02	13.05	62.04
44 Other clerical support workers	2.266	12.02	30.08	12.62	56.97
51 Personal services workers	5.136	8.476	13.24	8.693	35.55
52 Sales workers	3.992	8.393	19.43	8.848	40.66
53 Personal care workers	4.618	8.284	8.925	13.20	35.10
54 Protective services workers	2.204	5.471	16.18	2.472	26.33
61 Market-oriented skilled agricultural workers	2.285	4.727	12.50	12.34	31.85
62 Market-oriented skilled forestry, fishery and hunting workers	0	35.68	0	0	35.68
71 Building and related trades workers (excluding electricians)	1.375	3.751	10.37	3.617	19.14
72 Metal, machinery and related trades workers	1.256	3.370	14.83	6.609	26.07
73 Handicraft and printing workers	5.351	3.021	22.39	12.90	43.66
74 Electrical and electronics trades workers	4.527	11.39	24.57	3.573	44.07
75 Food processing, woodworking, garment and other craft and related trades workers	0.222	5.365	15.34	8.039	28.99
81 Stationary plant and machine operators	1.074	1.735	15.78	8.791	27.39
82 Assemblers	0.362	1.353	10.67	16.63	29.01
83 Drivers and mobile plant operators	1.219	1.620	8.087	4.579	15.52
91 Cleaners and helpers	1.891	3.981	8.171	13.97	28.01
92 Agricultural, forestry and fishery labourers	0	0	32.56	0	32.56
93 Labourers in mining, construction, manufacturing and transport	0.483	1.260	16.77	7.066	25.57
94 Food preparation assistants	1.198	0	6.329	4.834	12.36
96 Refuse workers and other elementary workers	5.749	6.449	6.911	6.244	25.35

Notes: The table reports WFH capacities and pre-pandemic WFH uptake by occupation (2-digit ISCO 2008). Data from the 2018 BIBB/BAuA Employment Survey.

Table B.4 : Tasks and Work Conditions in the 2018 BIBB/BAuA Survey

Survey Label	Task or Work Condition	Mean
F303	Manufacturing, producing goods & commodities	0.17
F304	Measuring, testing, quality control	0.47
F305	Monitoring, control of machines, plants, techn. processes	0.26
F306	Repairing, renovating	0.17
F307	Purchasing, procuring, selling	0.19
F308	Transporting, storing, shipping	0.26
F309	Advertising, Marketing, Public Relations	0.09
F310	Organizing, planning, preparing work processes	0.46
F311	Developing, researching, constructing	0.13
F312	Training, instructing, teaching, education	0.22
F313	Gathering information, researching, documenting	0.57
F314	Providing advice and information	0.58
F315	Entertaining, accommodating, preparing food	0.10
F316	Nursing, caring, healing	0.16
F317	Protecting, guarding, monitoring, regulating traffic	0.22
F318	Working with computers	0.70
F320	Cleaning, waste disposal, recycling	0.28
F600_01	Work standing up	0.54
F600_03	Lift or carry loads of $>$20 kg (men) $>$10 kg (women)	0.23
F600_04	Exposed to smoke, dust, gases, vapours	0.13
F600_05	Work under cold, heat, moisture, humidity, draughts	0.20
F600_06	Work with oil, grease, dirt	0.18
F600_07a	Manual work that requires high degree of skill, fast sequences of movements, or greater forces	0.39
F600_07b	Work in a bent, squatting, kneeling position or overhead	0.17
F600_12	Work under noise	0.27
F600_13	Handle microorganisms (pathogens, bacteria, moulds, viruses)	0.13
F605	Working majority of the time outdoors	0.11
F327	Reacting to and solving new problems	0.72
F327_02	Making difficult decisions	0.40
F327_03	Recognizing and closing knowledge gaps	0.36
F327_04	Taking responsibility for others	0.41
F327_05	Convincing and negotiating with others	0.43
F327_06	Communicating with others	0.91
F411_02	Execution of work prescribed in every detail	0.26
F411_03	Repeating same operation in every detail	0.46
F411_04	Confronted with new tasks	0.40
F411_05	Improving existing procedures or trying new things	0.28
F411_13	Working very fast	0.34
F301	Supervising others	0.28

Notes: The table lists survey labels and population averages of the tasks and work conditions considered in the analysis outlined in Section 2.3.2. Every job characteristic is coded as one if the respondent indicates that it applies *frequently* in her job and zero otherwise. “Supervising others” and “working majority of the working time outdoors” are recorded as binary variables (yes/no) in the survey and coded accordingly in the analysis. Means are computed using population weights. $N = 16,689$. Data from the 2018 BIBB/BAuA Employment Survey.

Table B.5 : Determinants of WFH Feasibility

	(1)	(2)	(3)	(4)	(5)
Tasks & work conditions					
Manufacturing, producing goods & commodities (m)	-0.01		-0.00	0.00	0.01
	(0.02)		(0.02)	(0.02)	(0.02)
Measuring, testing, quality control (c)	-0.02**		-0.03**	-0.02	-0.02*
	(0.01)		(0.01)	(0.01)	(0.01)
Monitoring, control of machines, plants, techn. processes (c)	-0.05***		-0.03**	-0.01	-0.00
	(0.01)		(0.01)	(0.01)	(0.01)
Repairing, renovating (m)	-0.02		0.00	-0.00	-0.00
	(0.02)		(0.02)	(0.02)	(0.02)
Purchasing, procuring, selling (c)	-0.00		0.00	0.02	0.02*
	(0.01)		(0.01)	(0.01)	(0.01)
Transporting, storing, shipping (m)	-0.06***		-0.04***	-0.00	-0.00
	(0.01)		(0.01)	(0.01)	(0.01)
Advertising, Marketing, Public Relations (c)	0.06***		0.07***	0.06***	0.06***
	(0.02)		(0.02)	(0.02)	(0.02)
Organizing, planning, preparing work processes (c)	0.05***		0.05***	0.05***	0.05***
	(0.01)		(0.01)	(0.01)	(0.01)
Developing, researching, constructing (c)	0.07***		0.05***	0.05***	0.05***
	(0.01)		(0.01)	(0.01)	(0.01)
Training, instructing, teaching, education (c)	0.03***		0.02	-0.01	-0.01
	(0.01)		(0.01)	(0.01)	(0.01)
Gathering information, researching, documenting (c)	0.07***		0.07***	0.05***	0.05***
	(0.01)		(0.01)	(0.01)	(0.01)
Providing advice and information (c)	0.05***		0.03***	0.03**	0.03**
	(0.01)		(0.01)	(0.01)	(0.01)
Entertaining, accommodating, preparing food (m)	-0.03		-0.02	-0.03	-0.04*
	(0.02)		(0.02)	(0.02)	(0.02)
Nursing, caring, healing (m)	-0.07***		-0.08***	-0.03*	-0.04**
	(0.02)		(0.02)	(0.02)	(0.02)
Protecting, guarding, monitoring, regulating traffic (m)	-0.02*		-0.01	0.00	0.00
	(0.01)		(0.01)	(0.01)	(0.01)
Working with computers (c)	0.14***		0.13***	0.09***	0.09***
	(0.01)		(0.02)	(0.02)	(0.02)
Cleaning, waste disposal, recycling (m)	-0.04***		-0.05***	-0.03*	-0.03*
	(0.01)		(0.02)	(0.01)	(0.01)
Work standing up	-0.13***		-0.12***	-0.09***	-0.09***
	(0.01)		(0.01)	(0.01)	(0.01)
Lift or carry loads of >20 kg (men) >10 kg (women) (m)	-0.04**		-0.04**	-0.02	-0.02
	(0.02)		(0.02)	(0.02)	(0.02)
Exposed to smoke, dust, gases, vapours	-0.04**		-0.04*	-0.03	-0.02
	(0.02)		(0.02)	(0.02)	(0.02)
Work under cold, heat, moisture, humidity, draughts	-0.05***		-0.04**	-0.03*	-0.03*
	(0.02)		(0.02)	(0.02)	(0.02)
Work with oil, grease, dirt	-0.02		-0.02	-0.01	-0.01
	(0.02)		(0.02)	(0.02)	(0.02)
Manual work that requires high degree of skill (m)	-0.05***		-0.05***	-0.03**	-0.03**
	(0.01)		(0.01)	(0.01)	(0.01)
Work in a bent, squatting, kneeling position or overhead	0.03*		0.04**	0.02	0.02
	(0.02)		(0.02)	(0.02)	(0.02)
Work under noise	-0.04***		-0.05***	-0.05***	-0.05***
	(0.01)		(0.01)	(0.01)	(0.01)
Handle microorganisms (m)	-0.04**		-0.04**	-0.01	-0.01
	(0.02)		(0.02)	(0.02)	(0.02)
Working majority of the time outdoors	-0.03		-0.02	0.00	0.00
	(0.02)		(0.02)	(0.02)	(0.02)
Reacting to and solving new problems (c)	0.02		0.01	0.01	0.01
	(0.01)		(0.01)	(0.01)	(0.01)
Making difficult decisions (c)	0.00		0.01	0.01	0.02
	(0.01)		(0.01)	(0.01)	(0.01)
Recognizing and closing knowledge gaps (c)	0.03**		0.02	0.01	0.01
	(0.01)		(0.01)	(0.01)	(0.01)
Taking responsibility for others	-0.03**		-0.02*	-0.01	-0.02
	(0.01)		(0.01)	(0.01)	(0.01)
Convincing and negotiating with others (c)	0.06***		0.05***	0.04***	0.04***
	(0.01)		(0.01)	(0.01)	(0.01)
Communicating with others (c)	0.01		0.01	-0.00	-0.01
	(0.02)		(0.02)	(0.02)	(0.02)
Execution of work prescribed in every detail	-0.04***		-0.03**	-0.02	-0.02*
	(0.01)		(0.01)	(0.01)	(0.01)
Repeating same operation in every detail	-0.03***		-0.02*	-0.02	-0.02
	(0.01)		(0.01)	(0.01)	(0.01)
Confronted with new tasks	0.04***		0.03***	0.03***	0.03***
	(0.01)		(0.01)	(0.01)	(0.01)
Improving existing procedures or trying new things (c)	0.05***		0.03***	0.03**	0.03**

Table B.5 *Continued*

	(1)	(2)	(3)	(4)	(5)
	(0.01)		(0.01)	(0.01)	(0.01)
Working very fast	-0.00		-0.01	-0.01	-0.01
	(0.01)		(0.01)	(0.01)	(0.01)
Supervising others (c)	0.03**		0.02*	0.04***	0.04***
	(0.01)		(0.01)	(0.01)	(0.01)
Worker characteristics					
Female		0.12***	0.05***	0.02*	0.01
		(0.01)	(0.01)	(0.01)	(0.01)
Migration background		-0.04**	-0.02	-0.01	-0.01
		(0.02)	(0.02)	(0.02)	(0.02)
Age (x10)		-0.04***	-0.02***	-0.02***	-0.02***
		(0.01)	(0.01)	(0.01)	(0.01)
Married		0.00	-0.00	-0.00	0.00
		(0.01)	(0.01)	(0.01)	(0.01)
Children under 11		0.00	-0.00	0.00	0.00
		(0.01)	(0.01)	(0.01)	(0.01)
Academic degree		0.29***	0.10***	0.06***	0.06***
		(0.01)	(0.01)	(0.01)	(0.01)
Gross monthly wage in EUR1000		0.07***	0.02***	0.01***	0.01***
		(0.00)	(0.00)	(0.00)	(0.00)
Weekly contractual working hours ($\times$10)		-0.04***	-0.02***	-0.01	-0.01
		(0.01)	(0.01)	(0.01)	(0.01)
Firm tenure in years ($\times$10)		0.01	0.01	0.00	0.00
		(0.01)	(0.01)	(0.01)	(0.01)
Firm with 100+ employees		0.00	-0.02**	-0.02*	-0.02*
		(0.01)	(0.01)	(0.01)	(0.01)
R^2	0.30	0.17	0.32	0.36	0.37
Observations	16,689	15,678	15,678	15,636	15,525
Occupation FE				$\times$	$\times$
Sector FE					$\times$

Notes: The table reports OLS estimates from regressing WFH feasibility on tasks & working conditions, worker characteristics, occupation fixed effects (2-digit level), and industry fixed effects (21 categories) at the individual level (Equation 2.1). Regressions use survey weights. Standard errors are robust to heteroskedasticity and reported in parentheses. Data from the 2018 BIBB/BAuA Employment Survey. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table B.6 : Variance Decomposition of WFH Feasibility

$Var(WFH\_feasibility_i)$	1.000
$Var(\mathbf{T}_i)$	.116
$Var(\mathbf{X}_i)$	.009
$Var(\alpha_{o(i)})$	.071
$Var(\alpha_{s(i)})$	.007
$Cov(\mathbf{T}_i, \alpha_{o(i)})$	.096
$Cov(\mathbf{X}_i, \alpha_{o(i)})$	.018
$Cov(\mathbf{T}_i, \alpha_{s(i)})$	.009
$Cov(\mathbf{X}_i, \alpha_{s(i)})$	.003
$Cov(\alpha_{s(i)}, \alpha_{o(i)})$	.006
$Cov(\mathbf{T}_i, \mathbf{X}_i)$	.031
$Var(\varepsilon_i)$	.635
R^2	.365
Observations	15,525

Notes: The table reports the share of variance in individual-level WFH feasibility explained by job tasks and work conditions ($\mathbf{T}_i$), worker characteristics ($\mathbf{X}_i$), 2-digit occupation fixed effects ($\alpha_{o(i)}$), and industry fixed effects ($\alpha_{s(i)}$) based on the regression specified in Equation 2.1. Data from the 2018 BIBB/BAuA Employment Survey.

Table B.7 : Determinants of Untapped WFH

	Employee-side untapped WFH			Employer-side untapped WFH		
	(1)	(2)	(3)	(4)	(5)	(6)
Worker Characteristics						
Female	0.03**	0.04***	0.02*	0.02	0.03*	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Migration background	0.04*	0.02	0.02	0.02	0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Age (x10)	0.03***	0.01	0.01*	-0.01	-0.02***	-0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Married	-0.02	-0.01	-0.01	-0.03	-0.02	-0.03*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Children under 11	-0.01	-0.01	-0.01	0.01	0.01	0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Academic degree	-0.17***	-0.08***	-0.06***	-0.22***	-0.13***	-0.09***
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Gross monthly wage in EUR1000	-0.05***	-0.03***	-0.03***	-0.07***	-0.05***	-0.05***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Weekly contractual working hours ($\times$10)	0.02**	0.03***	0.02**	0.08***	0.07***	0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Firm tenure in years ($\times$10)	0.01	0.01	0.01	0.02***	0.02***	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Firm with 100+ employees	0.07***	0.06***	0.04***	0.07***	0.04***	0.02
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Tasks & work conditions						
Manufacturing, producing goods & commodities (m)		0.03	0.03		0.05*	0.04
		(0.03)	(0.03)		(0.03)	(0.03)
Measuring, testing, quality control (c)		0.01	0.01		-0.03*	-0.03*
		(0.01)	(0.01)		(0.02)	(0.01)
Monitoring, control of machines, plants, techn. processes (c)		-0.02	-0.02		0.04**	0.03
		(0.02)	(0.02)		(0.02)	(0.02)
Repairing, renovating (m)		-0.04	-0.02		-0.04*	-0.03
		(0.03)	(0.03)		(0.03)	(0.02)
Purchasing, procuring, selling (c)		-0.02	-0.01		-0.04*	-0.03*
		(0.02)	(0.02)		(0.02)	(0.02)
Transporting, storing, shipping (m)		-0.00	-0.03		0.00	-0.01
		(0.02)	(0.02)		(0.02)	(0.02)
Advertising, Marketing, Public Relations (c)		-0.06***	-0.05***		-0.05**	-0.05***
		(0.02)	(0.02)		(0.02)	(0.02)
Organizing, planning, preparing work processes (c)		-0.03**	-0.03*		0.00	0.00
		(0.02)	(0.02)		(0.02)	(0.01)
Developing, researching, constructing (c)		-0.05***	-0.03*		-0.08***	-0.04**
		(0.02)	(0.01)		(0.02)	(0.02)
Training, instructing, teaching, education (c)		-0.10***	-0.04**		-0.08***	-0.01
		(0.02)	(0.02)		(0.02)	(0.02)
Gathering information, researching, documenting (c)		-0.07***	-0.06***		-0.05***	-0.05***
		(0.02)	(0.02)		(0.02)	(0.02)
Providing advice and information (c)		-0.05***	-0.05***		-0.06***	-0.06***
		(0.02)	(0.02)		(0.02)	(0.02)
Entertaining, accommodating, preparing food (m)		-0.04	-0.03		-0.12***	-0.06*
		(0.03)	(0.04)		(0.03)	(0.04)
Nursing, caring, healing (m)		0.05**	0.04*		-0.03	-0.05*
		(0.02)	(0.02)		(0.02)	(0.03)
Protecting, guarding, monitoring, regulating traffic (m)		-0.02	-0.03		-0.02	-0.02
		(0.02)	(0.02)		(0.02)	(0.02)
Working with computers (c)		-0.12***	-0.12***		-0.02	-0.02
		(0.03)	(0.03)		(0.02)	(0.02)
Cleaning, waste disposal, recycling (m)		0.01	-0.00		0.02	0.00
		(0.03)	(0.03)		(0.03)	(0.02)
Work standing up		-0.01	0.01		-0.02	-0.00
		(0.02)	(0.02)		(0.02)	(0.02)
Lift or carry loads of $>$20 kg (men) $>$410 kg (women) (m)		0.06*	0.04		0.05	0.03
		(0.03)	(0.03)		(0.03)	(0.03)
Exposed to smoke, dust, gases, vapours		0.07*	0.05		0.03	0.01
		(0.04)	(0.04)		(0.03)	(0.03)
Work under cold, heat, moisture, humidity, draughts		-0.07**	-0.06*		-0.05	-0.03
		(0.03)	(0.03)		(0.03)	(0.03)
Work with oil, grease, dirt		0.02	-0.02		0.06*	0.02
		(0.04)	(0.04)		(0.03)	(0.03)
Manual work that requires high degree of skill (m)		0.02	0.01		-0.00	-0.01
		(0.02)	(0.02)		(0.02)	(0.02)
Work in a bent, squatting, kneeling position or overhead		0.02	0.01		-0.03	-0.03
		(0.03)	(0.03)		(0.03)	(0.03)
Work under noise		0.01	0.04		-0.01	0.01
		(0.02)	(0.02)		(0.02)	(0.02)
Handle microorganisms (m)		0.01	0.01		0.05*	0.04
		(0.03)	(0.03)		(0.03)	(0.03)
Working majority of the time outdoors		-0.05	-0.05		0.02	-0.00
		(0.04)	(0.04)		(0.03)	(0.04)
Reacting to and solving new problems (c)		-0.05**	-0.03		0.00	0.01
		(0.02)	(0.02)		(0.02)	(0.02)
Making difficult decisions (c)		0.01	-0.00		-0.02	-0.03**
		(0.01)	(0.01)		(0.02)	(0.01)
Recognizing and closing knowledge gaps (c)		-0.00	0.00		-0.04***	-0.03*
		(0.01)	(0.01)		(0.02)	(0.01)

Table B.7 *Continued*

Taking responsibility for others		-0.01	-0.00		-0.00	0.01
		(0.02)	(0.02)		(0.02)	(0.02)
Convincing and negotiating with others (c)		-0.03**	-0.04**		-0.04**	-0.05***
		(0.02)	(0.02)		(0.02)	(0.02)
Communicating with others (c)		-0.13***	-0.13***		-0.04	-0.05*
		(0.04)	(0.03)		(0.03)	(0.03)
Execution of work prescribed in every detail		0.11***	0.09***		0.15***	0.12***
		(0.02)	(0.02)		(0.02)	(0.02)
Repeating same operation in every detail		0.02	0.02		0.08***	0.07***
		(0.02)	(0.02)		(0.02)	(0.02)
Confronted with new tasks		-0.01	-0.02		-0.03*	-0.03**
		(0.01)	(0.01)		(0.02)	(0.01)
Improving existing procedures or trying new things (c)		-0.03**	-0.02		-0.02	-0.00
		(0.01)	(0.01)		(0.02)	(0.02)
Working very fast		0.02	0.01		0.02	0.01
		(0.01)	(0.01)		(0.02)	(0.01)
Supervising others (c)		-0.01	-0.04***		-0.03	-0.05***
		(0.02)	(0.02)		(0.02)	(0.02)
R^2	0.11	0.23	0.27	0.15	0.24	0.30
Observations	7,272	7,272	7,204	8,981	8,981	8,903
Occupation FE			×			×
Sector FE			×			×

Notes: The table reports OLS estimates from regressing untapped WFH on tasks & working conditions, worker characteristics, occupation fixed effects (2-digit level), and industry fixed effects (21 categories) at the individual level. The sample is restricted to employees with a WFH feasible job. Employee-side untapped WFH is equal to one if the respondent never works from home and would not accept an offer to work from home, and zero otherwise. employer-side untapped WFH is equal to one if the respondent never works from home and would accept an offer to WFH, and zero otherwise. Regressions use survey weights. Standard errors are robust to heteroskedasticity and reported in parentheses. Data from the 2018 BIBB/BAuA Employment Survey. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table B.8 : Capacity to Work from Home by Sector

NACE main sections	frequent WFH	occasional WFH	untapped WFH (employer)	untapped WFH (employee)	WFH capacity
Overall	9.328	16.27	20.32	9.604	55.52
A Agriculture, Forestry and Fishing	7.066	8.811	13.64	7.790	37.31
B Mining and Quarrying	5.054	12.54	17.05	6.350	41.00
C Manufacturing	7.153	15.29	20.87	9.304	52.62
D Electricity, Gas, Steam and Air Conditioning Supply	11.10	22.65	24.69	9.991	68.43
E Water Supply; Sewerage, Waste Management and Remediation Activities	6.199	13.60	18.30	7.747	45.85
F Construction	4.865	12.08	17.48	7.202	41.62
G Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles	8.073	14.22	21.37	9.348	53.02
H Transportation and Storage	5.245	9.002	15.80	7.299	37.35
I Accommodation and Food Service Activities	8.789	9.817	12.84	8.621	40.06
J Information and Communication	17.89	35.34	22.26	9.271	84.76
K Financial and Insurance Activities	11.85	25.78	36.65	14.94	89.22
L Real Estate Activities	13.71	22.43	24.76	10.03	70.93
M Professional, Scientific and Technical Activities	12.50	24.36	27.59	11.67	76.12
N Administrative and Support Service Activities	7.732	12.39	17.43	10.05	47.60
O Public Administration and Defence; Compulsory Social Security	10.76	19.81	25.75	12.94	69.26
P Education	30.20	20.94	13.98	7.359	72.49
Q Human Health and Social Work Activities	6.762	13.97	17.46	9.638	47.83
R Arts, Entertainment and Recreation	16.60	18.87	17.21	7.214	59.89
S Other Service Activities	11.39	17.62	18.92	10.65	58.59
T Activities of Households as Employers; Household Production for Own Use	10.73	18.19	15.68	9.867	54.47
U Activities of Extraterritorial Organisations and Bodies	9.763	18.75	23.92	10.69	63.11

Notes: The table reports WFH capacities and pre-pandemic WFH uptake overall and by sector (NACE main sections). Data from the 2018 BIBB/BAuA Employment Survey, and employment statistics of the Federal Employment Agency (BA) 2019.

