Essays on the Economics of Automation

Competition, Labor Market Power, and
Political Participation

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Contents

Preface

The technological marvels of automation are all around us today. In our daily lives, we might encounter robots that clean our carpets, chatbots that assist us in booking flights, or self-driving cars that offer relief during long journeys. This pervasive presence of automation extends beyond our homes into the workplace. In modern work environments, we see sophisticated software managing logistics, AI algorithms streamlining customer service processes, and even robotic arms assembling products on factory floors. Of course, using machines to do human work is nothing new from a historical perspective. What is new, however, is the speed at which automation technologies are becoming more capable, the speed at which they are diffusing throughout the economy, and the breadth of tasks they can perform, transforming occupations and the labor market.

The trends towards increasing automation over the last decades with advances in robotics and artificial intelligence have sparked concerns among policy makers, academics and the general public about the future of employment, wages and the economic inequality. Yet, providing high-level guidance on this phenomenon to policy makers, especially as it relates to labor, seems to remain a challenge. I experienced this first-hand, as I found myself tasked with providing policy advice on labor market implications at the International Labour Organization in 2019. I was then confronted with a lack of systematic evidence on the phenomenon, with existing data limited to statistics aggregated by industry or country. This made it challenging for economists to inform global labor policies on the factors shaping automation and its effects on workers, firms and regions. As I delved deeper into the topic, I came across similar findings from leading academic researchers. Some even specifically called on academics to explore firm-level data on the adoption of automation technologies and apply rigorous empirical methods to better understand their long-term impact on the economy and society as a whole (Raj & Seamans, 2018). This dissertation aims to bridge this gap.

This goal called for an innovative approach to analyzing existing and new data sources. To do so, I adopted a perspective that integrates data across multiple layers, from products to workers and firms at the local level. To draw causal inference, I applied a wide range of econometric methods, ranging from established instrumental variable approaches to novel sources of policy variation, experimental variation and state-of-the-art production function estimation techniques.

When I started my research in 2019, the state of the literature was limited to studies that looked at the impact of automation either at the level of industries or at the level of local labor markets. I therefore adopted a local approach and looked at automation in U.S. local labor markets. To expand beyond the labor market focus, I also combined some of my results with local data on political participation, thus allowing for an innovative analysis of the societal impact of automation on communities.

Shortly after I had started my research, a series of new studies were published showing that automation, and in particular the use of industrial robots, remains a concentrated phenomenon, with only a small proportion of companies using robots (Acemoglu, Lelarge, & Restrepo, 2020; Koch, Manuylov, & Smolka, 2021; Zolas et al., 2021; Deng, Plümpe, & Stegmaier, 2023). Against the backdrop of changing demographics and pressure on labor costs, I found this intriguing. Why would not all companies embrace automation? Why do some firms automate more than others? This led me to look at market dynamics in both product and labor markets as possible drivers of firms' incentives to automate. Much of the existing data, however, was limited to cross-sectional survey data, which did not allow for the systematic observation of firm-level investments in automation technologies over time. To overcome this challenge, I used administrative firm-level data from Portugal, as it encompasses specific customs data enabling me to trace imports of automation technologies. In addition, the firm-level data provides granular information that allowed me to quantify the labor market power of firms and situate them in local labor markets.

As I was seeking to understand the relationship between automation and labor, I focused on automation technologies that are characterized by a high degree of substitutability with human work, such as industrial robots and numerically controlled machinery. I took advantage of the fact that these automation technologies, designed for physical production tasks, were readily quantifiable and had diffused over several decades. One should note that this approach does not include automation technologies such as software automation and artificial intelligence, which have broadened the scope of automatable tasks to cognitive work.

As a result of this approach, this dissertation contains the following chapters: Chapter I studies the specific impact of exposure to industrial robots on the political participation of workers in federal elections across US local labor markets. Chapter II then explores how rising competition in global markets contributes to disparities in automation technology adoption among Portuguese manufacturing exporters. Chapter III presents a theory on how imperfect competition in labor markets influences firms' incentives to automate and moderates the effect of automation on wages and employment, looking at the role of employer concentration. To conclude, Chapter IV offers novel firm-level evidence documenting a positive association between labor market power and automation technology adoption among Portuguese manufacturers.

Overall, this dissertation provides novel insights for different scientific debates with concrete policy implications. For example, it feeds into discussions on how to sustain social cohesion in the context of technological disruption and how globalization shapes technological change. It also relates to debates on increasing market concentration and concerns about the labor market power of firms. Finally, it contributes to the debate on the causes of excessive automation and more broadly on the influence of market structure on incentives to innovate.

Chapter I explores the societal implications of automation by investigating its impact on political participation – a critical indicator of social connectedness, civic engagement, and the health of communities. Voting is an important way to influence social and economic transformations.[1] Yet, adverse economic conditions can affect the decision of individuals to participate in elections in complex ways. Economic hardship may spur increased electoral participation as a form of grievance expression or could lead to diminished