Table B.9 : Capacity to Work from Home by Industry

NACE 2-digit industries	frequent WFH	occasional WFH	untapped WFH (employer)	untapped WFH (employee)	WFH capacity
Overall	9.328	16.27	20.32	9.604	55.52
Crop and animal production, hunting and related service activities	7.010	8.701	13.61	7.830	37.15
Forestry and logging	7.676	10.02	13.98	7.428	39.10
Fishing and aquaculture	7.353	9.333	13.98	6.939	37.61
Mining of coal and lignite	4.655	12.93	16.67	5.120	39.38
Extraction of crude petroleum and natural gas	7.886	17.91	20.23	7.101	53.13
Mining of metal ores	4.528	11.42	17.36	5.959	39.27
Other mining and quarrying	4.747	11.58	16.35	6.340	39.01
Mining support service activities	5.761	14.05	18.86	7.392	46.06
Manuf. of food products	6.066	10.93	16.93	7.909	41.83
Manuf. of beverages	8.632	14.09	18.43	8.260	49.41
Manuf. of tobacco products	8.470	15.92	20.64	9.534	54.56
Manuf. of textiles	7.039	16.21	24.32	10.34	57.91
Manuf. of wearing apparel	9.876	19.65	25.28	10.61	65.42
Manuf. of leather and related products	6.693	16.10	24.64	10.37	57.80
Manuf. of wood and of products of wood and cork, except furniture; manuf. of articles of straw and plaiting materials	5.076	10.47	16.24	11.04	42.82
Manuf. of paper and paper products	6.625	16.29	25.51	10.16	58.59
Printing and reproduction of recorded media	7.358	18.14	27.41	10.50	63.42
Manuf. of coke and refined petroleum products	8.507	19.61	23.76	9.369	61.24
Manuf. of chemicals and chemical products	8.227	19.15	23.52	9.895	60.79
Manuf. of pharmaceuticals, medicinal chemical and botanical products	8.608	20.11	23.86	10.02	62.59
Manuf. of rubber and plastics products	5.890	12.74	18.62	11.03	48.28
Manuf. of other non-metallic mineral products	5.984	13.31	17.99	6.323	43.61
Manuf. of basic metals	5.055	11.51	18.99	7.810	43.36
Manuf. of fabricated metal products, except machinery and equipment	5.144	11.33	18.95	7.915	43.33
Manuf. of computer, electronic and optical products	10.43	21.54	23.20	9.562	64.73
Manuf. of electrical equipment	9.409	19.34	22.94	9.605	61.29
Manuf. of machinery and equipment n.e.c.	7.836	16.38	21.74	9.399	55.36
Manuf. of motor vehicles, trailers and semi-trailers	7.034	16.17	21.86	10.05	55.12
Manuf. of other transport equipment	7.938	17.44	22.17	10.02	57.57
Manuf. of furniture	5.662	11.26	17.24	11.42	45.58
Other manufacturing	8.129	15.70	20.70	9.756	54.29
Repair and installation of machinery and equipment	7.953	16.53	21.57	9.588	55.64
Electricity, gas, steam and air conditioning supply	11.10	22.65	24.69	9.991	68.43
Water collection, treatment and supply	8.383	18.91	22.53	9.007	58.83
Sewerage	6.598	15.52	19.90	8.190	50.21
Waste collection, treatment and disposal activities; materials recovery	5.656	12.13	17.13	7.398	42.31
Remediation activities and other waste management services	7.010	14.69	18.32	8.062	48.08
Construction of buildings	4.375	11.41	17.91	6.980	40.68
Civil engineering	3.884	10.45	17.15	6.737	38.22
Specialized construction activities	5.135	12.50	17.43	7.328	42.39
Wholesale and retail trade and repair of motor vehicles and motorcycles	7.000	13.52	21.04	10.54	52.10
Wholesale trade, except of motor vehicles and motorcycles	12.57	19.33	22.82	9.340	64.06
Retail trade, except of motor vehicles and motorcycles	5.751	11.44	20.62	9.027	46.84
Land transport and transport via pipelines	3.917	7.350	12.49	6.100	29.85
Water transport	8.084	13.82	18.84	8.718	49.46
Air transport	6.696	10.31	17.98	8.055	43.04
Warehousing and support activities for transportation	6.186	10.66	17.85	8.033	42.73
Postal and courier activities	5.342	7.973	17.37	7.856	38.54
Accommodation	9.913	10.52	13.07	9.267	42.77
Food and beverage service activities	8.339	9.535	12.74	8.363	38.98
Publishing activities	16.74	30.50	26.10	10.29	83.62
Motion picture, video and television programme production, sound recording and music publishing activities	15.96	26.41	19.66	7.806	69.84
Programming and broadcasting activities	17.71	29.05	24.13	8.879	79.77
Telecommunications	13.28	26.30	24.32	9.589	73.49
Computer programming, consultancy and related activities	18.72	38.49	21.13	9.079	87.43
Information service activities	16.64	30.32	24.94	10.27	82.17
Financial service activities, except insurance and pension funding	11.20	25.22	37.66	15.35	89.43
Insurance, reinsurance and pension funding, except compulsory social security	12.43	26.56	35.92	14.63	89.55
Activities auxiliary to financial service and insurance activities	13.50	26.97	33.91	13.84	88.21
Real estate activities	13.71	22.43	24.76	10.03	70.93
Legal and accounting activities	10.88	24.03	36.49	16.20	87.59
Activities of head offices; management consultancy activities	13.89	26.00	25.62	11.02	76.53
Architectural and engineering activities; technical testing and analysis	10.19	23.69	26.30	10.51	70.69
Scientific research and development	17.48	22.55	21.44	9.091	70.56
Advertising and market research	14.57	26.63	26.59	10.29	78.08
Other professional, scientific and technical activities	12.20	22.58	25.68	10.34	70.79
Veterinary activities	3.938	11.98	18.61	9.094	43.62
Rental and leasing activities	11.24	18.20	21.15	9.403	59.98
Employment activities	6.010	11.47	18.29	8.604	44.37
Travel agency, tour operator, reservation service and related activities	12.18	15.85	17.70	9.907	55.64
Security and investigation activities	5.751	11.46	21.14	4.281	42.63
Services to buildings and landscape activities	6.180	7.314	11.99	12.67	38.15
Office administrative, office support and other business support activities	13.64	23.35	24.55	10.31	71.86
Public administration and defence; compulsory social security	10.76	19.81	25.75	12.94	69.26
Education	30.20	20.94	13.98	7.359	72.49
Human health activities	5.153	12.62	18.62	9.369	45.77
Residential care activities	7.853	14.51	15.25	9.973	47.59
Social work activities without accommodation	9.233	16.39	16.95	9.912	52.48

Table B.9 *Continued*

Creative, arts and entertainment activities	16.84	25.72	15.37	5.567	63.51
Libraries, archives, museums and other cultural activities	13.38	18.96	22.93	10.67	65.94
Gambling and betting activities	8.159	13.45	19.93	6.196	47.74
Sports activities and amusement and recreation activities	21.18	17.51	15.35	7.576	61.61
Activities of membership organizations	15.40	22.21	21.57	10.79	69.98
Repair of computers and personal and household goods	9.170	18.64	22.18	9.560	59.55
Other personal service activities	5.735	10.78	14.69	10.55	41.76
Activities of households as employers of domestic personnel	10.81	18.29	15.67	9.907	54.68
Undifferentiated goods- and services-producing activities of private households for own use	5.499	11.85	15.98	7.290	40.62
Activities of extraterritorial organizations and bodies	9.763	18.75	23.92	10.69	63.11

Notes: The table reports WFH capacities and pre-pandemic WFH uptake by industry (NACE 2-digit). Data from the 2018 BIBB/BAuA Employment Survey, and employment Statistics of the Federal Employment Agency (BA) 2019.

Table B.10 : Replicating Dingel and Neiman's (2020) Task-Exclusion WFH Measure with the 2018 BIBB/BAuA Survey

If respondents report any of the following as true, we code their job as not feasible with full-time WFH:

- Never using the Internet or E-Mail processing
- Frequently lifting or carrying loads of more than 10 kg (women) or 20 kg (men)
- Frequent exposure to smoke, dust, gases, or vapor
- Frequent exposure to cold, heat, moisture, humidity, or draughts
- Frequently handling microorganisms such as pathogens, bacteria, molds or viruses
- Frequently working with oil, grease, or dirt
- Works the majority of time outdoors
- Frequently repairing or renovating
- Frequently protecting, guarding, monitoring, or regulating traffic
- Frequently cleaning, disposing of waste, or recycling
- Frequently monitoring or controlling machines, plants, or technical processes

Notes: The table describes the replication of Dingel and Neiman's (2020) WFH feasibility index using individual-level task information from the 2018 BIBB/BAuA Employment Survey. The original measure uses O*NET data; in particular, an occupation is defined as one that cannot be performed from home if at least of the following conditions are met: Average respondent says they use email less than once per month; Average respondent says they deal with violent people at least once a week; Majority of respondents say they work outdoors every day; Average respondent says they are exposed to diseases or infection at least once a week; Average respondent says they are exposed to minor burns, cuts, bites, or stings at least once a week; Average respondent says they spent the majority of time walking or running; Average respondent says they spent the majority of time wearing common or specialized protective or safety equipment. Performing General Physical Activities is very important; Handling and Moving Objects is very important; Controlling Machines and Processes [not computers nor vehicles] is very important; Operating Vehicles, Mechanized Devices, or Equipment is very important; Performing for or Working Directly with the Public is very important; Repairing and Maintaining Mechanical Equipment is very important; Repairing and Maintaining Electronic Equipment is very important; Inspecting Equipment, Structures, or Materials is very important.

C Appendix to Chapter 3

C.1 Data Descriptions and Summary Statistics

Table C.1 : Summary Statistics of County-Level Variables

	Mean	SD	Min	p25	Median	p75	Max	N	Source
Outcome variable									
Share of STW in March/April 2020	33.00	7.73	11.84	27.27	32.39	37.63	74.42	401	BA 2019/2020
WFH measures									
WFH feasible (WFH feas)	52.69	4.18	45.55	49.73	51.50	54.82	67.47	401	BIBB/BAuA Survey 2018, BA June 2019
WFH at least occasionally (WFH occ)	23.52	3.04	18.40	21.47	22.54	24.82	36.14	401	BIBB/BAuA Survey 2018, BA June 2019
WFH frequently (WFH freq)	8.47	1.33	5.98	7.56	8.02	8.99	14.30	401	BIBB/BAuA Survey 2018, BA June 2019
WFH index (Dingel and Neiman, 2020)	33.33	4.92	24.71	30.01	31.92	35.79	50.65	401	Dingel and Neiman (2020)
Baseline controls									
Days since first Covid case (30 April)	65.17	10.51	48.00	58.00	63.00	68.00	95.00	401	RKI
log spatial infection rate (29 April)	-1.62	0.19	-1.93	-1.76	-1.67	-1.44	-1.02	401	RKI
log GDP	15.53	0.76	13.92	14.99	15.45	15.94	18.75	401	FSO, 2017
log settled area	8.82	0.67	6.95	8.50	8.84	9.29	10.81	401	FSO, Dec. 2018
log total population	11.98	0.66	10.44	11.55	11.95	12.40	15.11	401	FSO Dec. 2018
Economy controls									
Employment share in Wholesale/Retail	13.96	3.09	4.76	11.90	13.68	15.49	25.37	401	BA June 2019
Employment share in Manufacturing	23.79	10.37	2.02	16.02	22.67	31.28	57.83	399	BA June 2019
Employment share in Services	66.51	10.85	36.73	58.39	66.68	74.47	92.36	401	BA June 2019
Driving dist. to nearest airport (mins)	49.62	21.98	6.00	33.00	48.00	65.00	122.00	401	BBSR, 2018
Broadband coverage (50+ Mbps downl.)	76.67	15.45	27.40	67.30	77.10	90.50	99.60	401	BBSR, 2017
Share of commuters	0.83	0.31	0.30	0.60	0.78	0.97	2.33	401	BA June 2019
Share of low-income households	30.64	6.03	9.30	26.40	30.50	35.20	44.10	401	BBSR, 2016
Health controls									
Hospitals per 100T inhabitants	2.51	1.48	0.34	1.53	2.22	3.08	9.80	396	FSO, 2017
ICU beds per 100T inhabitants	41.33	34.51	4.40	18.53	31.54	50.48	239.47	394	DIVI Register
Share of working age population (15-64)	0.67	0.02	0.60	0.66	0.67	0.68	0.74	401	FSO Dec. 2018
Deaths per 1000 inhabitants	11.81	1.89	7.50	10.40	11.70	13.00	17.10	401	BBSR, 2017
Remaining life expectancy at age 60	23.70	0.66	22.02	23.27	23.68	24.18	25.72	401	BBSR, 2017
Share of inhabitants aged 65 and above	0.22	0.03	0.16	0.20	0.22	0.24	0.32	401	FSO, Dec. 2018
Share of male inhabitants	0.49	0.01	0.47	0.49	0.49	0.50	0.51	401	FSO, Dec. 2018
Social Capital controls									
Election turnout, Federal Election 2017	75.08	3.79	63.10	72.70	75.30	77.60	84.10	401	BBSR, 2017
Vote share for far left, Fed. Elec. 2017	8.82	4.54	3.60	5.70	6.80	10.30	23.30	401	BBSR, 2017
Vote share for far right, Fed. Elec. 2017	13.39	5.33	4.90	9.80	12.00	15.30	35.50	401	BBSR, 2017
Crimes per 100T inhabitants	5,658	2,292	2,299	3,940	5,222	6,896	15,194	401	BKA, 2019
Non-profit associations per 100T inhab.	688	197	100	567	667	781	1,734	401	Franzen and Botzen (2011)

Notes: The table reports summary statistics and the source of county-level variables used in our analyses. Share of short-time work (STW) applications in March and April 2020 is measured relative to June 2019 employment. See Section 3.2.1 for details on the construction of our WFH measures. FSO = Federal Statistical Office (*Statistische Ämter des Bundes und der Länder*); BBSR = Federal Institute for Research on Building, Urban Affairs and Spatial Development (*Bundesinstitut für Bau-, Stadt- und Raumforschung*); BA = Federal Employment Agency (*Bundesagentur für Arbeit*); RKI = Robert Koch Institute.

Table C.2 : Pairwise Correlation between WFH and County-Level Variables

	(1) *WFH feas*	(2) *WFH occ*	(3) *WFH freq*
Baseline controls			
Days since first COVID case	0.24***	0.22***	0.18***
log spatial infection rate	0.14**	0.089	-0.0071
log settled area	-0.22***	-0.17***	-0.14**
log total population	0.36***	0.39***	0.38***
log GDP	0.60***	0.61***	0.56***
Economy controls			
Share of commuters	0.55***	0.53***	0.48***
Reachability of airports	-0.43***	-0.43***	-0.40***
Broadband coverage	0.65***	0.61***	0.55***
Employment shr. manufacturing	-0.35***	-0.41***	-0.52***
Employment shr. wholesale / retail	-0.096	-0.099*	-0.092
Employment shr. services	0.54***	0.59***	0.68***
Share of low-income households	-0.070	-0.015	0.12*
Health controls			
Share of males	-0.32***	-0.32***	-0.37***
Share of inhabitants aged 65 and above	-0.46***	-0.43***	-0.36***
Share of working age population (15-64)	0.49***	0.47***	0.41***
Remaining life expectancy at age 60	0.33***	0.34***	0.30***
Deaths per 1000 inhabitants	-0.47***	-0.46***	-0.39***
ICU beds per 100T inhabitants	0.33***	0.34***	0.39***
Hospitals per 100T inhabitants	0.040	0.032	0.053
Social Capital controls			
Non-profit associations per 100T inhab.	0.15**	0.15**	0.18***
Crimes per 100T inhabitants	0.46***	0.47***	0.54***
Election turnout, federal election 2017	0.20***	0.20***	0.13**
Vote share for far right, fed. elec. 2017	-0.33***	-0.29***	-0.22***
Vote share for far left, fed. elec. 2017	0.037	0.11*	0.24***

Notes: The table reports pairwise correlation coefficients between our WFH measures and individual control variables at the county level. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.5$

Table C.3 : Summary Statistics of the ifo Business Survey Data

	Min	Mean	Max	SD	N
Outcome variables					
Applied for short-time work	0	0.478	1	0.500	6,840
Very negative Covid-19 impact	0	0.297	1	0.457	6,095
Explanatory variables					
Intensified telework	0	0.611	1	0.487	6,840
WFH feas	29.58	54.83	89.55	13.72	7,291
Mandatory shutdown	0	0.157	1	0.364	7,291
Demand drop due to Covid-19, sector avg. (3/20)	0	0.458	1	0.230	5,352
Business state (2019Q4)	-1	0.240	1	0.671	6,654
Business outlook (2019Q4)	-1	-0.123	1	0.591	6,648
Export share (9/18)	0	0.146	1	0.208	7,291
Firm size bins (2/20)					
1-9 employees	0	0.144	1	0.351	6,651
10-49 employees	0	0.378	1	0.485	6,651
50-99 employees	0	0.153	1	0.360	6,651
100-249 employees	0	0.140	1	0.347	6,651
>249 employees	0	0.185	1	0.388	6,651
Survey ID					
Construction	0	0.151	1	0.358	7,291
Services	0	0.297	1	0.457	7,291
Wholesale/Retail	0	0.249	1	0.432	7,291
Manufacturing	0	0.304	1	0.460	7,291

Notes: The table reports summary statistics of the April 2020 wave of the ifo Business Survey used in our firm-level analysis. The sample is complemented with averages of survey responses on business expectations and business conditions in Q4 of 2019 (elicited on three-point Likert scales), leave-one-out industry averages (employment weighted) of firms reporting a demand drop due to Covid-19 in March 2020 as well as firms' export share as of September 2018 and firm size in terms of employment elicited in February 2020.

C.1.1 Measuring WFH in Germany

This section provides a description of the construction of our three WFH measures at the county and industry level. We follow Alipour et al. (2023) and combine data from two sources: *i.* Employee-level information from the 2018 wave of the BIBB/BAuA Employment Survey and *ii.* Occupational employment counts at the county and industry level provided by the Federal Employment Agency (*Bundesagentur für Arbeit*). The BIBB/BAuA survey is jointly carried out by the German Federal Institute for Vocational Education and Training (BIBB) and the German Federal Institute for Occupation Safety and Health (BAuA). The 2018 wave contains rich information about 20,012 individuals surveyed between October 2017 and April 2018; for more details see Hall et al. (2020). In particular, the survey contains information about employee characteristics, the nature of their jobs and also reports about employees' work from home habits. Based on this information, we compute three measures: An indicator variable that identifies individuals who work from home "always" or "frequently" (*WFH freq*). Second, an indicator for respondents who report working at home at least occasionally (*WFH occ*). And third, a dummy identifying employees who ever work from home or who do not exclude the possibility of home-based work, provided the company grants the option (*WFH feas*). The latter measure hence identifies jobs that can (at least partly) be done from home, independently of a worker's previous teleworking experience.

To derive the geographical and industry-level distribution of teleworkable jobs, we collapse our WFH indicators to the occupational level, based on 36 KldB-2010 2-digit occupations (excluding military services), and combine the resulting shares with administrative employment data for each county (401 *Kreise and kreisfreie Städte*) and each industry (2-digit NACE rev. 2), respectively. Specifically, the WFH potential of county c is given by

$$WFH_c = \sum_o s_{oc} \times WFH_o, \tag{C.1}$$

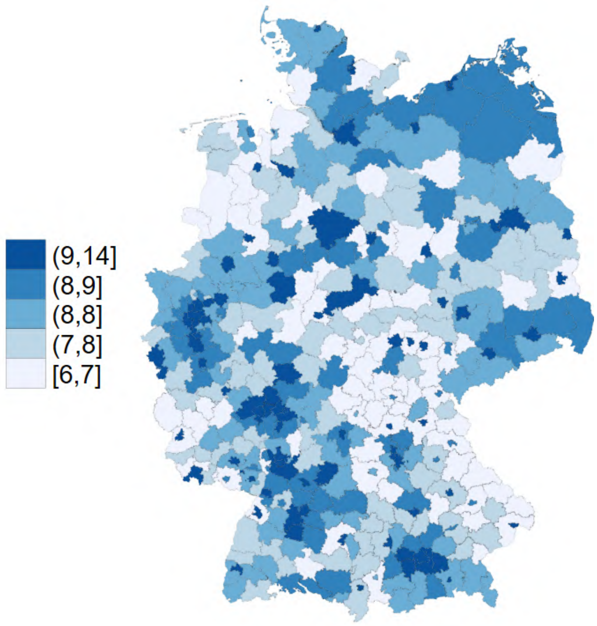
where o denotes occupations and s_{oc} is the employment share of occupation o in county c. WFH_o in turn denotes the occupation-specific WFH share. Analogously, the WFH potential of industry i is given by

$$WFH_i = \sum_o s_{oi} \times WFH_o, \tag{C.2}$$

where s_{oi} denotes the employment share of occupation o in industry i.

Table C.4 reports the occupation-specific WFH shares for each of our three measures. Figure C.1 displays the geographical distribution of teleworkable jobs as measured by *WFH freq*. A potential advantage of the survey-based approach to measuring WFH potentials compared to relying on information about the task content of occupations (as proposed by Dingel and Neiman, 2020) is that assessments about the possibility to WFH are independent of researchers' plausibility judgments. In Section C.7.1, we document that our measures are still highly correlated with Dingel and Neiman's task-based WFH index and show that our results do not hinge on the measure of WFH employed.

Figure C.1 : Geographical Distribution of Pre-Crisis Frequent Teleworkers



Notes: The map depicts the percentage share of pre-crisis frequent teleworkers (*WFH freq*) across NUTS-3 regions (counties) in Germany. Data are from BIBB/BAuA Employment Survey 2018 and the Federal Employment Agency (BA) 2019.

Table C.4 : WFH Shares by Occupation

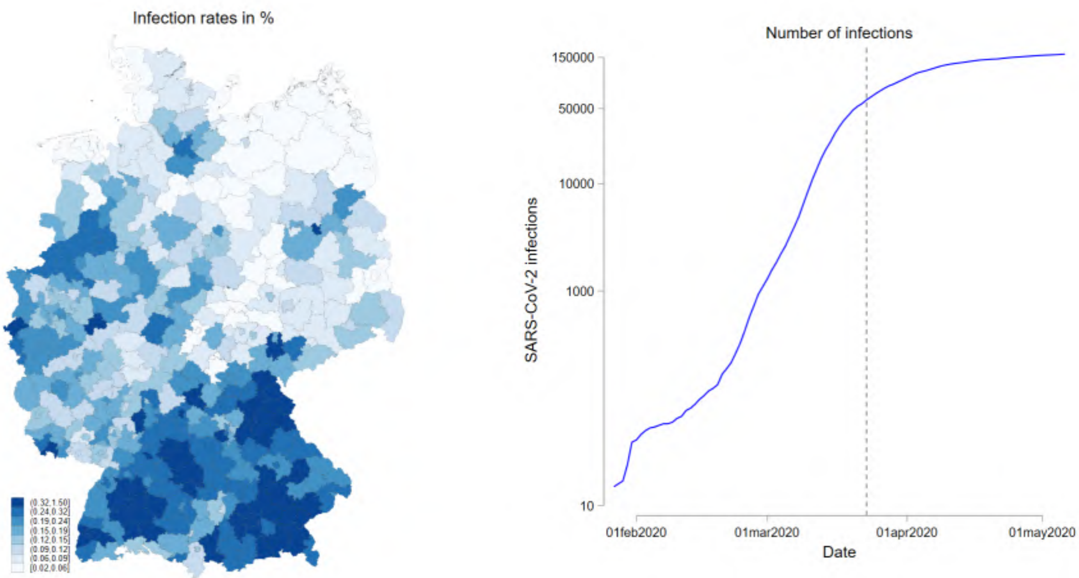
	Occupations (KldB 2010 2-digit)	*WFH freq*	*WFH occ*	*WFH feas*
11	Occupations in agriculture, forestry, and farming	7.59	14.52	30.44
12	Occupations in gardening and floristry	3.03	9.13	41.25
21	Occupations in production and processing of raw materials, glass and ceramic	0.00	6.85	16.56
22	Occupations in plastic-making and -processing, wood-working and -processing	1.21	4.99	28.91
23	Occupations in paper-making and -processing, printing & technical media design	2.98	17.60	58.23
24	Occupations in metal-making and -working, and in metal construction	0.62	3.42	22.13
25	Technical occupations in machine-building and automotive industry	4.13	14.07	45.50
26	Occupations in mechatronics, energy electronics and electrical engineering	8.77	28.43	58.49
27	Occupations in technical R&D, construction, production planning and scheduling	6.90	32.49	72.65
28	Occupations in textile- and leather-making and -processing	3.03	16.26	52.26
29	Occupations in food-production and -processing	4.93	12.53	28.97
31	Occupations in construction scheduling, architecture and surveying	10.49	38.57	81.92
32	Occupations in building construction above and below ground	0.80	5.73	24.17
33	Occupations in interior construction	1.08	6.24	20.96
34	Occupations in building services engineering and technical building services	3.09	14.41	34.12
41	Occupations in mathematics, biology, chemistry and physics	4.62	22.93	55.74
42	Occupations in geology, geography and environmental protection	20.75	46.19	73.57
43	Occupations in computer science, information and communication technology	23.78	75.95	96.77
51	Occupations in traffic and logistics (without vehicle driving)	5.12	11.96	38.06
52	Drivers and operators of vehicles and transport equipment	1.20	4.26	16.24
53	Occupations in safety and health protection, security and surveillance	4.94	15.40	39.79
54	Occupations in cleaning services	5.68	8.62	29.88
61	Occupations in purchasing, sales and trading	28.14	55.55	89.00
62	Sales occupations in retail trade	3.35	11.58	40.58
63	Occupations in tourism, hotels and restaurants	11.68	21.45	43.36
71	Occupations in business management and organisation	14.48	44.18	86.72
72	Occupations in financial services, accounting and tax consultancy	9.99	34.35	91.76
73	Occupations in law and public administration	8.97	28.10	84.23
81	Medical and health care occupations	2.92	13.74	40.39
82	Occupations in non-medical healthcare, body care, wellness & medical technicians	3.64	12.96	36.38
83	Occupations in education and social work, housekeeping, and theology	12.79	33.71	58.92
84	Occupations in teaching and training	64.61	85.23	91.32
91	Occupations in in philology, literature, humanities, social sciences, and economics	23.47	67.07	83.45
92	Occupations in advertising and marketing, in commercial and editorial media design	20.12	52.72	92.02
93	Occupations in product design, artisan craftwork, making of musical instruments	28.64	33.19	67.68
94	Occupations in the performing arts and entertainment	21.21	53.81	65.63

Notes: The table reports percentage shares of employees who report working from home frequently (*WFH freq*), at least occasionally (*WFH occ*) and who ever work from home or do not exclude the possibility to work from home, provided the employer grants the option (*WFH feas*) for each occupation at the 2-digit level according to the German classification KldB 2010 (*Klassifikation der Berufe*). Data are from the 2018 BIBB/BAuA Employment Survey.

C.1.2 Measuring SARS-CoV-2 Infections

In Germany, local health authorities are required by law to report suspected cases, infections, and proof of the SARS-CoV-2 virus at the county level on a daily basis (*Infektionsschutzgesetz*). This data on cases and fatalities is provided and administered by the Robert-Koch-Institut (RKI). Only cases with a positive laboratory diagnostic are counted, independently of their clinical evidence. After basic verification, this information is transferred electronically by local health authorities to the RKI, at the latest by the next working day. At the RKI, data are validated using an automatic validation algorithm. The RKI processes the reported new cases once a day at midnight and publishes them by the next morning. The final dataset contains daily information on the number of local infections and fatalities by sex and age cohort at the county level, where counties are based on individuals' places of residence. To minimize measurement issues caused by reporting lags over weekends, we consider weekly data measured on Wednesdays. Figure C.2 displays the geographical distribution of infection rates as of May 6, 2020, as well as cumulative Covid-19 cases in Germany. Table C.5 reports summary statistics of the infection data across counties.

Figure C.2 : SARS-CoV-2 Infections in Germany



Notes: The figure depicts the distribution of infection rates in percent across NUTS-3 regions in Germany for May 06, 2020 (left graph) and the aggregate time series of Covid-19 cases in Germany (right graph). The dashed vertical line indicates the date when strict confinement rules came into effect. Data are from the Robert-Koch-Institut.

Table C.5 : Summary of Infection Statistics at the County Level

	Mean	Std. Dev.	Min	25th	Median	75th	Max
Infection Rate in %							
on May 06, 2020	0.20	0.15	0.02	0.10	0.24	0.24	1.50
on Sep 30, 2020	0.33	0.19	0.04	0.19	0.41	0.41	1.63
Days since first infection							
on May 06, 2020	71.7	11.3	54	64	76	76	101

Notes: The table reports descriptive statistics for RKI infection data across 401 NUTS-3 regions in Germany.

C.2 Description of Confinement Measures during the First Wave of the Covid-19 Pandemic in Germany

Confinement On March 8, federal and state governments recommended the cancellation of all big public events. Governments then agreed on extensive confinement to restrict social contacts on Sunday, March 22. Most of these rules started to apply from the next Monday, March 23 onward, and were planned to stay in force until May 3-4 in most states. There was some regional variation across states regarding the exact timing of confinement: in SN and BY confinement started already on March 21; in BR confinement was planned to stay until May 8, in MV until May 10.

Ten states opted for more lax confinement rules (*Kontaktbeschränkungen*). In those states, staying in public was only allowed together with up to one person from another household (while keeping a personal distance of at least 1.5 m) or with members from the same household. In contrast, six states (BY, SL, ST, SN, BB, BE) opted for stricter confinement rules (*Ausgangsbeschränkungen*) which prohibited leaving the household without good reason. Reasons were work commutes or shopping for groceries, doctor visits, sports activities, and walks (with some exceptions in terms of strictness and timing at the county level).

Business Closures Closures of many stores and church services and playgrounds from Monday, March 16, 2020, onward. Stores providing necessities remained open. Restaurants were free to offer pickup service. Gradual reopening from April 19, onward.

Schools and Day Care With exceptions schools and kindergartens were closed from Monday, March 16 onward.

Obligatory Face Masks From April 27 onward, wearing a mouth-nose mask during public transport or while buying groceries was mandatory.

C.3 Employee-Level Differences in Access to WFH

A nascent literature examines differences in access to WFH across socioeconomic characteristics. A distinct feature that distinguishes employees with and without the possibility to work from home is the level of education (Adams-Prassl et al., 2022; Alipour et al., 2023; Mongey et al., 2021; Yasenov, 2020). For instance, in the BIBB/BAuA Survey, employees without a university degree are only half as likely to have a teleworkable job and nearly four times less likely to have teleworking experience before the pandemic. Apart from the educational disparity, this group appears also disproportionately more vulnerable in terms of other socioeconomic dimensions, such as income and the ownership of liquid assets. The differences in access to WFH are mainly attributable to different job task requirements that distinguish teleworkable from non-teleworkable jobs; in particular, a high task content of cognitive, non-manual tasks, which are typically performed by higher-skilled labor (Alipour et al., 2023; Mergener, 2020).

We shed some additional light on the potential inequalities in access to WFH during the pandemic by estimating WFH as a function of demographic and workplace characteristics as well as a set of occupation and sector fixed effects. Table C.6 reports the results for the outcome variables *WFH freq*, which identifies employees reporting frequently working from home (Columns 1-3), and *WFH feas*, which identifies employees with a teleworkable job (Columns 4-6).[1] Occupational variation alone explains 21 and 27 percent of the variation in *WFH freq* and *WFH feas*, respectively (Columns 1 and 4). Adding individual characteristics (Columns 2 and 5) and a set of industry dummies (Columns 3 and 6) does not substantially add to the overall explanatory power in terms of R^2. We find no statistically significant gender differences in WFH usage or access, holding other characteristics constant. An employee's age is correlated with WFH at a statistically significant level, however, the magnitude of the estimates appears very small. Holding a university degree is very strongly associated with having a teleworkable job, increasing the likelihood by about 17 and 15 p.p., respectively. By contrast, marital status, having children in the household, and having a migration background do not significantly affect the likelihood of having a teleworkable job; however, these factors drive the selection into actually working from home. With respect to workplace characteristics, having management responsibilities and using computers significantly increase both the

[1] Since this is a linear probability model, the coefficients on binary covariates can be interpreted as percentage-point changes in the probability of WFH when the dummy is switched on.

chance of having a teleworkable job and actually working regularly from home. Finally, plant sizes appear not significantly correlated with WFH practice or potential, all else equal. Overall, the results confirm the findings of earlier studies, demonstrating that it is especially the better-educated, higher-skilled employees who have the possibility to work from home.

Table C.6 : Worker-Level Correlations between WFH and Worker Characteristics

	WFH freq			*WFH feas*		
	(1)	(2)	(3)	(4)	(5)	(6)
Female		-0.003	-0.007		0.013	0.008
		(0.008)	(0.008)		(0.011)	(0.011)
Age		0.001***	0.001***		-0.002***	-0.002***
		(0.000)	(0.000)		(0.000)	(0.000)
University degree		0.077***	0.077***		0.178***	0.173***
		(0.009)	(0.009)		(0.011)	(0.011)
Migrant		-0.025***	-0.025***		-0.021	-0.024
		(0.009)	(0.009)		(0.015)	(0.015)
Married		0.019***	0.019***		0.007	0.008
		(0.007)	(0.007)		(0.011)	(0.011)
Children in the household		0.025***	0.024***		0.019*	0.017
		(0.007)	(0.007)		(0.011)	(0.011)
Contractual working hours		0.001	0.000		0.001	0.001
		(0.000)	(0.000)		(0.001)	(0.001)
Manager		0.036***	0.036***		0.075***	0.077***
		(0.007)	(0.007)		(0.011)	(0.011)
PC usage		0.046***	0.045***		0.155***	0.148***
		(0.006)	(0.006)		(0.018)	(0.018)
Plant size						
50-249 employees		-0.002	0.001		-0.004	-0.006
		(0.007)	(0.007)		(0.012)	(0.013)
250+ employees		-0.011	-0.006		-0.002	-0.003
		(0.007)	(0.007)		(0.012)	(0.012)
R^2	0.21	0.23	0.24	0.27	0.31	0.31
Employees	17,130	16,065	15,938	17,112	16,046	15,920
Occupation F.E.	×	×	×	×	×	×
Sector F.E.			×			×

Notes: The dependent variable in Columns (1)–(3) is a binary variable identifying employees who report working from home “frequently” or “always” (*WFH freq*). The dependent variable in Columns (4)–(6) is an indicator identifying workers who ever work from home or who do not exclude the possibility of doing so, provided the employer grants the option (*WFH feas*). Migrant, Children, and Manager take the value 1 for employees with migration background, children below the age of 13 living in the household, or with personnel responsibility, respectively. PC usage and academic degree are 1 for respondents who use a PC for work or who hold a university degree, respectively. The reference category of plant size is a plant size of 1-49 employees. Occupation fixed effects include 37 categories at the 2-digit KldB level. Sector fixed effects include 21 NACE rev.2 categories. Regressions use population weights. Robust standard errors reported in parentheses. Data are from the BIBB/BAuA Employment Survey 2018. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

C.4 Robustness: Effect of WFH on Short-Time Work at the County Level

Effect on Realized Short-Time Work This section provides robustness checks for the effect of WFH on short-time work at the regional level, presented in Section 3.2.2. In particular, we proxy regional labor market shocks with the share of *realized* STW claims instead of STW *applications* as in the main body of the paper. The Federal Employment Agency (BA) publishes data on realized short-time work with a lag of several months due to the approval and reimbursement process ensuing companies' notification at the local agency. As data on realized STW is available for the period before the onset of the Covid-19 pandemic in Germany, one can assess the differential effect of WFH on short-time work claims over time. It should be noted though that while the short-time-work scheme existed already before the Covid-19 crisis, the scheme was greatly expanded in March 2020 and the eligibility criteria were relaxed. As a result of these changes to the institutional framework, the comparison of effects before and during the pandemic should be interpreted with a degree of caution.

We first replicate the regression of Section 3.2.2 using realized STW claims for March and April 2020. The dependent variable is the percentage share of realized short-time work relative to local employment in June 2019. We use the same sets of control variables introduced in Section 3.2.2. The results presented in Table C.7 confirm that also realized STW claims are significantly negatively related to the regional WFH share. The effect size estimates of WFH are slightly larger for realized STW, suggesting that measuring adjustments in the labor market with STW applications underestimates spill-over effects from WFH.

Next, we present placebo regressions for the effect of WFH on realized short-time work in January 2020. Since the possibility to WFH before the pandemic should be unrelated to the degree of local labor market shocks, we expect a negligible association between WFH and STW in January. The results in Table C.8 confirm this intuition. They show that our three measures for WFH are very weakly correlated with STW in January and the point estimates are several orders of magnitude smaller than in March and April. Controlling for the full set of covariates (Column 5) renders the effect size statistically indistinguishable from zero, supporting the hypothesis that the mitigating effect of WFH is specific to the pandemic crisis.[2]

Finally, we assess the differential effect of WFH on realized STW over the first five months of the year 2020. The dependent variable STW_{im} is the inflow of STW claims normalized with

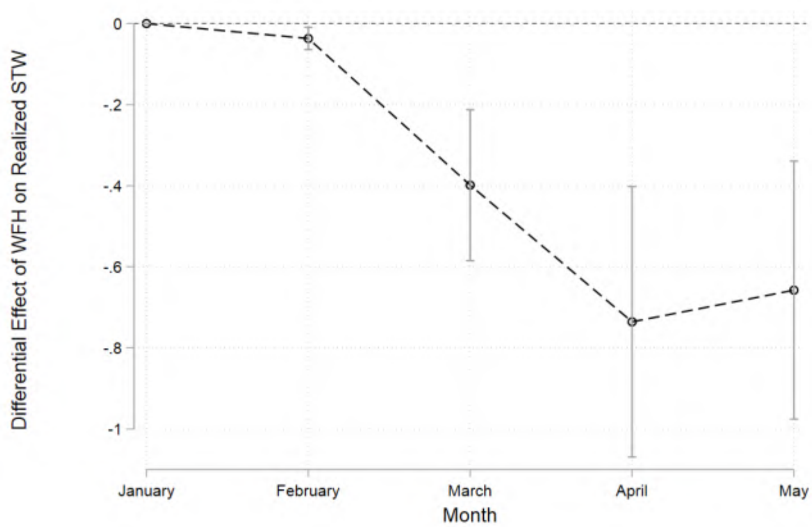
[2] Using STW claims in February 2020 instead of January yields very similar results.

total employment in June 2019 in county i in month m. We estimate:

$$STW_{im} = \sum_{m=1}^{5} \delta_m WFH_i \times m + \gamma_i + \gamma_m + \epsilon_{im}, \tag{C.3}$$

where γ_i and γ_m are county and month fixed effects, respectively. Figure C.3 displays the OLS estimates of δ_{im}, which capture the month-specific effect of *WFH freq* on STW inflows, taking January as the reference month. The estimates confirm the crisis-mitigating effect of WFH during the first wave of the pandemic. The null hypothesis that the WFH effect on STW in March, April and May is identical to the one in February can be clearly rejected (F = 18.49, $p <$ 0.01).

Figure C.3 : Robustness: The Effect of WFH on Realized Short-Time Work over Time



Notes: The figure plots coefficient estimates of $WFH_i \times m$ (using *WFH freq*, the percentage share of employees in the county with jobs that frequently do telework) on realized short-time work claims relative to June 2019 employment by month. The reference month is January 2020. Standard errors are clustered at the county level. 95-percent confidence intervals are reported.

Controlling for technological differences In Table C.9, we re-estimate the effect of WFH on STW applications while additionally controlling for regional technological differences. Panel A includes the log number of local patent applications provided by Eurostat and Panel B the average broadband download speed based on local Internet speed-test data for Q12020 collected by the company Ookla. We find that the results are robust to including these controls.

Table C.7 : Robustness: Effect of WFH and Realized STW in March/April 2020

	(1)	(2)	(3)	(4)	(5)
WFH feas	-1.22***	-1.01***	-1.38***	-1.39***	-1.21***
	(0.25)	(0.22)	(0.25)	(0.27)	(0.25)
R^2	0.22	0.23	0.30	0.25	0.34
NUTS-3 regions	401	399	391	401	389
WFH occ	-1.65***	-1.57***	-1.89***	-2.11***	-2.02***
	(0.27)	(0.24)	(0.28)	(0.31)	(0.29)
R^2	0.25	0.27	0.33	0.30	0.38
NUTS-3 regions	401	399	391	401	389
WFH freq	-3.11***	-3.20***	-3.56***	-4.37***	-4.18***
	(0.53)	(0.46)	(0.57)	(0.62)	(0.55)
R^2	0.24	0.26	0.30	0.30	0.37
NUTS-3 regions	401	399	391	401	389
Set of Controls					
Baseline	×	×	×	×	×
Economy		×			×
Health			×		×
Social Capital				×	×

Notes: Dependent variable is the percentage of the realized short-time work claims in March and April 2020 relative to employment in June 2019 based on data from the Federal Employment Agency. WFH is the percentage share of employees in the county with jobs that are suitable for telework (*WFH feas*) or who either at least occasionally (*WFH occ*) or frequently (*WFH freq*) worked from home in 2018. Observations correspond to NUTS-3 regions (counties) and estimates are weighted based on employment as of June 2019. *Baseline* control variables are region-specific log population, log settled area, region-specific log GDP, the number of days since the first infection and log spatial infection rates (defined as a weighted mean of infection rates in other counties using inverse distances as weights) as of April 30th. *Economy* controls include the fraction of (in- and outward) commuters in the local workforce, an infrastructure index that captures the reachability of airports, the fraction of households with broadband internet access ($\geq$ 50 Mbps), the fraction of low-income households ($\leq$ EUR 1,500 per month), the share of workers employed in services, manufacturing, and wholesale/retail sectors, respectively. *Health* controls include the fraction of male population, the fractions of the population of working age (15-64 yrs.) and elderly ($\geq$ 65 yrs.), the expected remaining lifetime of people with age 60, the death rate, intensive-care-unit beds per 100,000 inhabitants and hospitals per 100,000 inhabitants. *Social Capital* controls include crime rates, voter turnout, vote shares of populist parties, and the number of all registered associations per capita. Heteroskedasticity-robust standard errors reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table C.8 : Robustness: Effect of WFH and Realized STW in January 2020

	(1)	(2)	(3)	(4)	(5)
WFH feas	-0.03*	0.01	-0.02	-0.02	0.02
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)
R^2	0.08	0.20	0.10	0.11	0.25
NUTS-3 regions	401	399	391	401	389
WFH occ	-0.04**	0.01	-0.03	-0.03	0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
R^2	0.08	0.20	0.10	0.11	0.25
NUTS-3 regions	401	399	391	401	389
WFH freq	-0.09***	-0.01	-0.08**	-0.10**	0.03
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
R^2	0.09	0.20	0.11	0.12	0.25
NUTS-3 regions	401	399	391	401	389
Set of Controls					
Baseline	×	×	×	×	×
Economy		×			×
Health			×		×
Social Capital				×	×

Notes: Dependent variable is the percentage of the realized short-time work claims in January 2020 relative to employment in June 2019 based on data from the Federal Employment Agency. WFH is the percentage share of employees in the county with jobs that are suitable for telework (*WFH feas*) or who either at least occasionally (*WFH occ*) or frequently (*WFH freq*) worked from home in 2018. Observations correspond to NUTS-3 regions (counties) and estimates are weighted based on employment as of June 2019. *Baseline* controls include region-specific log population, log settled area, region-specific log GDP, the number of days since the first infection and log spatial infection rates (defined as a weighted mean of infection rates in other counties using inverse distances as weights) as of April 30th. *Economy* controls include the fraction of (in- and outward) commuters in the local workforce, an infrastructure index that captures the reachability of airports, the fraction of households with broadband internet access ($\geq$ 50 Mbps), the fraction of low-income households ($\leq$ EUR 1,500 per month), the share of workers employed in services, manufacturing, and wholesale/retail sectors, respectively. *Health* controls include the fraction of the male population, the fractions of the population of working age (15-64 yrs.) and elderly ($\geq$ 65 yrs.), the expected remaining lifetime of people with age 60, the death rate, intensive-care-unit beds per 100,000 inhabitants and hospitals per 100,000 inhabitants. *Social Capital* controls include crime rates, voter turnout, vote shares of populist parties, and the number of all registered associations per capita. Heteroskedasticity-robust standard errors reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table C.9 : Robustness: The Effect of WFH on STW Applications – Controlling for Patents and Broadband Speed

	(1)	(2)	(3)	(4)	(5)	(6)
WFH measure	*WFH feas*	*WFH feas*	*WFH occ*	*WFH occ*	*WFH freq*	*WFH freq*
Panel A:	*Controlling for Patent Applications*					
WFH	-0.86***	-1.04***	-1.38***	-1.87***	-2.84***	-4.17***
	(0.21)	(0.25)	(0.24)	(0.30)	(0.48)	(0.56)
R^2	0.27	0.33	0.29	0.37	0.29	0.38
NUTS-3 regions	394	384	394	384	394	384
Panel B:	*Controlling for Broadband Speed*					
WFH	-1.05***	-1.15***	-1.62***	-2.00***	-3.28***	-4.31***
	(0.22)	(0.26)	(0.24)	(0.31)	(0.45)	(0.59)
R^2	0.25	0.30	0.29	0.34	0.28	0.35
NUTS-3 regions	399	389	399	389	399	389
Set of Controls						
Baseline	×	×	×	×	×	×
Economy	×	×	×	×	×	×
Health		×		×		×
Social Capital		×		×		×

Notes: Dependent variable is the percentage of the total number of persons mentioned in short-time work applications in March and April 2020 relative to employment in June 2019 based on data from the Federal Employment Agency. WFH is the percentage share of employees in the county with jobs that are suitable for telework (*WFH feas*) or who either at least occasionally (*WFH occ*) or frequently (*WFH freq*) worked from home in 2018. Observations correspond to NUTS-3 regions (counties) and estimates are weighted based on employment as of June 2019. *Baseline* controls include region-specific log population, log settled area, region-specific log GDP, the number of days since the first infection and log spatial infection rates (defined as a weighted mean of infection rates in other counties using inverse distances as weights) as of April 30th. *Economy* controls include the fraction of (in- and outward) commuters in the local workforce, an infrastructure index that captures the reachability of airports, the fraction of households with broadband internet access ($\geq$ 50 Mbps), the fraction of low-income households ($\leq$ EUR 1,500 per month), the share of workers employed in services, manufacturing, and wholesale/retail sectors, respectively. *Health* controls include the fraction of the male population, the fractions of the population of working age (15-64 yrs.) and elderly ($\geq$ 65 yrs.), the expected remaining lifetime of people with age 60, the death rate, intensive-care-unit beds per 100,000 inhabitants and hospitals per 100,000 inhabitants. *Social Capital* controls include crime rates, voter turnout, vote shares of populist parties, and the number of all registered associations per capita. Panel A additionally controls for log patent applications and Panel B for average broadband speed. Heteroskedasticity-robust standard errors reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

C.5 Firm-Level Adoption of WFH during the Covid-19 Crisis and Firm-Level Robustness Accounting for Demand Shocks

In this section, we first present a validation exercise, showing that our WFH measures perform well in predicting firm-level teleworking patterns in April 2020. Second, we show that our analysis of the impact of WFH on firm distress presented in Section 3.2.3 is robust to accounting for self-reported demand contraction due to the pandemic.

Validation of WFH measures Table C.10 reports the coefficients from regressing the firm-level indicator identifying firms who reported intensified telework on our industry-level WFH measures. Our control variables are identical to the ones discussed in Section 3.2.3, in particular, controls include firm size, firms' export share, survey fixed effects, and fixed effects for the survey completion date (Baseline controls). Additional controls (even columns) include an indicator for firms operating in an industry subject to mandatory business closure as well as self-reported business conditions and business expectations in Q4 2019. All specifications include location fixed effects at the county level.

Columns (1), (3) and (5) show that a higher industry share of WFH measured by any of our proxies is associated with a statistically significant increase in the probability to expand telework during the crisis. In terms of magnitudes, increasing *WFH feas* by one p.p. increases the probability that a firm intensifies telework during the Covid-19 crisis by 0.9 p.p. The effects for *WFH occ* (1.45) and *WFH freq* (3 p.p.) are even larger. This is in line with the view that industries with higher WFH rates before the crisis could more easily switch to telework during the pandemic. The coefficient magnitudes are slightly reduced and remain highly significant when adding more covariates in Columns (2), (4), and (6). The effect of mandatory business closure is strongly negative as firms in the accommodation, restaurant, and retail trade sectors did not rely much on telework. Finally, firms reporting an unfavorable state of business before the crisis are slightly less likely to take up telework relative to firms in a neutral state. Overall, the results show that our measures perform well in predicting firms' teleworking patterns during the crisis.

Robustness to demand shock Table C.11 replicates Table 3.2 additionally controlling for self-reported contraction of demand due to the Covid-19 crisis for the subsample of sectors for which the information is available (Wholesale/Retail, Service, Manufacturing), keeping the sample constant. Specifically, *Demand Drop (Industry)* is the leave-one-out (employment weighted) industry average of firms reporting a demand drop within a 2-digit industry. A contraction in demand by one p.p. increases the probability of filing for STW (reporting an adverse Covid-19 impact) by 22 to 24 p.p. (19 to 20 p.p.). The effects are significant at the five and ten-percent level, respectively. The impact of controlling for demand on our estimate of interest only changes slightly: compared to the IV-estimates in Table 3.2, the estimates for the effect of relying on telework during the crises change from -49.42 to -52.65 (Panel A) and -39.13 to -40.14 (Panel B). Since businesses that were subjected to mandatory business closures experienced the most severe demand contraction, it is likely that our indicator for mandatory shutdowns already absorbs a lot of the demand effect. Overall, our results prove robust to demand-side shocks during the crisis.

Table C.10 : Intensified Telework Due to Covid-19 and WFH Potential – Firm-Level Evidence

	(1)	(2)	(3)	(4)	(5)	(6)
WFH feas	1.14***	0.92***				
	(0.16)	(0.10)				
WFH occ			1.45***	1.15***		
			(0.27)	(0.20)		
WFH freq					3.01***	2.43***
					(0.51)	(0.25)
Mandatory Shutdown		-18.10***		-20.78***		-26.14***
		(6.65)		(7.56)		(9.25)
State of Business 2019Q4						
negative		-2.61*		-2.84*		-2.97*
		(1.54)		(1.52)		(1.50)
positive		0.30		0.47		1.05
		(1.48)		(1.59)		(1.72)
R^2	0.33	0.34	0.32	0.34	0.29	0.33
Firms	6,028	5,796	6,028	5,796	6,028	5,796
Baseline	×	×	×	×	×	×
Controls		×		×		×

Notes: The dependent variable is an indicator (rescaled by 100) identifying firms who report having intensified telework in response to the Covid-19 crisis in April 2020. WFH is the percentage share of employees in the NACE-2 industry with jobs that are suitable for telework (*WFH feas*) or who either at least occasionally (*WFH occ*) or frequently (*WFH freq*) worked from home in 2018. Baseline controls (not reported) include firm size in terms of employment (5 size categories), the share of sales generated abroad, fixed effects for the date of survey completion, survey fixed effects (Construction, Wholesale/Retail, Service, and Manufacturing) and location fixed effects at the county level. Additional controls include a dummy for firms operating in an industry subject to mandatory business closures, pre-crisis business conditions in Q4 2019 (baseline: neutral), and business expectations in Q4 2019 (3 categories, not reported). Data are from the ifo Business Survey. Standard errors clustered at the 2-digit NACE level reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table C.11 : Robustness: Accounting for Demand Shock – Effect of WFH on STW and Covid-19 Shock

	RF			OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Participated in Short-Time Work Scheme									
Intensified Telework				-13.43***	-6.32***	-6.13***	-75.60***	-54.27***	-52.65***
				(3.84)	(1.87)	(1.64)	(11.74)	(14.49)	(12.95)
WFH feas	-0.82***	-0.48***	-0.46***						
	(0.19)	(0.12)	(0.12)						
Mandatory Shutdown		28.53***	27.93***		33.68***	32.89***		18.63***	18.35***
		(5.82)	(4.86)		(6.07)	(5.07)		(6.65)	(6.33)
State of Business 2019Q4									
negative		12.99***	12.71***		13.08***	12.79***		11.72***	11.49***
		(1.63)	(1.64)		(1.68)	(1.73)		(1.99)	(1.95)
positive		-10.64***	-10.47***		-11.13***	-10.94***		-9.94***	-9.80***
		(2.06)	(2.24)		(2.18)	(2.36)		(2.09)	(2.19)
Demand Drop (Industry)			22.94**			23.67**			22.05**
			(8.83)			(9.61)			(8.68)
R^2	0.17	0.21	0.22	0.14	0.21	0.21			
Firms	4,687	4,687	4,687	4,687	4,687	4,687	4,687	4,687	4,687
First stage estimate ($\times 100$)							1.09	0.88	0.88
First stage KP F stat							47.08	74.98	74.46
Panel B: Negative Corona Shock									
Intensified Telework				-16.21***	-7.37**	-7.25**	-77.21***	-41.42***	-40.14***
				(5.09)	(2.84)	(2.73)	(14.17)	(14.37)	(12.60)
WFH feas	-0.85***	-0.37***	-0.36***						
	(0.24)	(0.13)	(0.12)						
Mandatory Shutdown		39.90***	39.46***		43.15***	42.56***		32.73***	32.52***
		(7.09)	(6.06)		(7.39)	(6.27)		(6.36)	(5.68)
State of Business 2019Q4									
negative		10.63***	10.39***		10.61***	10.36***		9.45***	9.25***
		(2.50)	(2.54)		(2.62)	(2.66)		(3.00)	(3.03)
positive		-10.46***	-10.26***		-10.85***	-10.62***		-10.23***	-10.03***
		(1.99)	(2.19)		(2.00)	(2.22)		(1.96)	(2.13)
Demand Drop (Industry)			19.59*			20.09*			19.18*
			(10.33)			(10.88)			(10.18)
R^2	0.17	0.25	0.26	0.14	0.25	0.25			
Firms	4,147	4,147	4,147	4,147	4,147	4,147	4,147	4,147	4,147
First stage estimate ($\times 100$)							1.10	0.90	0.90
First stage KP F stat							48.19	77.50	78.03
Baseline	×	×	×	×	×	×	×	×	×
Controls		×	×		×	×		×	×

Notes: The dependent variable is an indicator (rescaled by 100) identifying firms who participated in the short-time work scheme (Panel A) or who report a "very negative" impact of the Covid-19 crisis in April 2020 (Panel B). *Intensified telework* is a binary variable identifying firms who report an intensified usage of telework in response to the Covid-19 crisis. Baseline controls (not reported) include firm size in terms of employment (5 size categories), the share of sales generated abroad, fixed effects for the date of survey completion, survey fixed effects (Wholesale/Retail, Service and Manufacturing), and location fixed effects at the county level. *Demand Drop (Industry)* is the leave-one-out (employment-weighted) share of firms reporting a drop in demand due to the Covid-19 crisis in each 2-digit NACE industry. Additional controls include a dummy for firms operating in an industry subject to mandatory business closures, pre-crisis business conditions in Q4 2019 (baseline: neutral), and business expectations in Q4 2019 (3 categories, not reported). The sample is kept constant across all specifications. Data are from the ifo Business Survey. Standard errors clustered at the 2-digit NACE level reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

C.6 Details and Robustness: WFH and the Spread of Covid-19

This section presents additional results and robustness checks regarding the relationship between the spread of SARS-CoV-2 and opportunities to work from home.

Fatalities Table C.12 considers fatality rates instead of infection rates as an outcome and replicates the specifications in Table 3.3. The coefficient of WFH is negative throughout all specifications and in most cases significant at the one-percent level. Compared to the coefficient estimates on infection rates, the coefficients on fatality rates are quantitatively larger.

Poisson estimates Since there are several counties in our data that report zero Covid-19 fatalities, we report Poisson estimates using infections and fatalities as dependent variables, replicating the specifications in Tables 3.3 and C.12. Results in Tables C.13 and C.14 imply a negative relation between WFH and infections or fatalities which is significant in all but one specification.

Interactions with labor market characteristics In Table C.15, we interact our measures of WFH with the fraction of the population in working age (Panel A) or the fraction of population in employment (Panel B). If our measure of WFH indeed captures reduced work-related interactions that prevent the spread of SARS-CoV-2 infections, we would expect larger effects of WFH in counties with *i.* a larger share of people in working age and *ii.* a larger share of people in employment. The results in Table C.15 are consistent with this mechanism, as the interaction term is negative and significant in most specifications and the direct effect of WFH turns positive.

Interactions with household incomes In Table C.16, we interact WFH with the fraction of low-income households within the county (household income $\leq$ EUR 1,500 per month, Panel A) and with the fraction of high-income households within the county (household income $\geq$ EUR 3,600 per month, Panel B). We find the health benefits of WFH to be stronger in more affluent counties and weaker in less affluent counties.

Spillover effects from commuting In Table C.17, we study spillover effects from commuting. Potentially, the health benefits of WFH can spill over across counties when residents have their workplaces in adjacent counties. We address this by using data from the German *Pendleratlas* that provides a matrix of commuting flows across county pairs. Using this data and based on the 30 closest counties, we calculate the log number of inward and outward commuters for each county. Furthermore, we calculate a place-of-residence-based WFH measure and WFH averages for the adjacent counties that are either residence- or workplace-based. Panel A of Table C.17 studies spillovers from inward commuting. Besides the usual local health benefits of WFH, we find positive spillover effects of WFH from commuters for the counties where they live. Similarly to the local WFH effects, spillover effects of WFH appear significant at the one-percent level. Panel B instead considers spillover effects from outward commuting and finds similar spillover effects for counties where commuters work that also appear to be significant at the one-percent level.

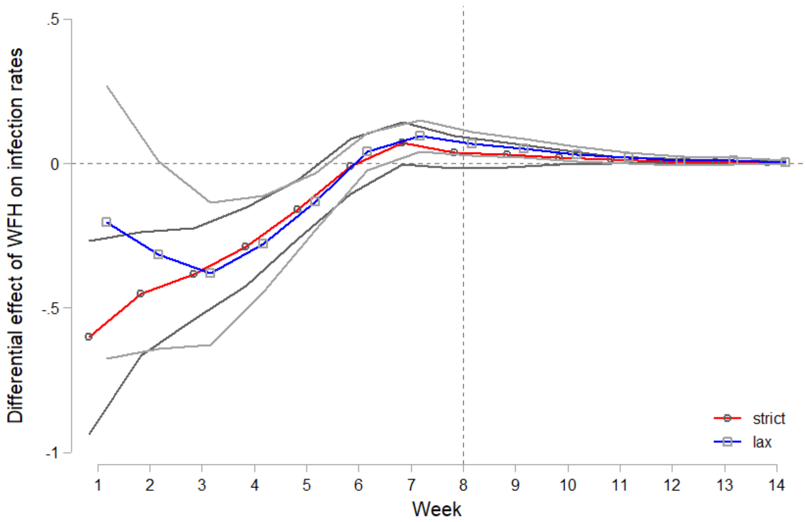
Controlling for technological differences In Table C.18, we additionally control for regional technological differences. Panel A includes the log number of local patent applications provided by Eurostat and Panel B the average broadband download speed based on local Internet speed-test data for Q12020 collected by the company Ookla. We find health benefits of WFH to be robust to including these controls.

Infection-reducing effect of WFH over time We estimate a simple difference-in-differences specification in which we regress weekly county-level infection rates on an interaction of our WFH measures with a *pre confinement* dummy that indicates weeks before the confinement (weeks 1-7) including week and county fixed effects. In line with the weekly estimates reported in Figure 3.1, the results in Table C.19 imply that infection-reducing effects of WFH were largest before the confinement suggesting a substitutive relationship between confinement and WFH.

Interaction with confinement strictness In Figure C.4, we replicate the estimates shown in Figure 3.1 but split our sample into two subsamples to show further robustness on the claim that there is no complementarity between WFH and confinement strictness. During the first wave of the Covid-19 pandemic 6 of the 16 German states opted for more strict confinement (*Ausgangsbeschränkungen*, see Appendix C.2). However, we find very similar dynamic health benefits of WFH for both samples.

Using infection data from dates after the first wave of the Covid-19 pandemic In all our analyses, we focused on infection data from the first wave of the pandemic for the benefit of a cleaner empirical setting. Here, we report estimates for later dates (July 29 and September 30). After the end of the first confinement period in the beginning of May, there was substantial regional heterogeneity in post-confinement social distancing rules. Moreover, the timing of summer holidays, when few people worked and a large share of the population traveled, varies substantially across German states. These factors make it harder to identify the impact of WFH at the regional level during the summer. However, our results are robust: Tables C.20 and C.21 imply that the negative relation between WFH and infections still holds.

Figure C.4 : Robustness: The Effect of WFH on SARS-CoV-2 Infections by Confinement Strictness over Time



Notes: The figure plots coefficient estimates of $WFH_i \times t$ (using *WFH freq*, the percentage share of employees in the county with jobs that frequently do telework) on log infection rates by week (week 15 is absorbed by fixed effects) for two subsamples (*lax* and *strict*). Subsample *lax* contains counties from 10 states with more lax confinement rules (*Kontaktbeschränkungen*), subsample *strict* contains counties from 6 states with stricter confinement rules (*Ausgangsbeschränkungen*). The dashed vertical line for week 8 indicates the week when the majority of confinement rules were set into force by federal states. The gray shaded area corresponds to 95-percent confidence intervals (with clustering at the county level).

Table C.12 : Robustness: The Effect of WFH on SARS-CoV-2 Fatalities across Counties

	(1)	(2)	(3)	(4)	(5)
WFH feas	-0.088***	-0.086***	-0.088***	-0.089***	-0.086***
	(0.023)	(0.027)	(0.024)	(0.025)	(0.031)
R^2	0.27	0.31	0.29	0.31	0.34
NUTS-3 regions	369	367	362	369	360
WFH occ	-0.12***	-0.11***	-0.11***	-0.12***	-0.11***
	(0.029)	(0.033)	(0.031)	(0.032)	(0.040)
R^2	0.28	0.31	0.29	0.31	0.33
NUTS-3 regions	369	367	362	369	360
WFH freq	-0.23***	-0.18**	-0.20***	-0.21***	-0.13
	(0.067)	(0.081)	(0.073)	(0.076)	(0.097)
R^2	0.28	0.30	0.29	0.30	0.33
NUTS-3 regions	369	367	362	369	360
Set of Controls					
Baseline	×	×	×	×	×
Economy		×			×
Health			×		×
Social Capital				×	×

Notes: Dependent variable is the SARS-CoV-2 fatality rate (in logs) up to May 06, 2020 (the end date of the first confinement period) based on data from the Robert-Koch-Institut. WFH is the percentage share of employees in the county with jobs that are suitable for telework (*WFH feas*) or who either at least occasionally (*WFH occ*) or frequently (*WFH freq*) worked from home in 2018. Observations correspond to NUTS-3 regions (counties) and estimates are weighted based on population size. *Baseline* controls include region-specific log population, log settled area, log GDP, the number of days since the first infection and log spatial infection rates defined as a weighted mean of infection rates in other counties using inverse distances as weights. *Economy* controls include the region-specific fraction of (in- and outward) commuters in the local workforce, an infrastructure index that captures the reachability of airports, the fraction of households with broadband internet access ($\geq$ 50 Mbps), the fraction of low-income households ($\leq$ EUR 1,500 per month), the share of workers employed in services, manufacturing, and wholesale/retail sectors, respectively. *Health* controls include the fraction of the male population, the fractions of the population of working age (15-64 yrs.) and elderly ($\geq$ 65 yrs.), the expected remaining lifetime of people with age 60, the death rate, intensive-care-unit beds per 100,000 inhabitants and hospitals per 100,000 inhabitants. *Social Capital* controls include crime rates, voter turnout, vote shares of populist parties, and the number of all registered associations per capita. Heteroskedasticity-robust standard errors reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table C.13 : Robustness: The Effect of WFH on SARS-CoV-2 Infections across Counties – Poisson Estimates

	(1)	(2)	(3)	(4)	(5)
WFH feas	-0.051***	-0.058***	-0.045***	-0.052***	-0.048***
	(0.015)	(0.017)	(0.015)	(0.015)	(0.018)
R^2	0.88	0.89	0.90	0.90	0.92
NUTS-3 regions	401	399	391	401	389
WFH occ	-0.065***	-0.071***	-0.057***	-0.066***	-0.068***
	(0.018)	(0.021)	(0.019)	(0.020)	(0.023)
R^2	0.88	0.90	0.90	0.90	0.92
NUTS-3 regions	401	399	391	401	389
WFH freq	-0.12***	-0.12**	-0.11***	-0.12**	-0.11**
	(0.040)	(0.051)	(0.039)	(0.045)	(0.055)
R^2	0.88	0.89	0.90	0.90	0.92
NUTS-3 regions	401	399	391	401	389
Set of Controls					
Baseline	×	×	×	×	×
Economy		×			×
Health			×		×
Social Capital				×	×

Notes: Dependent variable is the number of SARS-CoV-2 infections up to May 06, 2020 (the end date of the first confinement) based on data from the Robert-Koch-Institut. WFH is the percentage share of employees in the county with jobs that are suitable for telework (*WFH feas*) or who either at least occasionally (*WFH occ*) or frequently (*WFH freq*) worked from home in 2018. Observations correspond to NUTS-3 regions (counties) and estimates are weighted based on population size. *Baseline* controls include region-specific log population, log settled area, log GDP, the number of days since the first infection and log spatial infection rates defined as a weighted mean of infection rates in other counties using inverse distances as weights. *Economy* controls include the region-specific fraction of (in- and outward) commuters in the local workforce, an infrastructure index that captures the reachability of airports, the fraction of households with broadband internet access ($\geq$ 50 Mbps), the fraction of low-income households ($\leq$ EUR 1,500 per month), the share of workers employed in services, manufacturing, and wholesale/retail sectors, respectively. *Health* controls include the fraction of male population, the fractions of the population of working age (15-64 yrs.) and elderly ($\geq$ 65 yrs.), the expected remaining lifetime of people with age 60, the death rate, intensive-care-unit beds per 100,000 inhabitants and hospitals per 100,000 inhabitants. *Social Capital* controls include crime rates, voter turnout, vote shares of populist parties, and the number of all registered associations per capita. Heteroskedasticity-robust standard errors reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table C.14 : Robustness: The Effect of WFH on SARS-CoV-2 Fatalities across Counties – Poisson Estimates

	(1)	(2)	(3)	(4)	(5)
WFH feas	-0.11***	-0.097***	-0.10***	-0.11***	-0.089***
	(0.023)	(0.027)	(0.027)	(0.026)	(0.032)
R^2	0.54	0.58	0.59	0.58	0.67
NUTS-3 regions	401	399	391	401	389
WFH occ	-0.13***	-0.11***	-0.12***	-0.13***	-0.11**
	(0.029)	(0.036)	(0.032)	(0.034)	(0.042)
R^2	0.55	0.58	0.59	0.58	0.67
NUTS-3 regions	401	399	391	401	389
WFH freq	-0.24***	-0.17*	-0.20***	-0.23***	-0.11
	(0.067)	(0.088)	(0.070)	(0.078)	(0.10)
R^2	0.54	0.58	0.59	0.57	0.67
NUTS-3 regions	401	399	391	401	389
Set of Controls					
Baseline	×	×	×	×	×
Economy		×			×
Health			×		×
Social Capital				×	×

Notes: Dependent variable is the number of SARS-CoV-2 fatalities up to May 06, 2020 (the end date of the first confinement) based on data from the Robert-Koch-Institut. WFH is the percentage share of employees in the county with jobs that are suitable for telework (*WFH feas*) or who either at least occasionally (*WFH occ*) or frequently (*WFH freq*) worked from home in 2018. Observations correspond to NUTS-3 regions (counties) and estimates are weighted based on population size. *Baseline* controls include region-specific log population, log settled area, log GDP, the number of days since the first infection and log spatial infection rates defined as a weighted mean of infection rates in other counties using inverse distances as weights. *Economy* controls include the region-specific fraction of (in- and outward) commuters in the local workforce, an infrastructure index that captures the reachability of airports, the fraction of households with broadband internet access ($\geq$ 50 Mbps), the fraction of low-income households ($\leq$ EUR 1,500 per month), the share of workers employed in services, manufacturing, and wholesale/retail sectors, respectively. *Health* controls include the fraction of the male population, the fractions of the population of working age (15-64 yrs.) and elderly ($\geq$ 65 yrs.), the expected remaining lifetime of people with age 60, the death rate, intensive-care-unit beds per 100,000 inhabitants and hospitals per 100,000 inhabitants. *Social Capital* controls include crime rates, voter turnout, vote shares of populist parties, and the number of all registered associations per capita. Heteroskedasticity-robust standard errors reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table C.15 : Robustness: The Effect of WFH on SARS-CoV-2 Infections across Counties – Labor Market Interactions

	(1)	(2)	(3)
WFH measure	*WFH feas*	*WFH occ*	*WFH freq*
Panel A:	*Working Age Population Share (%)*		
WFH × Working age	-0.0047***	-0.0056**	-0.0079
	(0.0016)	(0.0023)	(0.0062)
WFH	0.28**	0.32**	0.43
	(0.11)	(0.16)	(0.43)
Working age	0.30***	0.18***	0.12**
	(0.087)	(0.059)	(0.060)
R^2	0.57	0.57	0.57
NUTS-3 regions	401	401	401
Panel B:	*Employment Share (%)*		
WFH × Employment	-0.0045***	-0.0058***	-0.014***
	(0.0012)	(0.0017)	(0.0041)
WFH	0.14***	0.18**	0.43**
	(0.052)	(0.072)	(0.17)
Employment	0.26***	0.16***	0.13***
	(0.068)	(0.044)	(0.038)
R^2	0.56	0.56	0.56
NUTS-3 regions	401	401	401
Baseline controls	×	×	×

Notes: Dependent variable is the SARS-CoV-2 infection rate (in logs) up to May 06, 2020 (the end date of the first confinement) based on data from the Robert-Koch-Institut. WFH is the percentage share of employees in the county with jobs that are suitable for telework (*WFH feas*) or who either at least occasionally (*WFH occ*) or frequently (*WFH freq*) worked from home in 2018. Observations correspond to NUTS-3 regions (counties) and estimates are weighted based on population size. Panel A includes interactions with the regional percentage share of the working age population and Panel B includes interactions with regional percentage employment shares. *Baseline* controls include region-specific log population, log settled area, log GDP, the number of days since the first infection and log spatial infection rates defined as a weighted mean of infection rates in other counties using inverse distances as weights. Heteroskedasticity-robust standard errors reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table C.16 : Robustness: The Effect of WFH on SARS-CoV-2 Infections across Counties – Income Group Interactions

	(1)	(2)	(3)
WFH measure	*WFH feas*	*WFH occ*	*WFH freq*
Panel A:	*Share of Low-Income Households (%)*		
WFH × share low income	0.0028***	0.0034***	0.0068***
	(0.00065)	(0.00095)	(0.0025)
WFH	-0.12***	-0.14***	-0.29***
	(0.018)	(0.025)	(0.072)
share low income	-0.17***	-0.11***	-0.081***
	(0.037)	(0.025)	(0.024)
R^2	0.59	0.59	0.58
NUTS-3 regions	401	401	401
Panel B:	*Share of High-Income Households (%)*		
WFH × share high income	-0.0028***	-0.0033***	-0.0069***
	(0.00070)	(0.00100)	(0.0026)
WFH	0.021	0.021	0.047
	(0.022)	(0.030)	(0.072)
share high income	0.18***	0.10***	0.079***
	(0.041)	(0.028)	(0.027)
R^2	0.58	0.57	0.56
NUTS-3 regions	401	401	401
Baseline controls	×	×	×

Notes: Dependent variable is the SARS-CoV-2 infection rate (in logs) up to May 06, 2020 (the end date of the first confinement) based on data from the Robert-Koch-Institut. WFH is the percentage share of employees in the county with jobs that are suitable for telework (*WFH feas*) or who either at least occasionally (*WFH occ*) or frequently (*WFH freq*) worked from home in 2018. Observations correspond to NUTS-3 regions (counties) and estimates are weighted based on population size. Panel A includes interactions with the regional percentage share of low-income households ($\leq$ EUR 1,500 per month) and Panel B includes interactions with the regional percentage share of high-income households ($\geq$ EUR 3,600 per month). *Baseline* controls include region-specific log population, log settled area, log GDP, the number of days since the first infection and log spatial infection rates defined as a weighted mean of infection rates in other counties using inverse distances as weights. Heteroskedasticity-robust standard errors reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table C.17 : Robustness: The Effect of WFH on SARS-CoV-2 Infections across Counties – Regional Spillovers from Commuting

	(1)	(2)	(3)	(4)	(5)	(6)
WFH measure	*WFH feas*		*WFH occ*		*WFH freq*	
Panel A:	*Spillovers from Inward Commuters*					
WFH	-0.046***	-0.040***	-0.061***	-0.053***	-0.11***	-0.11***
	(0.010)	(0.010)	(0.013)	(0.013)	(0.028)	(0.028)
Commuters	0.043	2.18***	0.065	1.46***	0.087	1.25***
	(0.071)	(0.52)	(0.071)	(0.34)	(0.071)	(0.32)
WFH (adjacent)	0.0027	0.41***	-0.021	0.56***	-0.14**	1.21***
	(0.017)	(0.091)	(0.023)	(0.13)	(0.054)	(0.36)
WFH (adjacent) × Commuters		-0.039***		-0.056***		-0.13***
		(0.0092)		(0.013)		(0.035)
R^2	0.65	0.66	0.65	0.67	0.65	0.66
NUTS-3 regions	401	401	401	401	401	401
Panel B:	*Spillovers from Outward Commuters*					
WFH	-0.016*	-0.016*	-0.035***	-0.034***	-0.080***	-0.080***
	(0.0094)	(0.0092)	(0.012)	(0.012)	(0.026)	(0.026)
Commuters	0.065	4.51***	0.12*	2.76***	0.13**	1.80***
	(0.076)	(0.77)	(0.072)	(0.50)	(0.066)	(0.51)
WFH (adjacent)	-0.017	0.85***	-0.060**	1.08***	-0.24***	1.74***
	(0.020)	(0.14)	(0.027)	(0.21)	(0.062)	(0.59)
WFH (adjacent) × Commuters		-0.083***		-0.11***		-0.19***
		(0.014)		(0.020)		(0.057)
R^2	0.63	0.66	0.64	0.66	0.65	0.66
NUTS-3 regions	401	401	401	401	401	401
Baseline	×	×	×	×	×	×

Notes: Dependent variable is the SARS-CoV-2 infection rate (in logs) up to May 06, 2020 (the end date of the first confinement) based on data from the Robert-Koch-Institut. WFH is the percentage share of employees (Panel A) or residents (Panel B) in the county with jobs that are suitable for telework (*WFH feas*) or who either at least occasionally (*WFH occ*) or frequently (*WFH freq*) worked from home in 2018. Observations correspond to NUTS-3 regions (counties) and estimates are weighted based on population size. Panel A includes the following variables based on the 30 most adjacent counties: the log number of inward commuters from these counties, WFH (residence-weighted), and their interaction. Panel B includes the following variables based on the 30 most adjacent counties: the log number of outward commuters to these counties, WFH (workplace-weighted), and their interaction. *Baseline* controls include region-specific log population, log settled area, log GDP, the number of days since the first infection and log spatial infection rates defined as a weighted mean of infection rates in other counties using inverse distances as weights. Heteroskedasticity-robust standard errors reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table C.18 : Robustness: The Effect of WFH on SARS-CoV-2 Infections across Counties – Controlling for Patents and Broadband Speed

	(1)	(2)	(3)	(4)	(5)	(6)
WFH measure	*WFH feas*		*WFH occ*		*WFH freq*	
Panel A:	*Controlling for Patent Applications*					
WFH	-0.047***	-0.044***	-0.059***	-0.059***	-0.073*	-0.071
	(0.014)	(0.015)	(0.019)	(0.019)	(0.043)	(0.046)
R^2	0.59	0.63	0.59	0.63	0.58	0.63
NUTS-3 regions	394	384	394	384	394	384
Panel B:	*Controlling for Broadband Speed*					
WFH	-0.043***	-0.043***	-0.054***	-0.058***	-0.072*	-0.075*
	(0.014)	(0.014)	(0.018)	(0.019)	(0.041)	(0.045)
R^2	0.60	0.66	0.60	0.66	0.60	0.65
NUTS-3 regions	399	389	399	389	399	389
Set of Controls						
Baseline	×	×	×	×	×	×
Economy	×	×	×	×	×	×
Health		×		×		×
Social Capital		×		×		×

Notes: Dependent variable is the SARS-CoV-2 infection rate (in logs) up to May 06, 2020 (the end date of the first confinement) based on data from the Robert-Koch-Institut. WFH is the percentage share of employees in the county with jobs that are suitable for telework (*WFH feas*) or who either at least occasionally (*WFH occ*) or frequently (*WFH freq*) worked from home in 2018. Observations correspond to NUTS-3 regions (counties) and estimates are weighted based on population size. *Baseline* controls include region-specific log population, log settled area, log GDP, the number of days since the first infection and log spatial infection rates defined as a weighted mean of infection rates in other counties using inverse distances as weights. *Economy* controls include the region-specific fraction of (in- and outward) commuters in the local workforce, an infrastructure index that captures the reachability of airports, the fraction of households with broadband internet access ($\geq$ 50 Mbps), the fraction of low-income households ($\leq$ EUR 1,500 per month), the share of workers employed in services, manufacturing, and wholesale/retail sectors, respectively. *Health* controls include the fraction of the male population, the fractions of the population of working age (15-64 yrs.) and elderly ($\geq$ 65 yrs.), the expected remaining lifetime of people with age 60, the death rate, intensive-care-unit beds per 100,000 inhabitants and hospitals per 100,000 inhabitants. *Social Capital* controls include crime rates, voter turnout, vote shares of populist parties, and the number of all registered associations per capita. Panel A additionally controls for log patent applications and Panel B for average broadband speed. Heteroskedasticity-robust standard errors reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table C.19 : The Spread of SARS-CoV-2 Pre and Post Confinement and WFH

	(1)	(2)	(3)
WFH measure	*WFH feas*	*WFH occ*	*WFH freq*
WFH × Pre confinement	-0.018**	-0.026**	-0.053**
	(0.0077)	(0.010)	(0.023)
R^2	0.96	0.96	0.96
Observations	4,270	4,270	4,270
County F.E.	×	×	×
Week F.E.	×	×	×

Notes: Dependent variable is the weekly SARS-CoV-2 infection rate (in logs) at the NUTS-3 level based on data from the Robert-Koch-Institut. WFH is the percentage share of employees in the county with jobs that are suitable for telework (*WFH feas*) or who either at least occasionally (*WFH occ*) or frequently (*WFH freq*) worked from home in 2018. *Pre confinement* is a dummy variable that indicates weeks 1-7. Observations correspond to individual weeks within NUTS-3 regions (counties). Controls are region-specific weekly rainfall and log weekly spatial infection rates defined as a weighted mean of infection rates in other counties using inverse distances as weights. Standard errors are corrected for clustering at the NUTS-3 county level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table C.20 : Robustness: The Effect of WFH on SARS-CoV-2 Infections across Counties – Other Weeks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	July 29, 2020					September 30, 2020				
WFH feas	-0.050***	-0.051***	-0.048***	-0.053***	-0.046***	-0.045***	-0.045***	-0.042***	-0.046***	-0.035***
	(0.012)	(0.014)	(0.012)	(0.011)	(0.014)	(0.0097)	(0.012)	(0.0096)	(0.0088)	(0.011)
R^2	0.55	0.60	0.59	0.61	0.64	0.65	0.68	0.69	0.70	0.73
NUTS-3 regions	401	399	391	401	389	401	399	391	401	389
WFH occ	-0.066***	-0.063***	-0.062***	-0.068***	-0.060***	-0.060***	-0.057***	-0.054***	-0.060***	-0.046***
	(0.014)	(0.017)	(0.015)	(0.013)	(0.017)	(0.012)	(0.015)	(0.012)	(0.011)	(0.014)
R^2	0.55	0.60	0.59	0.61	0.64	0.65	0.68	0.69	0.70	0.73
NUTS-3 regions	401	399	391	401	389	401	399	391	401	389
WFH freq	-0.12***	-0.087**	-0.11***	-0.11***	-0.071*	-0.11***	-0.085**	-0.098***	-0.100***	-0.061*
	(0.033)	(0.039)	(0.034)	(0.033)	(0.043)	(0.028)	(0.034)	(0.028)	(0.028)	(0.034)
R^2	0.55	0.59	0.58	0.60	0.63	0.65	0.67	0.69	0.69	0.72
NUTS-3 regions	401	399	391	401	389	401	399	391	401	389
Set of Controls										
Baseline	×	×	×	×	×	×	×	×	×	×
Infrastructure		×			×		×			×
Health			×		×			×		×
Social Capital				×	×				×	×

Notes: Dependent variables are the SARS-CoV-2 infection rates (in logs) up to July 29 or September 30, 2020, at the NUTS-3 level based on data from the Robert-Koch-Institut. WFH is the percentage share of employees in the county with jobs that are suitable for telework (*WFH feas*) or who either at least occasionally (*WFH occ*) or frequently (*WFH freq*) worked from home in 2018. Observations correspond to NUTS-3 regions (counties) and estimates are weighted based on population size. *Baseline* controls include region-specific log population, log settled area, log GDP, the number of days since the first infection and log spatial infection rates defined as a weighted mean of infection rates in other counties using inverse distances as weights. *Economy* controls include the region-specific fraction of (in- and outward) commuters in the local workforce, an infrastructure index that captures the reachability of airports, the fraction of households with broadband internet access ($\geq$ 50 Mbps), the fraction of low-income households ($\leq$ EUR 1,500 per month), the share of workers employed in services, manufacturing, and wholesale/retail sectors, respectively. *Health* controls include the fraction of the male population, the fractions of the population of working age (15-64 yrs.) and elderly ($\geq$ 65 yrs.), the expected remaining lifetime of people with age 60, the death rate, intensive-care-unit beds per 100,000 inhabitants and hospitals per 100,000 inhabitants. *Social Capital* controls include crime rates, voter turnout, vote shares of populist parties, and the number of all registered associations per capita. Heteroskedasticity-robust standard errors reported in parentheses. $^{***}\ p < 0.01$, $^{**}\ p < 0.05$, $^{*}\ p < 0.1$

Table C.21 : Robustness: The Effect of WFH on SARS-CoV-2 Fatalities across Counties – Other Weeks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	July 29, 2020					September 30, 2020				
WFH feas	-0.073***	-0.062**	-0.072***	-0.074***	-0.068**	-0.080***	-0.076***	-0.073***	-0.074***	-0.068**
	(0.021)	(0.025)	(0.022)	(0.022)	(0.026)	(0.022)	(0.026)	(0.023)	(0.023)	(0.028)
R^2	0.28	0.31	0.31	0.30	0.34	0.27	0.31	0.30	0.30	0.34
NUTS-3 regions	377	375	370	377	368	372	370	365	372	363
WFH occ	-0.10***	-0.089***	-0.097***	-0.10***	-0.098***	-0.11***	-0.10***	-0.097***	-0.10***	-0.090**
	(0.027)	(0.030)	(0.028)	(0.028)	(0.034)	(0.028)	(0.032)	(0.029)	(0.029)	(0.035)
R^2	0.29	0.32	0.31	0.31	0.35	0.28	0.31	0.30	0.31	0.34
NUTS-3 regions	377	375	370	377	368	372	370	365	372	363
WFH freq	-0.20***	-0.16**	-0.18***	-0.20***	-0.15*	-0.22***	-0.18**	-0.18**	-0.19***	-0.11
	(0.064)	(0.074)	(0.068)	(0.066)	(0.083)	(0.067)	(0.079)	(0.070)	(0.070)	(0.088)
R^2	0.29	0.31	0.30	0.30	0.34	0.28	0.30	0.29	0.30	0.33
NUTS-3 regions	377	375	370	377	368	372	370	365	372	363
Set of Controls										
Baseline	×	×	×	×	×	×	×	×	×	×
Infrastructure		×			×		×			×
Health			×		×			×		×
Social Capital				×	×				×	×

Notes: Dependent variables are the SARS-CoV-2 fatality rates (in logs) up to July 29 or September 30, 2020, at the NUTS-3 level based on data from the Robert-Koch-Institut. WFH is the percentage share of employees in the county with jobs that are suitable for telework (*WFH feas*) or who either at least occasionally (*WFH occ*) or frequently (*WFH freq*) worked from home in 2018. Observations correspond to NUTS-3 regions (counties) and estimates are weighted based on population size. *Baseline* controls include region-specific log population, log settled area, log GDP, the number of days since the first infection and log spatial infection rates defined as a weighted mean of infection rates in other counties using inverse distances as weights. *Economy* controls include the region-specific fraction of (in- and outward) commuters in the local workforce, an infrastructure index that captures the reachability of airports, the fraction of households with broadband internet access ($\geq$ 50 Mbps), the fraction of low-income households ($\leq$ EUR 1,500 per month), the share of workers employed in services, manufacturing, and wholesale/retail sectors, respectively. *Health* controls include the fraction of the male population, the fractions of the population of working age (15-64 yrs.) and elderly ($\geq$ 65 yrs.), the expected remaining lifetime of people with age 60, the death rate, intensive-care-unit beds per 100,000 inhabitants and hospitals per 100,000 inhabitants. *Social Capital* controls include crime rates, voter turnout, vote shares of populist parties, and the number of all registered associations per capita. Heteroskedasticity-robust standard errors reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

C.7 A Dynamic Spatial Count Model of Covid-19 Infections

To show the robustness of our results regarding the impact of working from home on SARS-CoV-2 infections and its differential effect before the confinement period, in this Appendix we estimate a dynamic spatial count model of disease transmission, based on a standard modeling approach from the epidemiological literature (Höhle, 2016). The econometric model has been specifically designed for routine surveillance data, such as those reported by the RKI, and does not require information about the number of susceptibles.[3]

This econometric model is significantly more flexible than the linear models we have used in the main body of the paper. We now use counts of *new* infections $Y_{it} = I_{it} - I_{it-1}$ in region i in week t as the dependent variable, which implies that unobserved county-specific effects affecting the level of infections are already differenced out. Moreover, instead of normalizing infections by regional population, we now use the latter as an explanatory variable, to allow for flexible interaction effects between them. We assume that Y_{it} is drawn, alternatively, from a Poisson or negative Binomial (type-1) distribution with mean

$$\mu_{it} = e_i \nu_{it} + \lambda Y_{it-1} + \phi \sum_{j \neq i} w_{ij} Y_{jt-1}. \tag{C.4}$$

Here e_i is the population share of region i, ν_{it} is the endemic mean of the process that depends on county-specific covariates, λY_{it-1} captures the autoregressive (epidemic) component of infections and $\phi \sum_{j \neq i} w_{ij} Y_{jt-1}$ is the spatial component, capturing transmission from other counties. The spatial weights are modeled as power functions of distance, $w_{ij} = o_{ij}^{-d}$. Here o_{ij} is the adjacency order of regions i and j, corresponding to the number of regions that need to be crossed to get from i to j, and d is a spatial decay parameter to be estimated.[4]

The county-specific endemic component is modeled as the product of the county's population share e_i, accounting for regional exposure, and ν_{it}, which is an exponential process including *WFH freq*, the interaction of *WFH freq* with a dummy for the pre-confinement period *Preconf*$_t$, a vector of county controls $\mathbf{Z}_{it}$, and a flexible time trend with a seasonal component:

$$\log \nu_{it} = \beta_0 WFH_i + \beta_1 WFH_i \times \textit{Preconf}_t + \mathbf{Z_{it}}'\beta^{\nu} + \delta_t + \gamma_1 \sin \omega t + \gamma_2 \cos \omega t. \tag{C.5}$$

[3] The formal inspiration for the model was the spatial branching process with immigration, which means that observation time and generation time have to correspond. For Covid-19 the generation time has been estimated to be roughly 5.5 days (Ganyani et al., 2020). In a series of successive papers, the original modeling approach of Held et al. (2005) was subsequently extended such that it now constitutes a powerful and flexible regression approach for multivariate count data time series.
[4] We estimate the model using the R package *surveillance*, see (Meyer et al., 2017).

$\mathbf{Z}_{it}$ includes the set of baseline controls.

The results for this model are reported in Table C.22. Columns (1) and (2) report coefficients for the Poisson model and Columns (3) and (4) for the negative Binomial model. The odd columns only include the direct impact of *WFH freq*, while the even columns additionally allow for a differential effect of *WFH freq* in the pre-confinement period. In all specifications, *WFH freq* has a negative effect on infection counts, which is significant at the one-percent level. Moreover, the interaction term $WFH_i \times \textit{Preconf}_t$ is also negative and highly significant, confirming the additional infection-reducing impact of WFH before the confinement from the linear model.[5] The autoregressive coefficient λ is quantitatively large and highly significant, indicating the importance of the epidemic component. Finally, the spatial component ϕ is also positive and significant, indicating that transmission from other regions plays a role. The AIC criterion suggests that the Negative Binomial model provides a better fit of the data than the Poisson model but the coefficient estimates are extremely similar across models.

[5] Due to the non-linearity of the econometric model, only the signs of the coefficients allow for a straightforward interpretation, while the magnitudes of the coefficient estimates depend on the full set of covariates. In particular, the conditional expectation of the number of counts is given by $E(Y_{it}|X_{it}) = \mu_{it} = \exp\left(e_i\nu_{it} + \lambda Y_{it-1} + \phi \sum_{j\neq i} w_{ij} Y_{jt-1}\right)$. Thus, the marginal effect of the WFH share (the expected change in the number of infections when increasing the WHS share by one unit) is given by $\frac{\partial E(Y_{it}|X_{it})}{\partial WFH_i} = (\beta_0 + \beta_1 \times \textit{Preconf}_t)\nu_{it} e_i \mu_{it}$.

Table C.22 : SARS-CoV-2 Infections and WFH: Dynamic Spatial Count Model

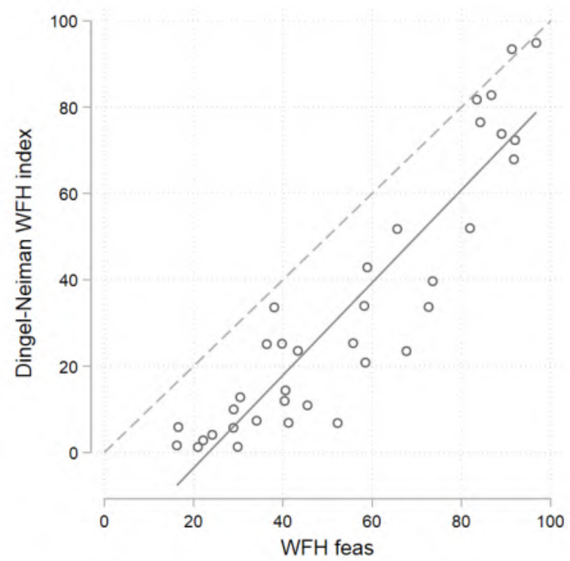
	(1)	(2)	(3)	(4)
	Infections			
	Poisson		*Negative Binomial*	
WFH	-0.1039***	-0.0938***	-0.1091***	-0.0879***
	(0.0076)	(0.0077)	(0.0245)	(0.0255)
WFH $\times$ Pre confinement		-0.0334***		-0.0325***
		(0.0077)		(0.0108)
λ	0.7101**	0.7108***	0.6705***	0.6731***
	(0.0046)	(0.0034)	(0.0142	(0.0142)
ϕ	0.0841***	0.0969***	0.1450***	0.1540***
	(0.0026)	(0.0026)	(0.0075)	(0.0072)
Controls	$\times$	$\times$	$\times$	$\times$
log L	-29,279	-29,222	-15,956	-15,952
AIC	58,578	58,466	31,935	31,928
Obs.	5,614	5,614	5,614	5,614
NUTS-3 regions	401	401	401	401

Notes: The table reports estimated coefficients from a dynamic spatial epidemic count model. The dependent variable is the weekly number of SARS-CoV-2 infections at the NUTS-3 level based on data from the Robert-Koch-Institut. WFH is the percentage share of employees in the county with jobs that are frequently (*WFH freq*) doing telework. *Pre confinement* is a dummy variable that indicates weeks 1-7. Observations correspond to NUTS-3 regions (counties). Columns (1) and (2) report results from a Poisson model, Columns (3) and (4) from a Negative Binomial model (Type 1). Controls are population interacted with region-specific log settled area and log GDP. The spatial term includes the number of cases in other regions with estimated spatial weights.*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

C.7.1 Details and Robustness: Relation to Dingel and Neiman (2020)

To assess the robustness of our results with respect to the employed WFH measures, we replicate our analyses using the WFH feasibility index proposed by Dingel and Neiman (2020), hereafter DN. In their study, DN determine occupational tasks that are incompatible with working from home (e.g., working outdoors) based on US task information provided by O*NET- and classify occupations as either suitable or unsuitable for home-based work accordingly. We use their measures, which are published for download, and proceed in the same manner as described in Section 3.2.1 to compute WFH feasibility at the county and industry level. In the aggregate, 37 percent of German jobs are suitable for WFH according to the DN measure, a figure significantly lower than the estimated 56 percent WFH capacity estimated from the BIBB/BAuA Employment Survey. It is likely that the difference stems from DN's approach to measuring the capacity for full-time WFH, whereas our WFH-feasibility measure includes also jobs suitable for part-time WFH. Discrepancies might also be explained by different task profiles of occupations in Germany compared to the US. Plotting DN's WFH index against our measure of overall WFH feasibility (*WFH feas*) at the 2-digit occupation level (Figure C.5) shows that the two measures indeed differ mostly in terms of the level of WFH potential (occupations clustered below the dashed 45-degree line), while the correlation between the two measures is very high ($\rho = 0.92$). The correlation at the county level is even higher ($\rho = 0.95$) as the measures are aggregated to regional WFH potential using identical occupation shares.

Figure C.5 : Correlation between *WFH feas* and Dingel-Neiman WFH index at the Occupation Level



Notes: The figure plots Dingel and Neiman's task-based WFH index against our survey-based measure of WFH feasibility (*WFH feas*) at the 2-digit occupation level (KldB 2010). The solid line reports the linear fit between the two measures ($R^2 = 0.84$). The dashed line highlights the 45-degree line.

Robustness on STW using DN's measure of WFH First, we replicate the relationship between short-time work applications and WFH at the county level discussed in Section 3.2.2. Analogously to Table 3.1, which uses our WFH measures as key explanatory variables, Table C.23 reports results from estimating the effect of WFH on the share of employees registered for STW in March and April 2020 using DN's WFH index. The estimates are always negative and significant at the one-percent level. In terms of magnitude, the coefficient estimates are closest to those using *WFH feas*.

Robustness on STW using industry-level data and DN's measure of WFH Second, we show that the relationship between WFH and the share of employees registered for STW in March and April 2020 holds when estimated at the 2-digit industry level instead of the county level. Analogously to our county-level measures of WFH, industry-specific WFH is computed as a weighted sum over occupation-specific WFH-shares using industries' occupational composition obtained from the Federal Employment Agency (see Section 3.2.1 for details) as weights. Table C.24 reports OLS results from estimating the effect of WFH on the share of STW for our three survey-based WFH measures and DN's task-based WFH index. The estimates are negative and significant at the one-percent level. Again, the coefficient associated with DN's WFH index is closest to the coefficient of *WFH feas*.

Robustness on SARS-CoV-2 cases and fatalities using DN's measure of WFH Third, we replicate the relationship between the spread of SARS-CoV-2 and WFH at the county level discussed previously in Section 3.3. Table C.25 reports estimates on infection rates and fatality rates using DN's WFH measure. The specifications are analogous to those from Tables 3.3 (for infections) and C.12 (for fatalities). The estimates are negative and significant at the one- or the five-percent level across all specifications. Also in this case the coefficient estimates are quantitatively close to those using *WFH feas*.

Table C.23 : Robustness: Short-Time Work and DN's WFH Measure

	(1)	(2)	(3)	(4)	(5)
WFH DN	-1.04***	-0.65***	-1.07***	-1.03***	-0.76***
	(0.19)	(0.19)	(0.19)	(0.22)	(0.22)
R^2	0.26	0.33	0.29	0.29	0.37
NUTS-3 regions	401	399	391	401	389
Set of Controls					
Baseline	×	×	×	×	×
Economy		×			×
Health			×		×
Social Capital				×	×

Notes: Dependent variable is the percentage of the total number of persons mentioned in short-time work applications in March and April 2020 relative to employment in June 2019 based on data from the Federal Employment Agency. WFH is the WFH feasibility index proposed by Dingel and Neiman (2020). Observations correspond to NUTS-3 regions (counties) and estimates are weighted based on employment as of June 2019. For a description of control variables, see table notes of Table 3.1. Heteroskedasticity-robust standard errors reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table C.24 : Robustness: Short-Time Work and WFH at the Industry Level

	(1)	(2)	(3)	(4)
WFH feas	-0.55***			
	(0.19)			
WFH occ		-0.66***		
		(0.21)		
WFH freq			-0.99***	
			(0.29)	
WFH DN				-0.51***
				(0.17)
R^2	0.13	0.10	0.06	0.15
NACE 2-digit industries	88	88	88	88

Notes: Dependent variable is the percentage of the total number of persons mentioned in short-time work applications in March and April 2020 relative to employment in June 2019 based on data from the Federal Employment Agency. WFH is the percentage share of employees in the county with jobs that are suitable for telework (*WFH feas*) or who either at least occasionally (*WFH occ*) or frequently (*WFH freq*) worked from home in 2018. *WFH DN* is the feasibility index proposed by Dingel and Neiman (2020). Observations correspond to NACE 2-digit industries and estimates are weighted based on employment as of June 2019. Heteroskedasticity-robust standard errors reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

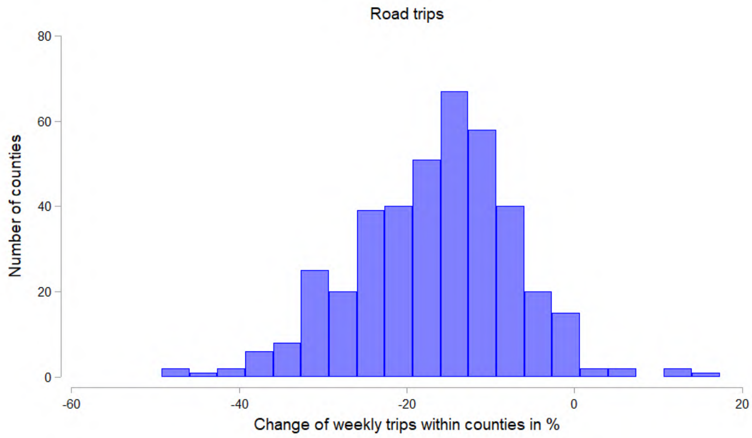
Table C.25 : Robustness: The Spread of SARS-CoV-2 across Counties and DN WFH

	(1)	(2)	(3)	(4)	(5)
	Log Infection Rate				
WFH DN	-0.033***	-0.028**	-0.035***	-0.038***	-0.028**
	(0.0089)	(0.013)	(0.0090)	(0.0086)	(0.013)
R^2	0.54	0.60	0.58	0.62	0.65
NUTS-3 regions	401	399	391	401	389
	Log Mortality Rate				
WFH DN	-0.066***	-0.063**	-0.066***	-0.064***	-0.058**
	(0.019)	(0.025)	(0.020)	(0.021)	(0.028)
R^2	0.27	0.30	0.29	0.30	0.33
NUTS-3 regions	369	367	362	369	360
Set of Controls					
Baseline	×	×	×	×	×
Economy		×			×
Health			×		×
Social Capital				×	×

Notes: Dependent variable is the SARS-CoV-2 infection rate or the fatality rate (in logs) up to May 06, 2020 (the alleviation date of the first confinement) based on data from the Robert-Koch-Institut. WFH is the WFH feasibility index proposed by Dingel and Neiman (2020). Observations correspond to NUTS-3 regions (counties) and estimates are weighted based on population size. For a description of control variables, see table notes of Table 3.3. Heteroskedasticity-robust standard errors reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

C.7.2 Details and Robustness: Changes in Mobility Patterns

Figure C.6 : Decline in Regional Mobility during the Covid-19 Crisis



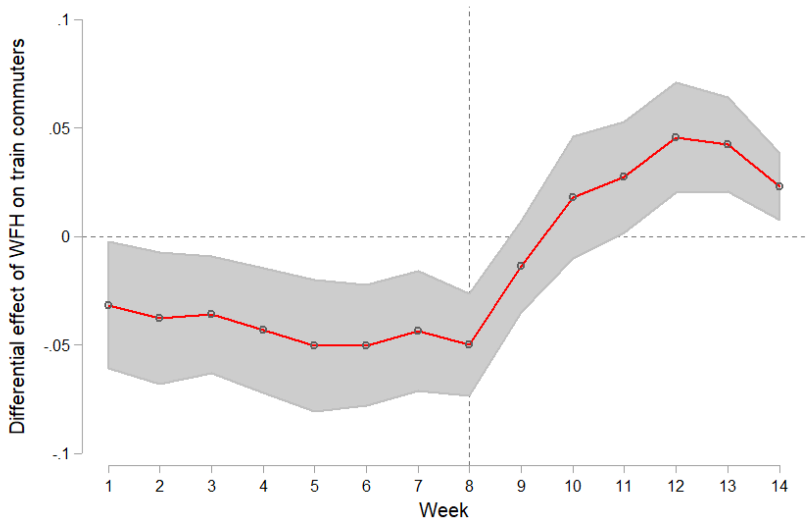
Notes: The figure plots the cross-county distribution of 15-week changes in the number of car trips within counties (from week 1: Jan 23-29, 2020 to week 15: Apr 29 - May 15, 2020).

Table C.26 : Road Trips and WFH Pre and Post Confinement

	(1)	(2)	(3)
WFH	-0.15***	-0.14***	
	(0.028)	(0.029)	
WFH $\times$ Pre confinement		-0.033***	-0.031***
		(0.0054)	(0.0053)
R^2	0.12	0.12	0.99
Obs.	6,015	6,015	6,015
County F.E.			$\times$
Week F.E.	$\times$	$\times$	$\times$

Notes: Dependent variable is the weekly number of road trips within a county during each week (in logs) at the NUTS-3 level based on data from Teralytics (from week 1: Jan 23-29, 2020 to week 15: Apr 29 - May 15, 2020). WFH is the percentage share of employees in the county with jobs that are frequently doing telework (*WFH freq*). *Pre confinement* is a dummy variable that indicates weeks 1-7. Observations correspond to individual weeks within NUTS-3 regions (counties). All specification control for weekly rainfall. Standard errors are corrected for clustering at the NUTS-3 county level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Figure C.7 : Robustness: The Effect of WFH on Train Commutes over Time

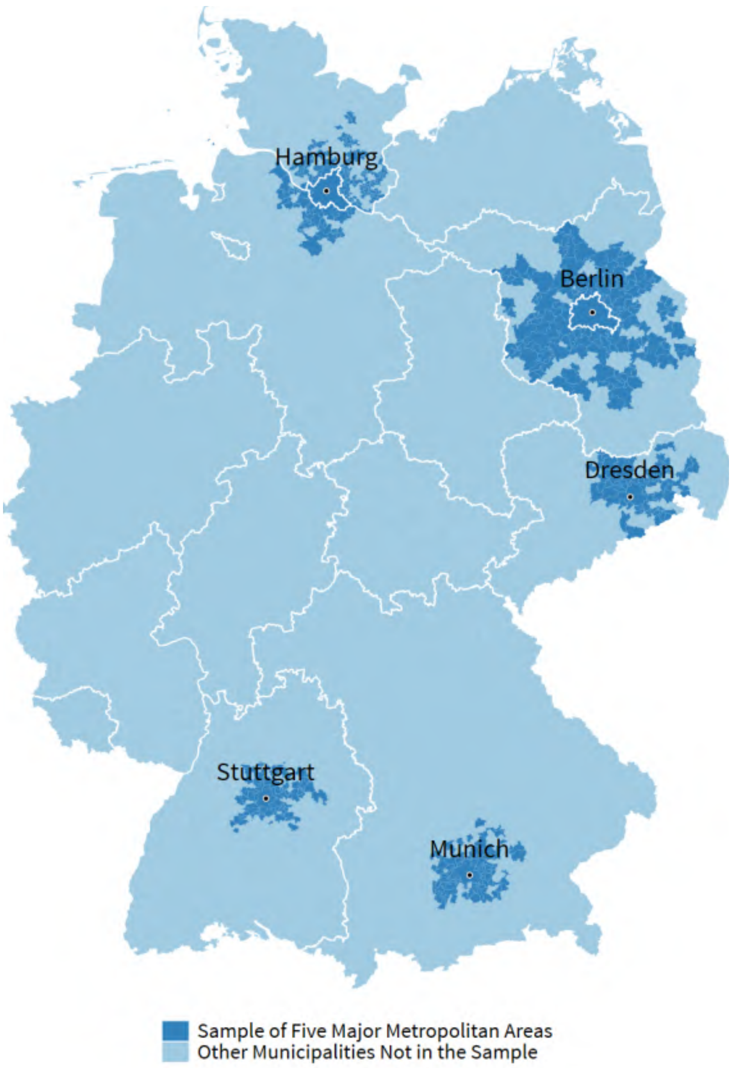


Notes: The figure plots coefficient estimates of $WFH_i \times t$ (using *WFH freq*) on the log number of inbound train trips by week (week 15 is absorbed by fixed effects). The dashed vertical line for week 8 indicates the week when the majority of confinement rules were set into force by federal states. The gray shaded area corresponds to 95-percent confidence intervals (with clustering at the county level).

D Appendix to Chapter 4

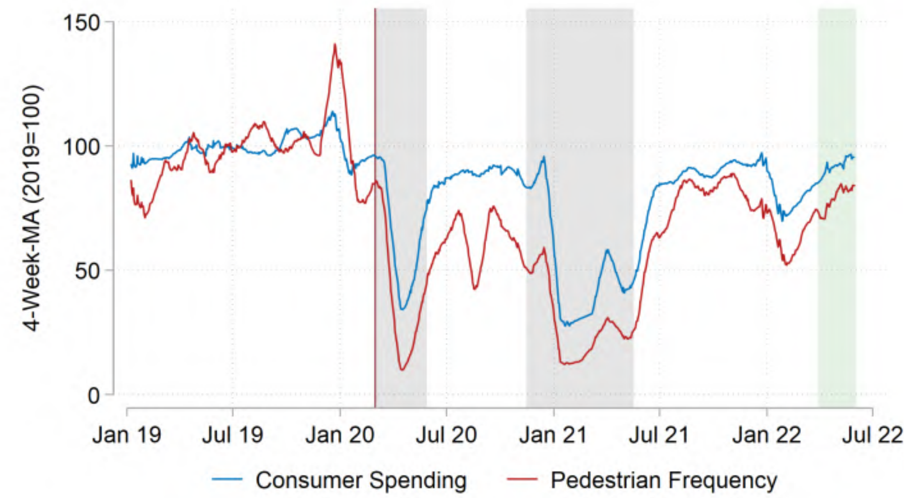
D.1 Figures

Figure D.1 : Sample Illustration of Five Major German Metro Areas



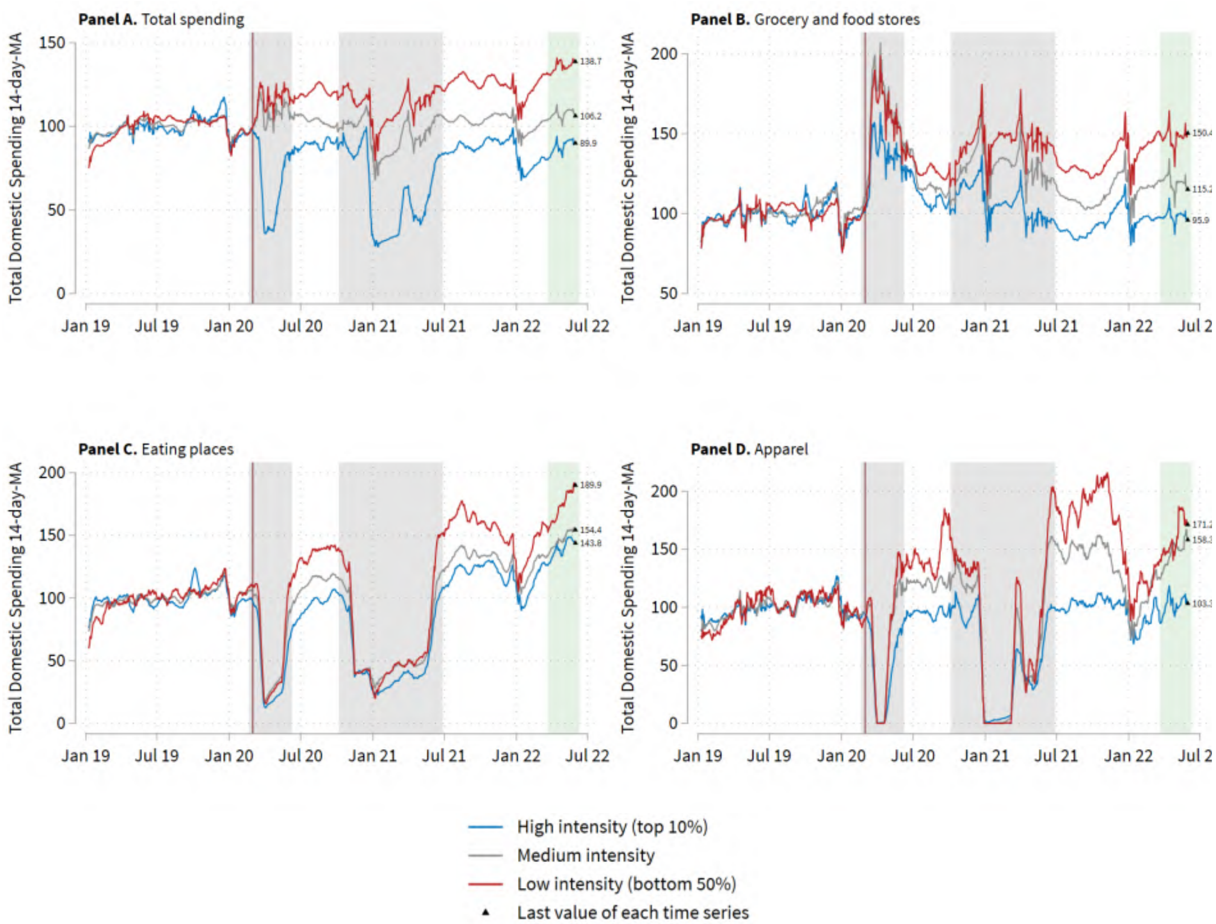
Notes: This map of Germany shows our sample of five major German cities and their surrounding areas: Berlin, Munich, Hamburg, Stuttgart, and Dresden. The municipalities with postcodes belonging to the sample are highlighted in dark blue. The 16 German federal states are delineated by white border lines.

Figure D.2 : Representativity of Consumer Spending Data: Comparison with Pedestrian Frequency 2019-2022



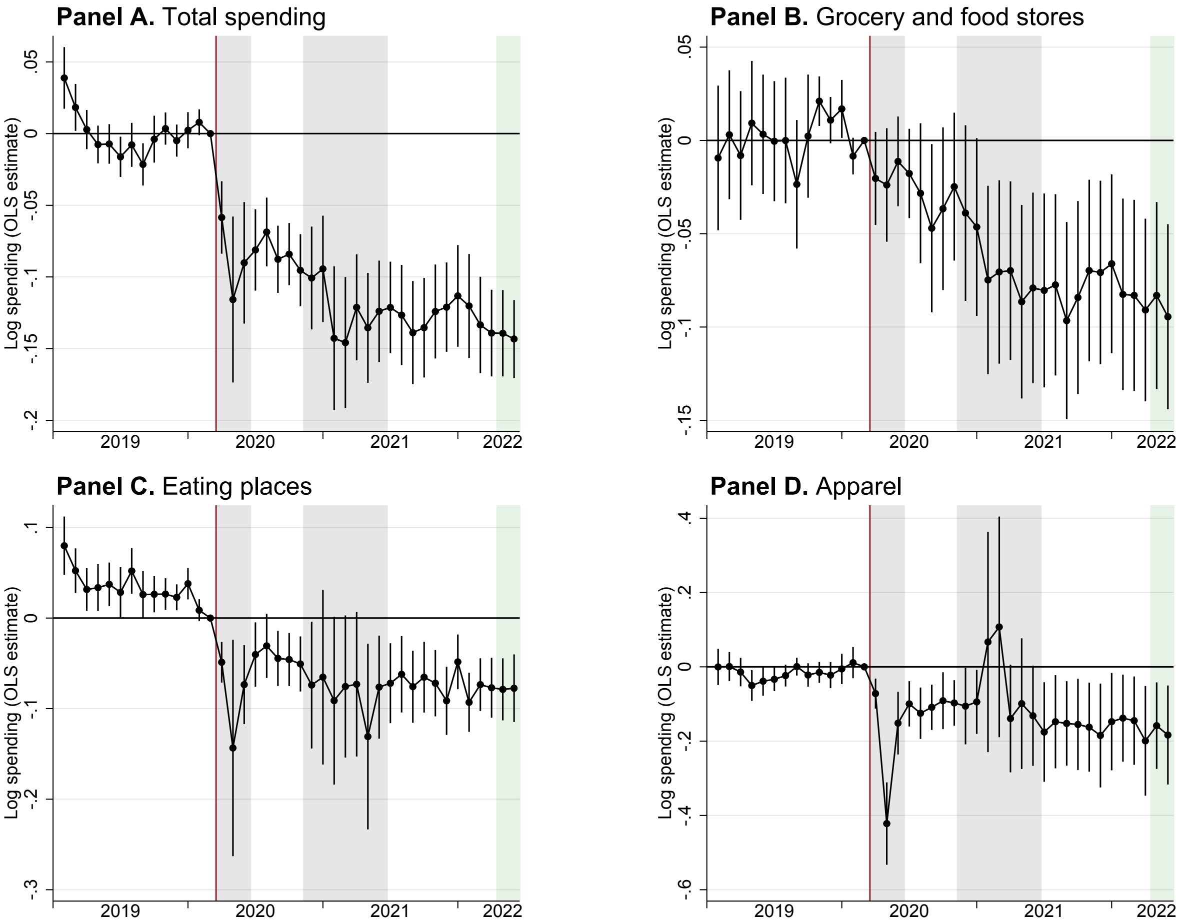
Notes: The figure shows the co-evolution of offline consumer spending (blue) and pedestrian frequency (red) in highly frequented postcodes. Time series show 4-week moving averages normalized by the 2019 average. The vertical red line marks the outbreak of the Covid-19 pandemic between February and March 2020. The gray-shaded areas highlight lockdown periods, characterized by closures of non-essential businesses and other severe containment measures. The green-shaded area marks the period after March 2022, when nearly all restrictions were lifted. The consumer spending data comprise debit and credit card payments. The pedestrian frequency data are provided by Hystreet (2022) who use laser scanners to track the number of pedestrians at measurement sites at prominent city locations.

Figure D.3 : Spending Development by Consumption Intensity in Selected Sectors 2019-2022



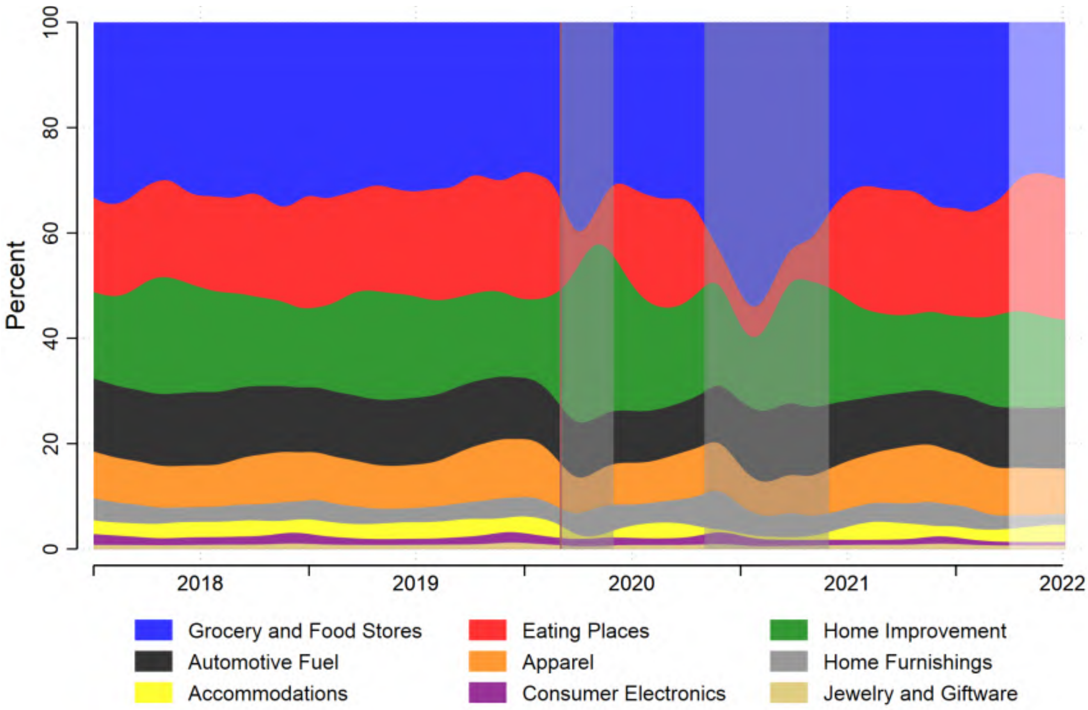
Notes: The figure shows the evolution of offline spending overall (Panel A), in grocery and food stores (Panel B), in eating places (Panel C), and in apparel stores (Panel D) by high, medium, and low 2019 consumption intensity. Time series show 14-day moving averages normalized by the 2019 average in each category. The vertical red line marks the outbreak of the Covid-19 pandemic between February and March 2020. The gray-shaded areas highlight lockdown periods, characterized by closures of non-essential businesses and other severe containment measures. The green-shaded area marks the period after March 2022, when nearly all restrictions were lifted. The consumer spending data comprise debit and credit card payments.

Figure D.4 : DiD Results on the Association of Pre-Covid Consumption Intensity and Consumer Spending: Heterogeneity by Spending Categories



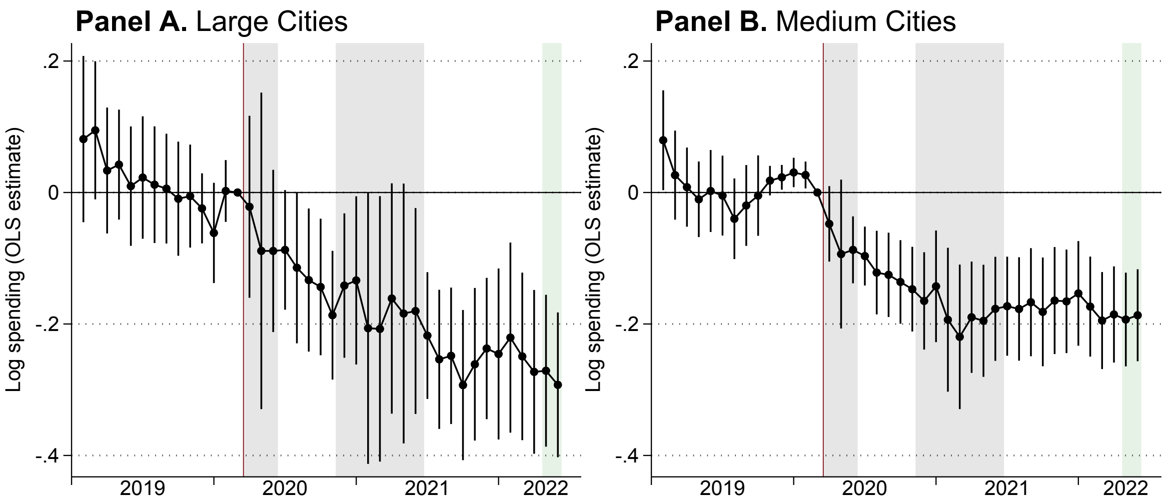
Notes: The figure plots the DiD estimates $\hat{\beta}^k$ on the interaction terms between standardized 2019 consumption intensity and monthly dummies (Equation 4.1). The dependent variables are average daily offline card spending overall (Panel A), spending in grocery and food stores (Panel B), spending in eating places (Panel C), and spending in apparel stores (Panel D). 95-percent confidence intervals are drawn using standard errors clustered at the postcode level. The vertical red line marks the outbreak of the Covid-19 pandemic between February and March 2020. The gray-shaded areas highlight lockdown periods, characterized by closures of non-essential businesses and other severe containment measures. The green-shaded area marks the period after March 2022, when nearly all restrictions were lifted. The consumer spending data comprise debit and credit card payments.

Figure D.5 : Composition of Spending from 2018 to 2022



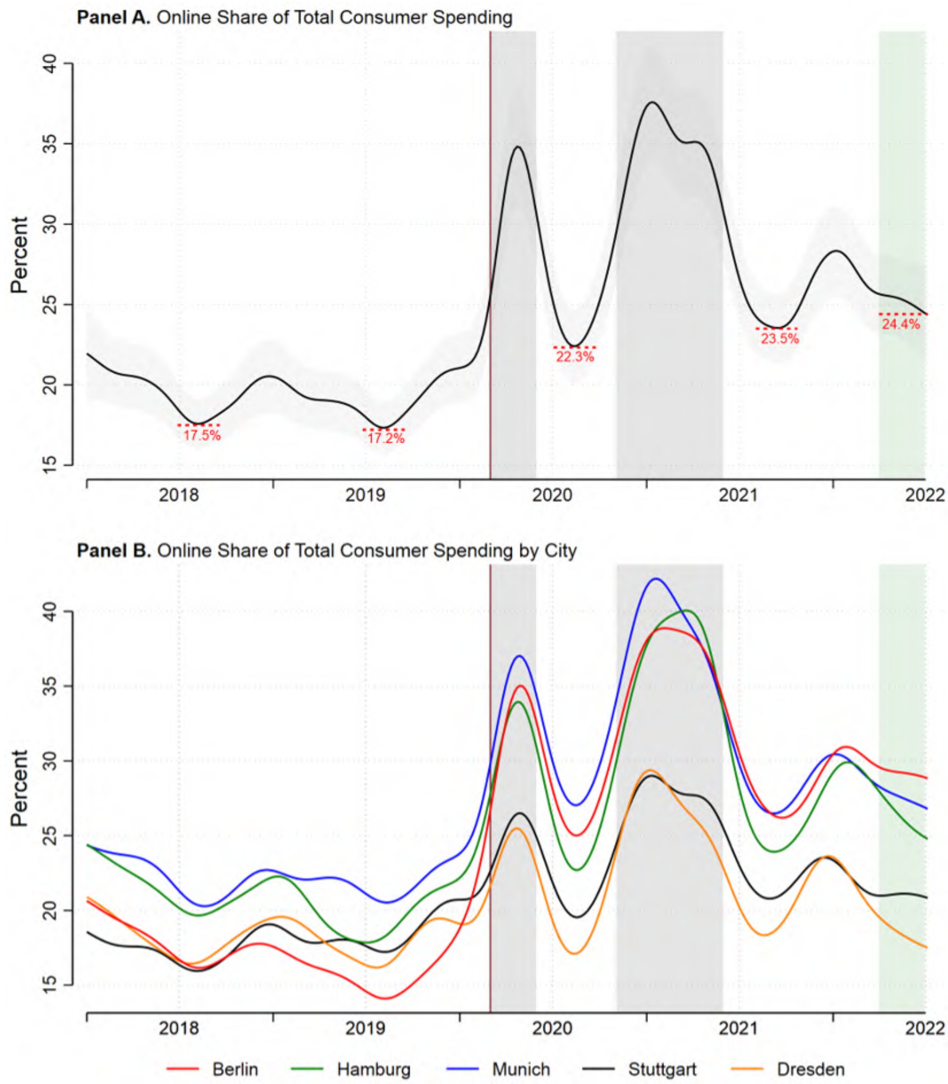
Notes: The stacked chart shows the composition of consumer spending from January 2018 through May 2022. The vertical red line marks the outbreak of the Covid-19 pandemic between February and March 2020. The gray-shaded areas highlight lockdown periods, characterized by closures of non-essential businesses and other severe containment measures. The green-shaded area marks the period after March 2022, when nearly all restrictions were lifted. The data come from Mastercard Spending Pulse, which comprises transaction information in the sample regions including online and offline spending.

Figure D.6 : DiD Results on the Association of Pre-Covid Consumption Intensity and Consumer Spending: Heterogeneity by City Size



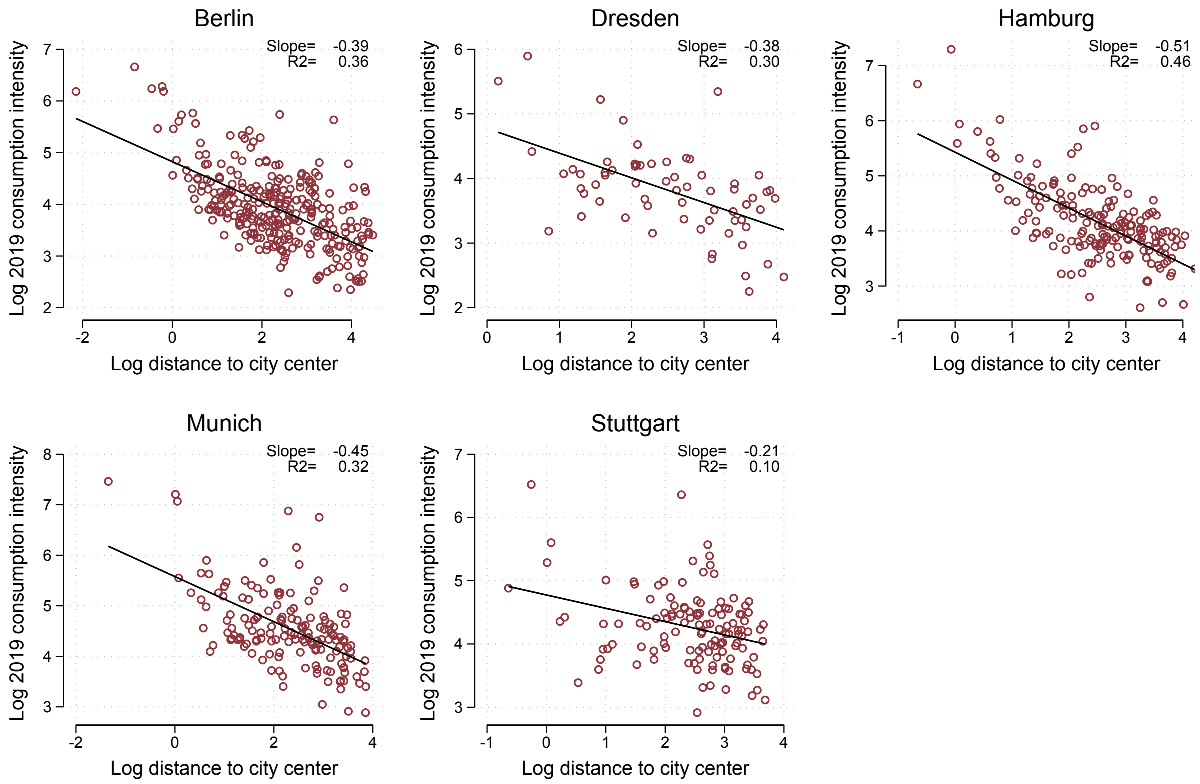
Notes: The figure plots the DiD estimates $\hat{\beta}^k$ on the interaction terms between standardized 2019 consumption intensity and monthly dummies (Equation 4.1). The dependent variables are average daily offline card spending overall in large cities (Panel A) and in medium cities (Panel B). Based on our sample, large cities are Berlin, Munich, and Hamburg, whereas medium cities are Stuttgart and Dresden. 95-percent confidence intervals are drawn using standard errors clustered at the postcode level. The vertical red line marks the outbreak of the Covid-19 pandemic between February and March 2020. The gray-shaded areas highlight lockdown periods, characterized by closures of non-essential businesses and other severe containment measures. The green-shaded area marks the period after March 2022, when nearly all restrictions were lifted. The consumer spending data comprise debit and credit card payments.

Figure D.7 : Share of Online Payments in Total Consumer Spending, 2018-2022



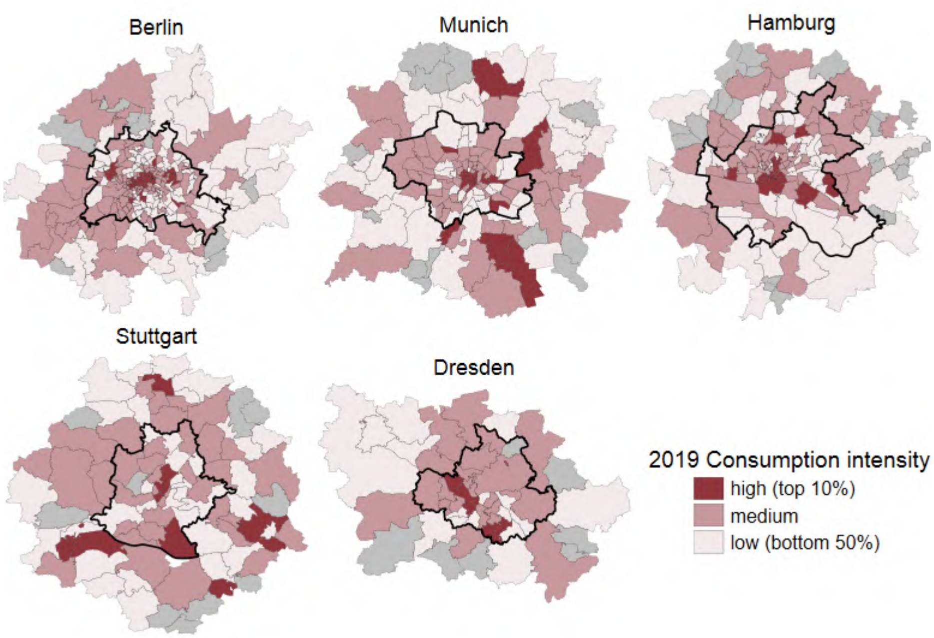
Notes: This figure shows smoothed daily online card payments as a share of total consumer spending from January 2018 through July 2022 (local polynomial smoothing). Panel A displays the weighted average of the five metro areas including the 95 percent confidence intervals. The values under the dashed red horizontal lines report the minima for the summers of each year. Panel B displays the same time series for each of the metro areas individually. The vertical red line marks the outbreak of the Covid-19 pandemic between February and March 2020. The gray-shaded areas highlight lockdown periods, characterized by closures of non-essential businesses and other severe containment measures. The green-shaded area marks the period after March 2022, when nearly all restrictions were lifted. The spending data are based on anonymized and aggregated transactions via cash, debit, and credit cards.

Figure D.8 : Distance to the City Center and 2019 Consumption Intensity by Metro Area



Notes: The figure plots the linear fit between log 2019 consumption intensity and log distance to the city center at the postcode level by metro area. All slopes are statistically different from zero at the one percent level. The consumer spending data comprise debit and credit card payments from *Mastercard* and the area characteristics data are provided by *infas360*.

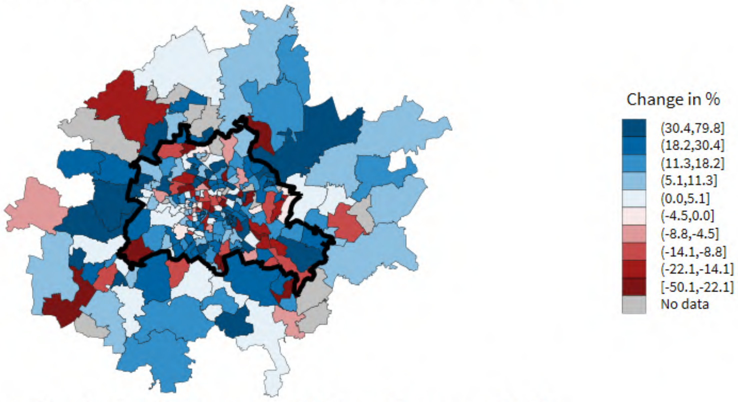
Figure D.9 : Spatial Distribution of 2019 Consumption Intensity



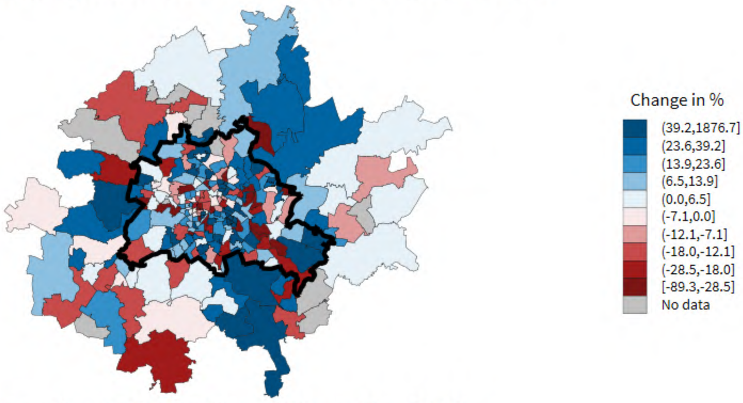
Notes: The figure displays the spatial distribution of 2019 consumption intensity at the postcode-level in the five sample cities and their surrounding areas. The black line marks the border between the city of Dresden and the surrounding municipalities. The classification distinguishes between high-consumption-intensity areas in dark red (top 10 percent of pre-pandemic spending), medium-consumption-intensity areas in light red, and low-consumption-intensity areas (bottom 50 percent of pre-pandemic spending) in very bright red. The consumer spending data comprise debit and credit card payments.

Figure D.10 : Spatial Changes in Offline Spending in the Berlin Metro Area

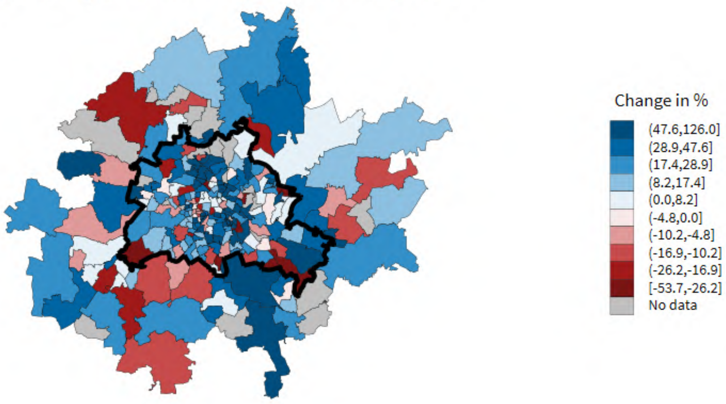
Panel A. Spending in Berlin Summer 2020 vs. Summer 2019



Panel B. Spending in Berlin Summer 2021 vs. Summer 2019

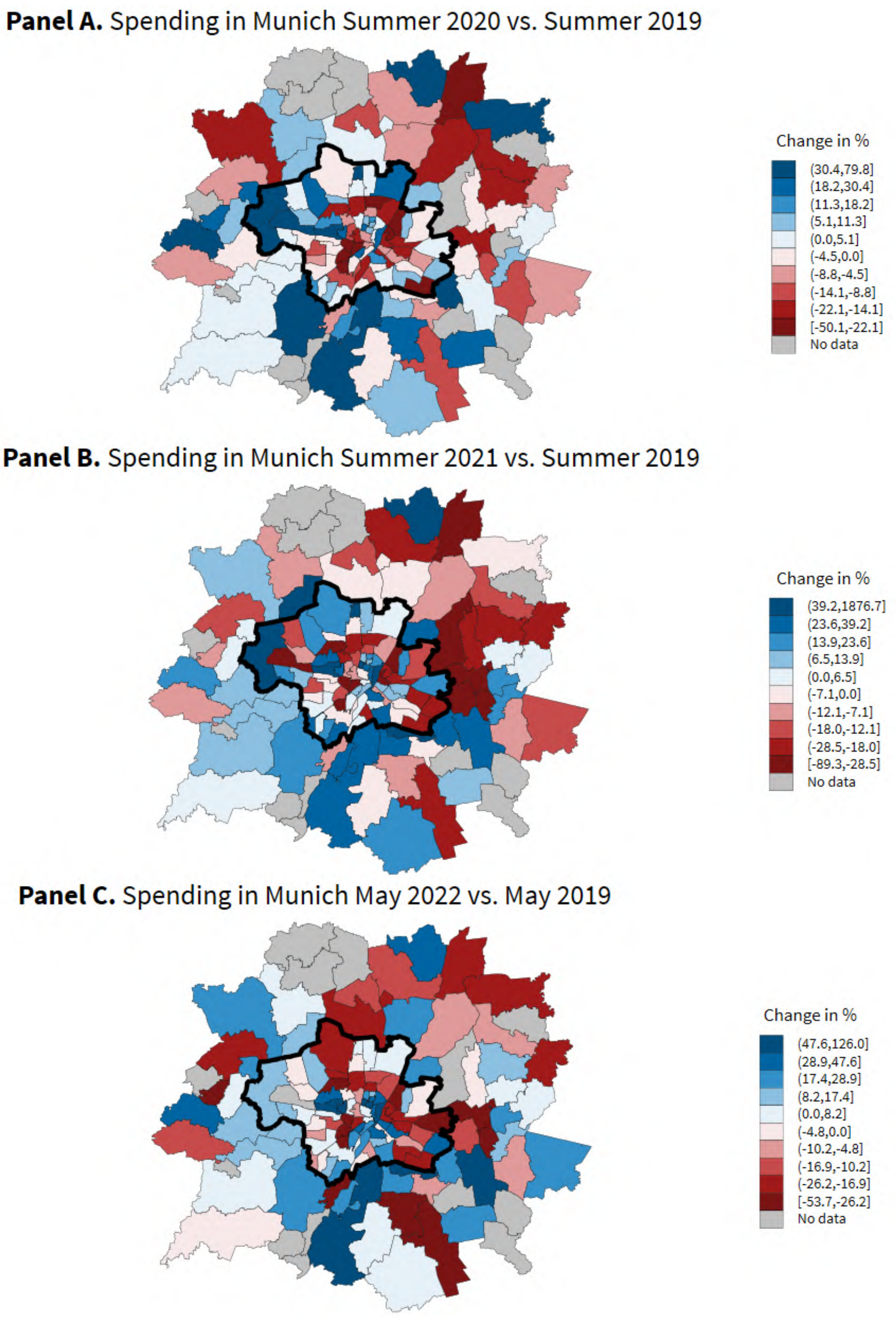


Panel C. Spending in Berlin May 2022 vs. May 2019



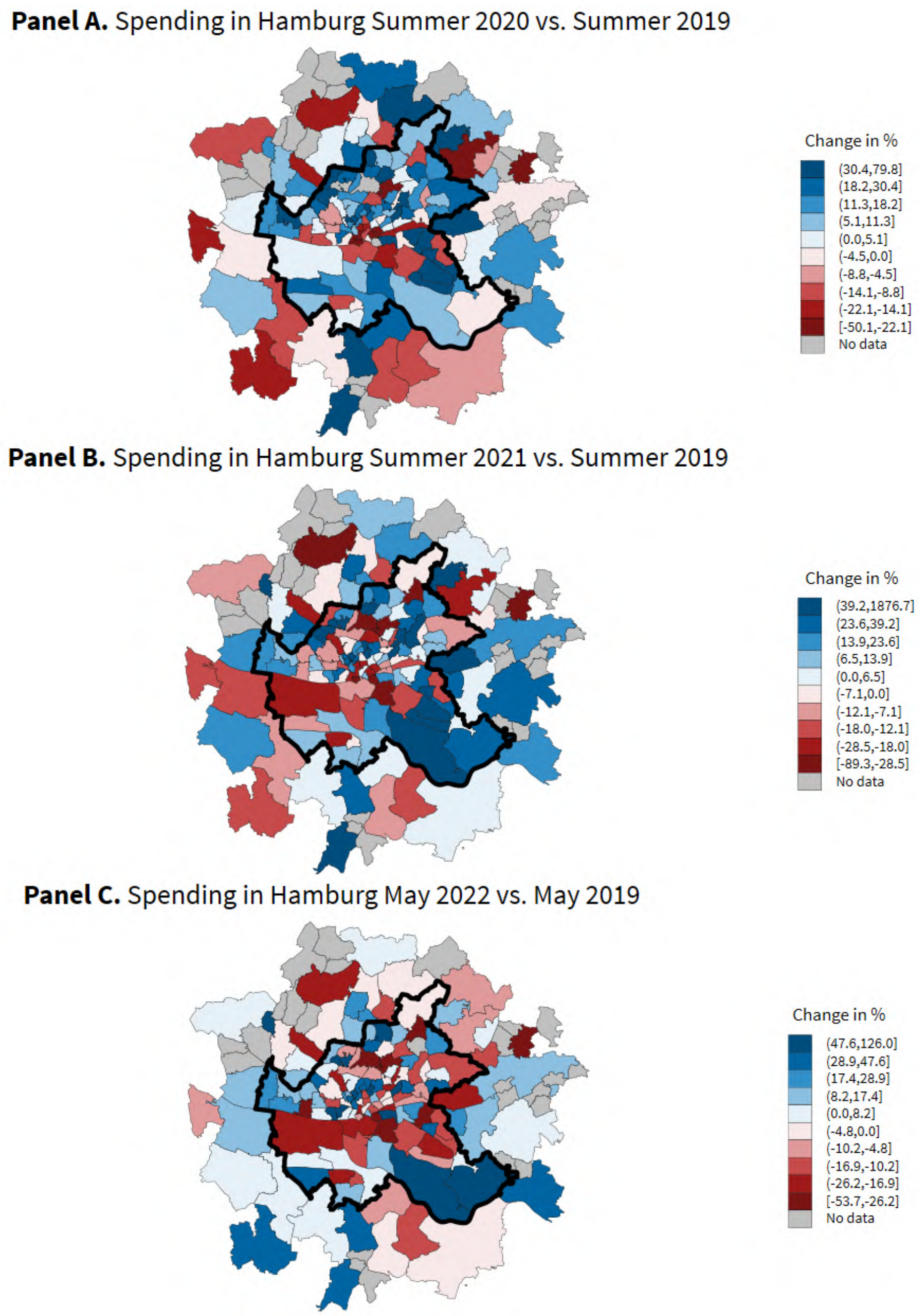
Notes: This figure shows changes in total offline spending by postcode in the metro area of Berlin. The black line marks the border between the city of Berlin and the surrounding municipalities. Panel A displays the changes in consumer spending in June-September 2020, Panel B shows the spending development in June-September 2021, and Panel C the most recent spending changes from May 2022 – all compared with the respective pre-pandemic period in 2019. The consumer spending data comprise debit and credit card payments.

Figure D.11 : Spatial Changes in Offline Spending in the Munich Metro Area



Notes: This figure shows changes in total offline spending by postcode in the metro area of Munich. The black line marks the border between the city of Munich and the surrounding municipalities. Panel A displays the changes in consumer spending in June-September 2020, Panel B shows the spending development in June-September 2021, and Panel C the most recent spending changes from May 2022 – all compared with the respective pre-pandemic period in 2019. The consumer spending data comprise debit and credit card payments.

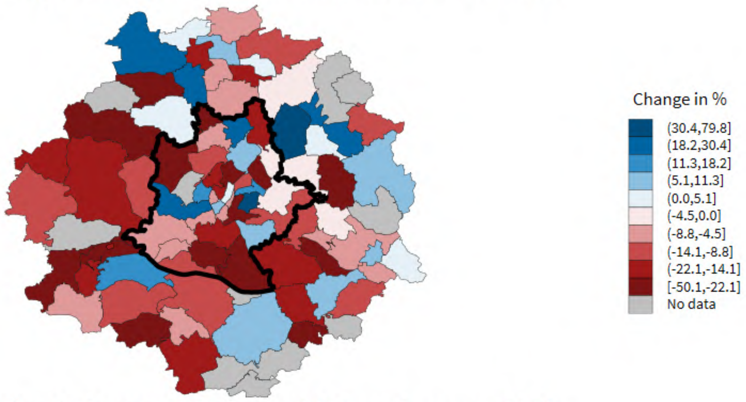
Figure D.12 : Spatial Changes in Offline Spending in the Hamburg Metro Area



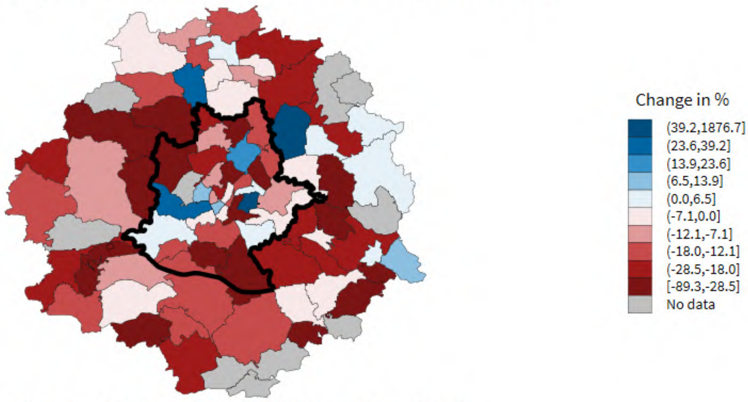
Notes: This figure shows changes in total offline spending by postcode in the metro area of Hamburg. The black line marks the border between the city of Hamburg and the surrounding municipalities. Panel A displays the changes in consumer spending in June-September 2020, Panel B shows the spending development in June-September 2021, and Panel C the most recent spending changes from May 2022 – all compared with the respective pre-pandemic period in 2019. The consumer spending data comprise debit and credit card payments.

Figure D.13 : Spatial Changes in Offline Spending in the Stuttgart Metro Area

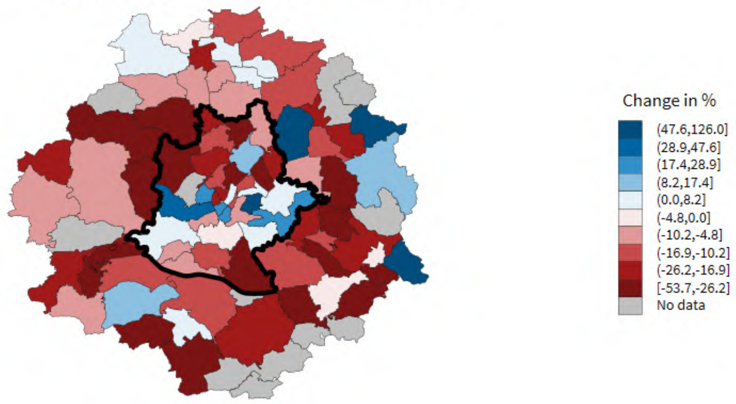
Panel A. Spending in Stuttgart Summer 2020 vs. Summer 2019



Panel B. Spending in Stuttgart Summer 2021 vs. Summer 2019

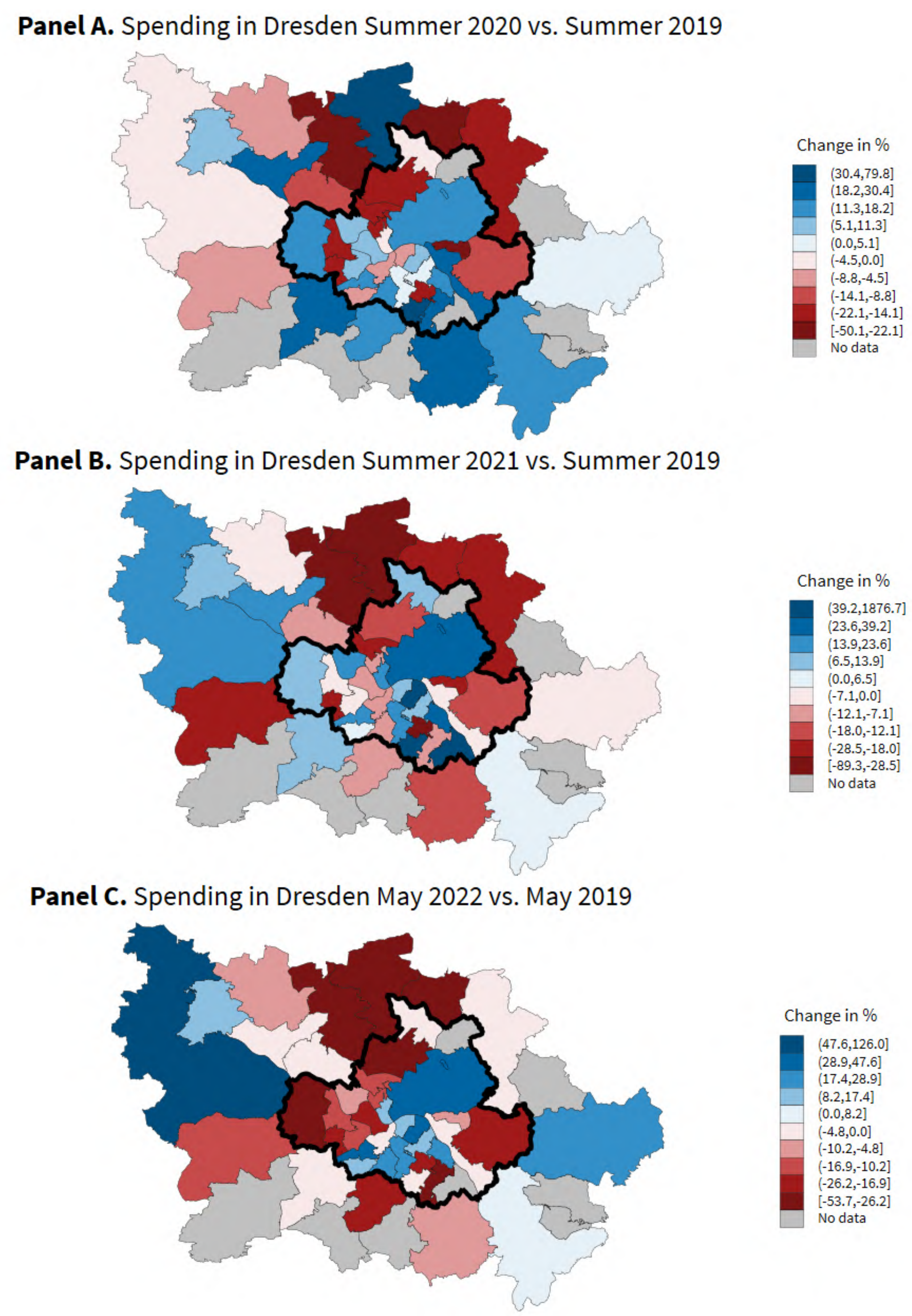


Panel C. Spending in Stuttgart May 2022 vs. May 2019



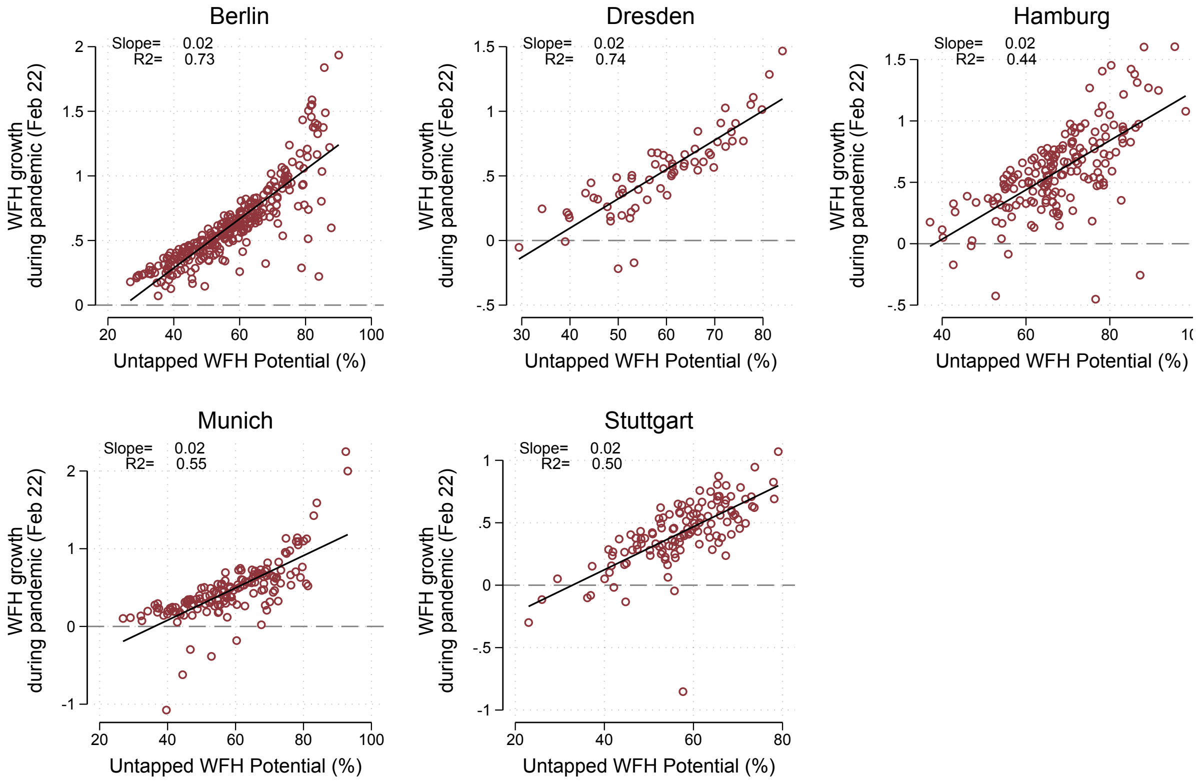
Notes: This figure shows changes in total offline spending by postcode in the metro area of Stuttgart. The black line marks the border between the city of Stuttgart and the surrounding municipalities. Panel A displays the changes in consumer spending in June-September 2020, Panel B shows the spending development in June-September 2021, and Panel C the most recent spending changes from May 2022 – all compared with the respective pre-pandemic period in 2019. The consumer spending data comprise debit and credit card payments.

Figure D.14 : Spatial Changes in Offline Spending in the Dresden Metro Area



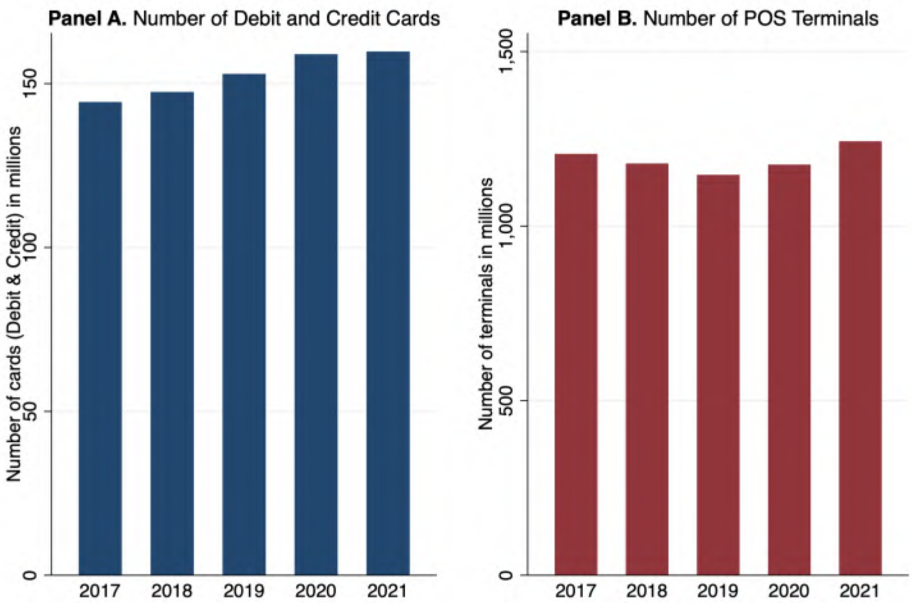
Notes: This figure shows changes in total offline spending by postcode in the metro area of Dresden. The black line marks the border between the city of Dresden and the surrounding municipalities. Panel A displays the changes in consumer spending in June-September 2020, Panel B shows the spending development in June-September 2021, and Panel C the most recent spending changes from May 2022 – all compared with the respective pre-pandemic period in 2019. The consumer spending data comprise debit and credit card payments.

Figure D.15 : Untapped WFH Potential and WFH Growth by Metro Area



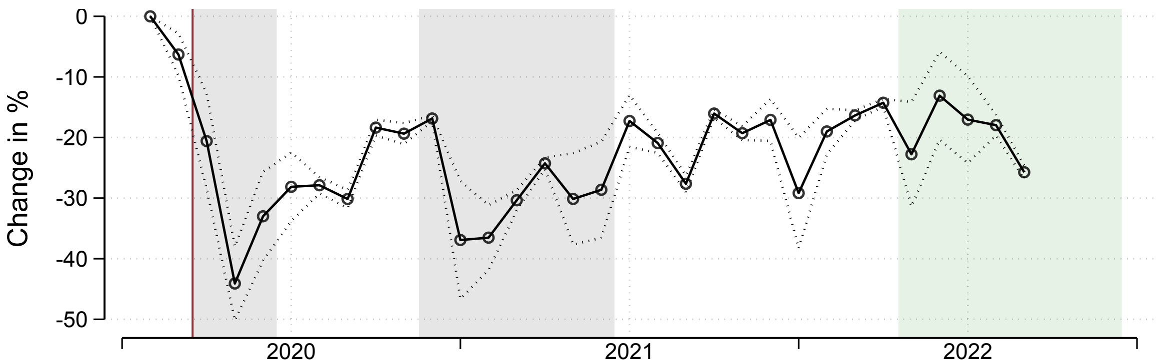
Notes: The figure plots the linear fit between local WFH growth during the pandemic (February 2020) and pre-Covid untapped WFH at the postcode level by metro area. All slopes are statistically different from zero at the one percent level. An auxiliary F-test cannot reject the hypothesis that the slopes are jointly equal to each other (p =0.13). Data are from *infas360*.

Figure D.16 : Number of Consumer Payment Cards and POS Terminals, 2017-2021



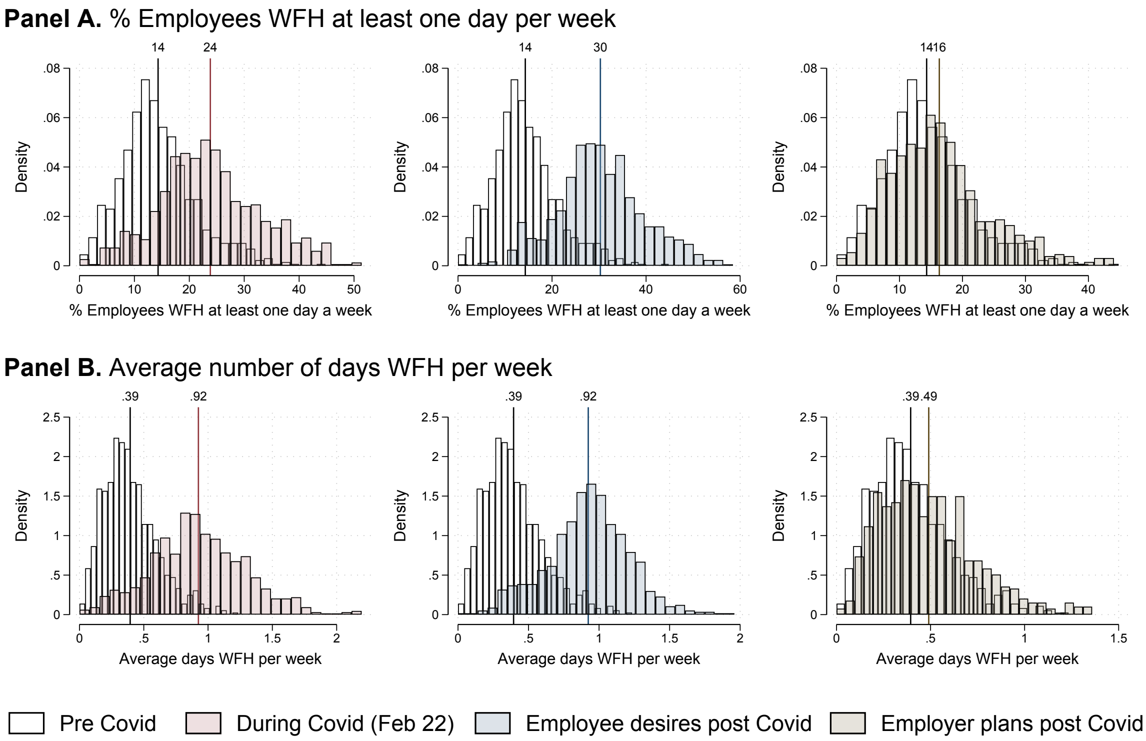
Notes: Panel A shows the development of the number of debit and credit cards issued in Germany from 2017 to 2021. Panel B shows the number of POS terminals used by merchants for accepting card payments during the same period. The data are from administrative payment statistics for Germany compiled by the European Central Bank.

Figure D.17 : Google Workplace Mobility in Germany



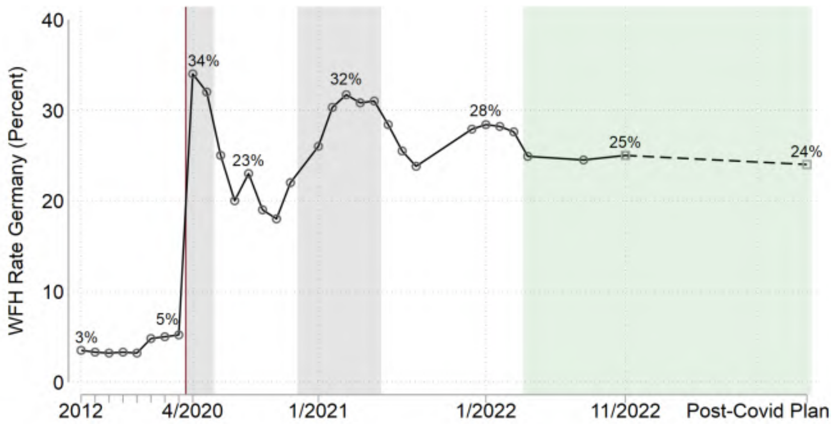
Notes: The figure plots Google's workplace mobility index for Germany. The index shows the average monthly percentage change in the number of workplace trips during business days (Mo-Fr) relative to January 2020 based on cellphone data. Dotted lines are the bootstrapped upper and lower bounds of the 95-percent confidence interval. The vertical red line marks the outbreak of the Covid-19 pandemic between February and March 2020. The gray-shaded areas highlight lockdown periods, characterized by closures of non-essential businesses and other severe containment measures. The green-shaded area marks the period after March 2022, when nearly all restrictions were lifted. The data are from Google (2022).

Figure D.18 : WFH before, during, and after the Covid-19 Pandemic



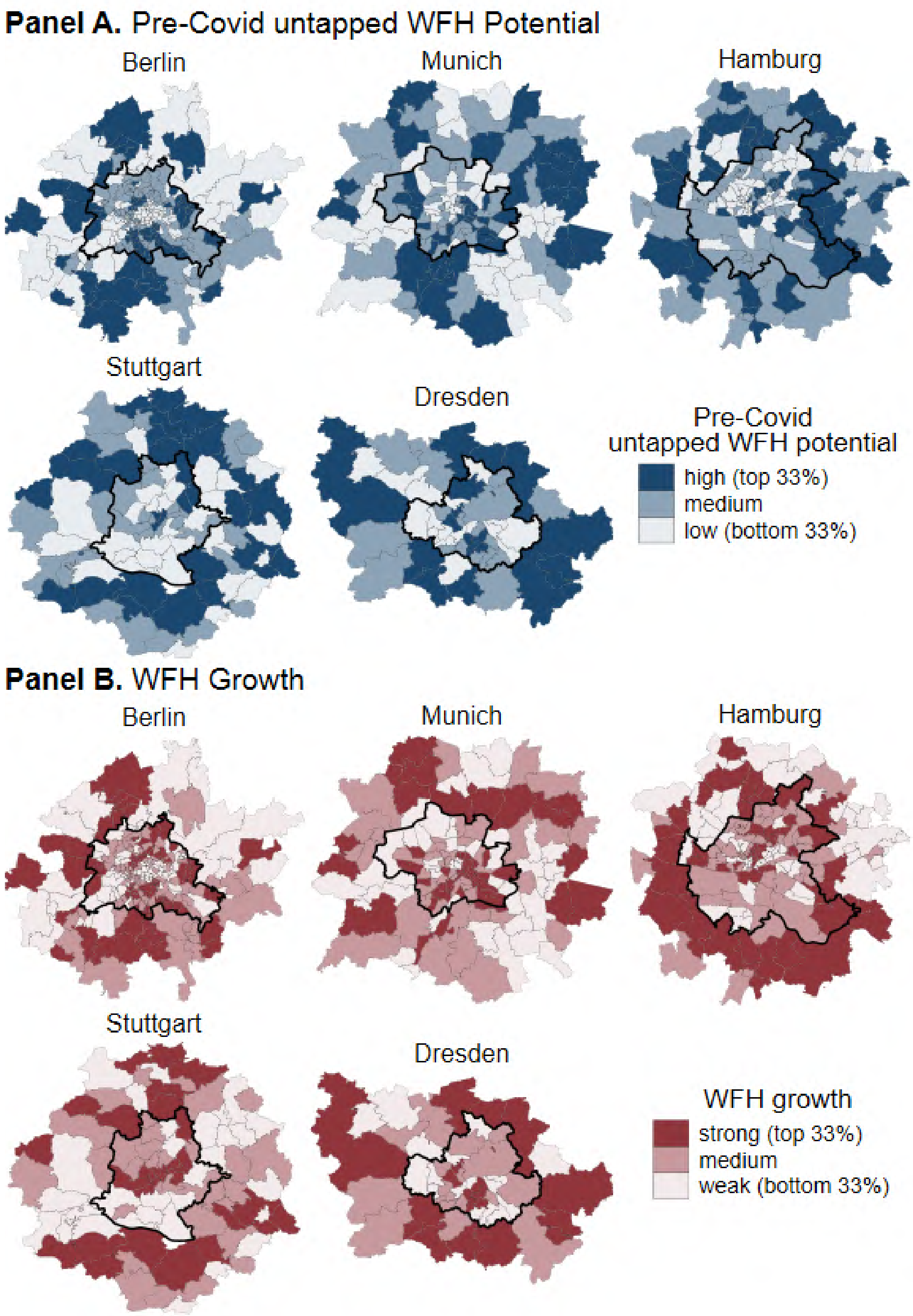
Notes: The figure plots histograms of the percentage of employees who WFH at least one day per week (Panel A) and of the average number of days of WFH per week (Panel B) pre-Covid, during Covid, according to self-reported desires for the post-Covid future, and according to employee-reported plans of their employers for the post-Covid future. Vertical lines highlight the mean of the distribution. The data are based on a representative survey conducted at the postcode level.

Figure D.19 : WFH Rate in Germany over Time



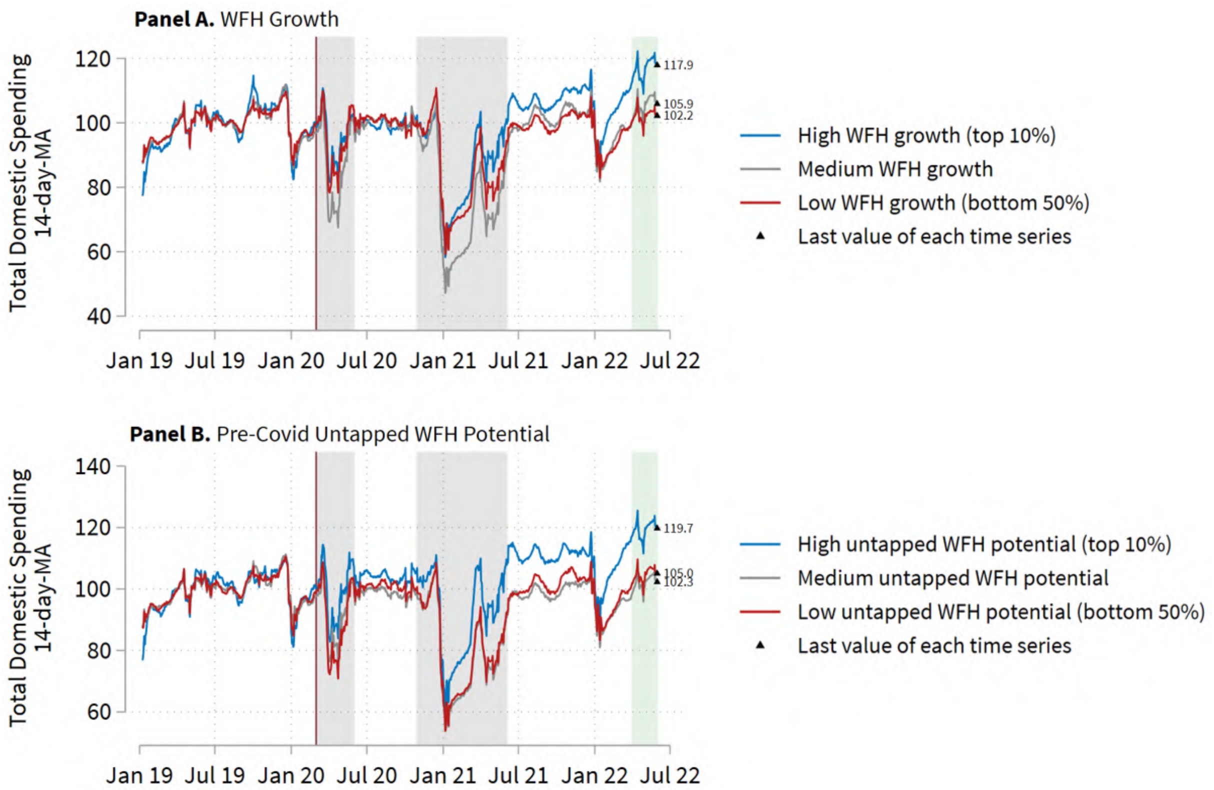
Notes: The chart shows the WFH rate in Germany since 2012, with the latest data point in November 2022 and including the post-Covid plans. The WFH rate is defined as the share of employees who WFH at least one day per week. The vertical red line marks the outbreak of the Covid-19 pandemic between February and March 2020. The gray-shaded areas highlight lockdown periods, characterized by closures of non-essential businesses and other severe containment measures. The green-shaded area marks the period after March 2022, when nearly all restrictions were lifted. The WFH data are based on Eurostat (2012–2019), infas360 and ifo Institute for Economic Research (2020–2022), and our representative survey for the post-pandemic WFH plans.

Figure D.20 : Spatial Distribution of Untapped WFH Potential and WFH Growth



Notes: The figure displays the spatial distribution of pre-Covid untapped WFH potential (Panel A) and WFH growth during the Covid-19 pandemic (February 2022) relative to pre-Covid levels (Panel B) for the five cities and their surroundings. Black solid lines delineate the core cities. Different shadings indicate whether postcodes belong to the top, medium, or bottom tercile of the city-specific distribution. The data are based on a representative survey conducted at the postcode level.

Figure D.21 : Spending Development by WFH Growth and Untapped Potential



Notes: The figure shows the evolution of offline spending by high, medium, and low WFH growth (Panel A) and pre-Covid untapped WFH potential (Panel B). Time series show 14-day moving averages normalized by the 2019 average in each category. The vertical red line marks the outbreak of the Covid-19 pandemic between February and March 2020. The gray-shaded areas highlight lockdown periods, characterized by closures of non-essential businesses and other severe containment measures. The green-shaded area marks the period after March 2022, when nearly all restrictions were lifted. The consumer spending data comprise debit and credit card payments.

D.2 Tables

Table D.1 : Summary Statistics

	Mean	SD	Min	Max
Panel A. Consumer Spending				
Total Spending (Index)	86.92	138.74	0.00	3376.07
2019 Consumption Intensity (Index)	90.62	132.54	9.50	1740.62
Panel B. Working From Home				
WFH Prior to Covid (Percent)	14.32	6.78	0.00	44.80
WFH Prior to Covid (Average Days per Week)	0.39	0.21	0.00	1.23
WFH Untapped Potential (Percent)	60.09	13.32	22.99	98.11
WFH During Covid (Percent)	23.84	9.24	0.00	51.38
WFH Growth (Percent)	83.84	76.35	-65.88	847.65
WFH Employee Desires After Covid (Percent)	30.28	9.28	0.00	58.48
WFH Employee Desires After Covid (Average Days per Week)	0.92	0.29	0.00	1.96
WFH Employer Plans After Covid (Percent)	16.33	7.93	0.00	44.04
WFH Employer Plans After Covid (Average Days per Week)	0.49	0.25	0.00	1.36
Panel C. Socioeconomic Indicators				
2019 Unemployment Rate	0.05	0.03	0.01	0.16
Purchasing Power (Per Capita)	25.53	5.90	15.39	51.69
Low-Income Households (Share)	0.22	0.18	0.00	0.88
Residents with Academic Degree (Share)	0.23	0.08	0.05	0.48
Living Space Per Household (sqm)	96.75	21.01	55.00	160.00
Average Rent (EUR/sqm)	9.51	2.64	5.25	18.47
Panel D. Population Structure				
Population	16291.22	7996.61	8	44608
Working Age Residents (Share)	0.66	0.05	0.51	0.88
Residents under 15 (Share)	0.14	0.02	0.02	0.27
Residents aged 65+ (Share)	0.20	0.05	0.04	0.39
Single Residents (Share)	0.30	0.12	0.11	0.77
Married Residents (Share)	0.38	0.09	0.12	0.56
Foreign Residents (Share)	0.15	0.10	0.01	0.53
Panel E. Area Characteristics				
Distance to City Center (km)	16.88	15.38	0.12	87.57
Residential Address Share (Percent)	61.74	17.62	0.00	86.04
Mixed-Use Address Share (Percent)	18.34	13.71	0.00	73.06
Commercial Address Share (Percent)	5.65	5.61	1.04	61.00
Panel F. Industry Composition				
Firms (Number)	1255.71	918.00	88.00	10914.00
Firm Density (Number per Inhabitant)	0.10	0.37	0.01	9.21
Manufacturing Firms (Share)	0.04	0.02	0.01	0.11
Food and Accommodation Firms (Share)	0.03	0.02	0.01	0.20
ICT Firms (Share)	0.04	0.02	0.00	0.13
Retail Firms (Share)	0.15	0.03	0.05	0.30
Financial Firms (Share)	0.05	0.02	0.01	0.14

Notes: The table reports summary statistics for 810 postcodes included in our sample. Payment data are from Mastercard (Panel A). WFH data and other postcode characteristics are collected and provided by infas360.

E Appendix to Chapter 5

E.1 Aggregating Trade Flows to the Industry Level

This section describes how trade flows from the CEPII-BACI database, recorded at the product level (6-digit level of the Harmonized System), are aggregated to the 4-digit level of the North American Industry Classification System (NAICS).

The mapping of products into industries is based on concordance tables developed by Pierce and Schott (2012). The table maps 10-digit HS product codes into 6-digit NAICS industry codes for the United States. Since HS labels are assigned consistently across countries only up to the 6th digit, it is impossible to match all products in the data with the corresponding industry in one step. Thus, for the remaining 1,687 HS codes, I apply a simple algorithm:

1. First, I investigate up to which level of disaggregation products are consistently assigned to the same industry. If all HS codes starting with the same j digits are mapped into the same 4-digit NAICS industry, I assign all unmatched products with the corresponding j digits to this industry. I follow this rule from a lower to a higher level of disaggregation. 1,398 out of 1,687 HS6 codes are matched in this way.

2. For 289 products in the sample, ambiguity exists at the 6-digit or higher level of the HS in the concordance table. Thus, each remaining product is matched to the industry to which most of its sub-products (at the 8- and 10-digit level) belong. 186 HS6 codes are matched in this way.

3. 103 HS6 products, which could not be successfully matched, are dropped from the analysis.

E.2 Tables and Figures

Table E.1 : Components of Industry-Level Complexity Measure

Tasks	Description
Work Activities	
Getting Information	Observing, receiving, and otherwise obtaining information from all relevant sources
Coordinating the Work and Activities of Others	Getting members of a group to work together to accomplish tasks
Interpreting the Meaning of Information for Others	Translating or explaining what information means and how it can be used
Provide Consultation and Advice to Others	Providing guidance and expert advice to management or other groups on technical, systems-, or process-related topics
Thinking Creatively	Developing, designing, or creating new applications, ideas, relationships, systems, or products, including artistic contributions
Making Decisions and Solving Problems	Analyzing information and evaluating results to choose the best solution and solve problems
Developing Objectives and Strategies	Establishing long-range objectives and specifying the strategies and actions to achieve them
Analyzing Data or Information	Identifying the underlying principles, reasons, or facts of information by breaking down information or data into separate parts
Processing Information	Compiling, coding, categorizing, calculating, tabulating, auditing, or verifying information or data.
Handling and Moving Objects*	Using hands and arms in handling, installing, positioning, and moving materials, and manipulating things
Operating Vehicles, Mechanized Devices, or Equipment*	Running, maneuvering, navigating, or driving vehicles or mechanized equipment, such as forklifts, passenger vehicles, aircraft, or watercraft
Updating and Using Relevant Knowledge	Keeping up-to-date technically and applying new knowledge to your job
Work Contexts	
Contact With Others	How much does this job require the worker to be in contact with others (face-to-face, by telephone, or otherwise) in order to perform it?
Work With Work Group or Team	How important is it to work with others in a group or team in this job?
Coordinate or Lead Others	How important is it to coordinate or lead others in accomplishing work activities in this job?
Importance of Repeating Same Tasks*	How important is repeating the same physical activities (e.g., key entry) or mental activities (e.g., checking entries in a ledger) over and over, without stopping, to performing this job?

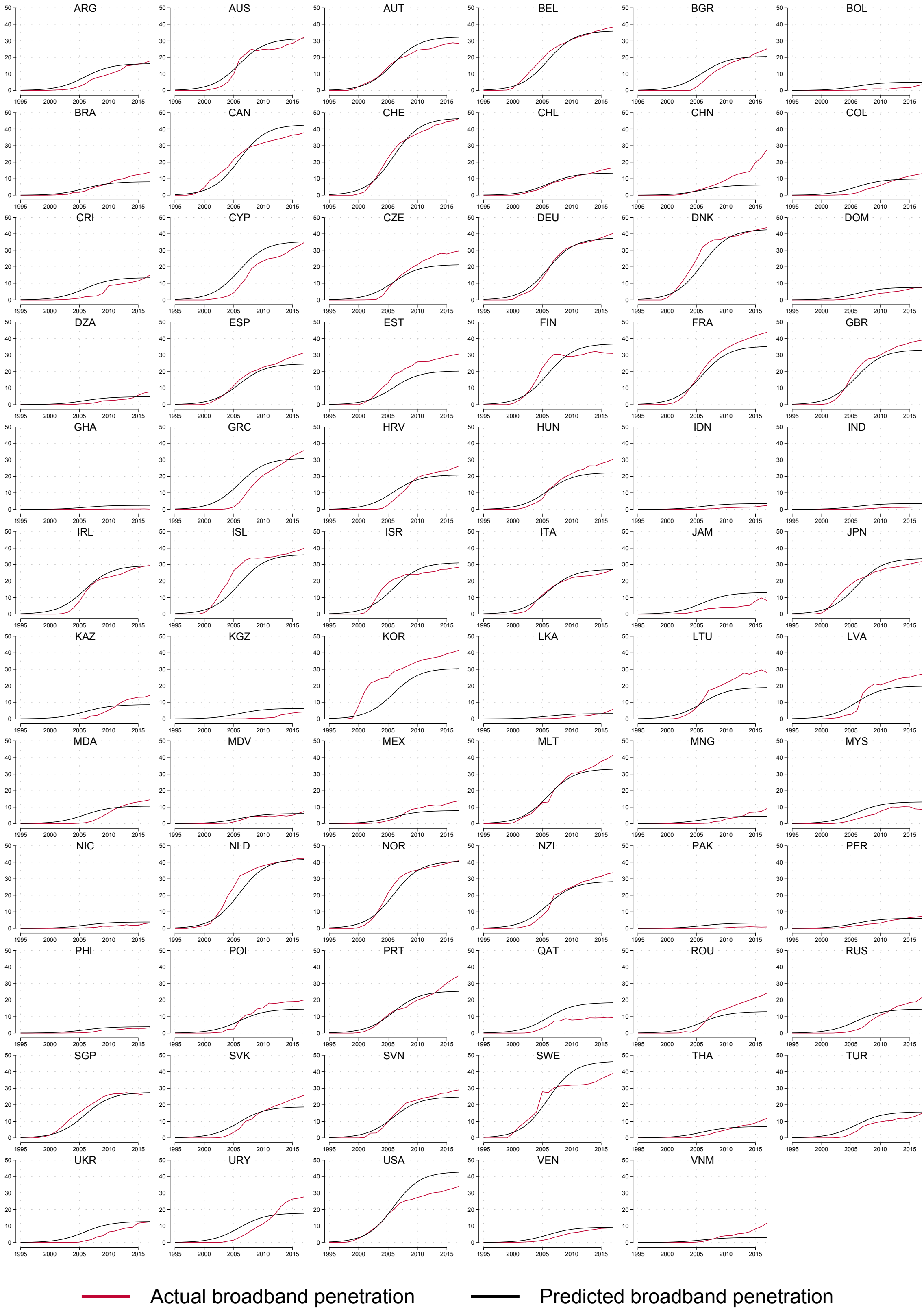
Notes: The table lists work activities and work contexts used to compute industry-level complexity (see Section 5.3.3). *Task enters complexity scores with inverted weights. Data are from O*NET.

Table E.2 : Industry-Level Complexity

	Industry (NAICS 4-digit)	Complexity
1	3341 Computer and Peripheral Equipment Manufacturing	15.50
2	3342 Communications Equipment Manufacturing	14.35
3	3345 Navigational, Measuring, Electromedical, and Control Instruments Manufacturing	14.29
4	3344 Semiconductor and Other Electronic Component Manufacturing	13.69
5	3364 Aerospace Product and Parts Manufacturing	13.65
6	3333 Commercial and Service Industry Machinery Manufacturing	13.41
7	3343 Audio and Video Equipment Manufacturing	13.35
8	3332 Industrial Machinery Manufacturing	13.19
9	3152 Cut and Sew Apparel Manufacturing	13.17
10	3254 Pharmaceutical and Medicine Manufacturing	13.17
11	3346 Manufacturing and Reproducing Magnetic and Optical Media	13.15
12	3391 Medical Equipment and Supplies Manufacturing	13.05
13	3159 Apparel Accessories and Other Apparel Manufacturing	12.95
14	3353 Electrical Equipment Manufacturing	12.89
15	3169 Other Leather and Allied Product Manufacturing	12.89
16	3351 Electric Lighting Equipment Manufacturing	12.85
17	3399 Other Miscellaneous Manufacturing	12.85
18	3339 Other General Purpose Machinery Manufacturing	12.84
19	3231 Printing and Related Support Activities	12.84
20	3369 Other Transportation Equipment Manufacturing	12.76
21	3325 Hardware Manufacturing	12.73
22	3162 Footwear Manufacturing	12.72
23	3149 Other Textile Product Mills	12.71
24	3336 Engine, Turbine, and Power Transmission Equipment Manufacturing	12.66
25	3359 Other Electrical Equipment and Component Manufacturing	12.61
26	3352 Household Appliance Manufacturing	12.60
27	3379 Other Furniture Related Product Manufacturing	12.60
28	3335 Metalworking Machinery Manufacturing	12.60
29	3361 Motor Vehicle Manufacturing	12.56
30	3331 Agriculture, Construction, and Mining Machinery Manufacturing	12.55
31	3322 Cutlery and Handtool Manufacturing	12.51
32	3334 Ventilation, Heating, Air-Conditioning, and Commercial Refrigeration Equipment Manufacturing	12.50
33	3329 Other Fabricated Metal Product Manufacturing	12.49
34	3372 Office Furniture (including Fixtures) Manufacturing	12.44
35	3133 Textile and Fabric Finishing and Fabric Coating Mills	12.39
36	3363 Motor Vehicle Parts Manufacturing	12.35
37	3122 Tobacco Manufacturing	12.33
38	3365 Railroad Rolling Stock Manufacturing	12.33
39	3362 Motor Vehicle Body and Trailer Manufacturing	12.25
40	3327 Machine Shops; Turned Product; and Screw, Nut, and Bolt Manufacturing	12.25
41	3256 Soap, Cleaning Compound, and Toilet Preparation Manufacturing	12.24
42	3371 Household and Institutional Furniture and Kitchen Cabinet Manufacturing	12.23
43	3241 Petroleum and Coal Products Manufacturing	12.18
44	3255 Paint, Coating, and Adhesive Manufacturing	12.16
45	3326 Spring and Wire Product Manufacturing	12.11
46	3141 Textile Furnishings Mills	12.04
47	3323 Architectural and Structural Metals Manufacturing	12.04
48	3118 Bakeries and Tortilla Manufacturing	12.01
49	3321 Forging and Stamping	12.01
50	3324 Boiler, Tank, and Shipping Container Manufacturing	12.01
51	3121 Beverage Manufacturing	11.99
52	3259 Other Chemical Product and Preparation Manufacturing	11.98
53	3251 Basic Chemical Manufacturing	11.95
54	3271 Clay Product and Refractory Manufacturing	11.93
55	3222 Converted Paper Product Manufacturing	11.93
56	3261 Plastics Product Manufacturing	11.92
57	3252 Resin, Synthetic Rubber, and Artificial Synthetic Fibers and Filaments Manufacturing	11.89
58	3272 Glass and Glass Product Manufacturing	11.88
59	3279 Other Nonmetallic Mineral Product Manufacturing	11.88
60	3366 Ship and Boat Building	11.85
61	3113 Sugar and Confectionery Product Manufacturing	11.81
62	3119 Other Food Manufacturing	11.81
63	3219 Other Wood Product Manufacturing	11.77
64	3161 Leather and Hide Tanning and Finishing	11.75
65	3151 Apparel Knitting Mills	11.75
66	3312 Steel Product Manufacturing from Purchased Steel	11.75
67	3314 Nonferrous Metal (except Aluminum) Production and Processing	11.73
68	3253 Pesticide, Fertilizer, and Other Agricultural Chemical Manufacturing	11.73
69	3111 Animal Food Manufacturing	11.71
70	3112 Grain and Oilseed Milling	11.67
71	3262 Rubber Product Manufacturing	11.64
72	3132 Fabric Mills	11.61
73	3315 Foundries	11.56
74	3131 Fiber, Yarn, and Thread Mills	11.54
75	3114 Fruit and Vegetable Preserving and Specialty Food Manufacturing	11.52
76	3115 Dairy Product Manufacturing	11.52
77	3117 Seafood Product Preparation and Packaging	11.52
78	3221 Pulp, Paper, and Paperboard Mills	11.51
79	3313 Alumina and Aluminum Production and Processing	11.50
80	3212 Veneer, Plywood, and Engineered Wood Product Manufacturing	11.46
81	3116 Animal Slaughtering and Processing	11.44
82	3273 Cement and Concrete Product Manufacturing	11.44
83	3274 Lime and Gypsum Product Manufacturing	11.42
84	3311 Iron and Steel Mills and Ferroalloy Manufacturing	11.30
85	3211 Sawmills and Wood Preservation	11.01

Notes: The table ranks manufacturing industries by the complexity of their production. Complexity is computed using O*NET data and US BLS employment statistics. See Section 5.3.3 for details.

Figure E.1 : Observed and Predicted Broadband Penetration



Notes: The figure plots actual and predicted domestic broadband penetration, defined as the number of subscriptions to fixed broadband Internet ($\geq$ 256 kbit/s downstream speed) per 100 inhabitants, for the period 1998-2017. Predicted broadband penetration is obtained from a nonlinear diffusion model (see Section 5.4.2 for details). Data is from the ITU's Telecommunication/ICT Indicators Database.

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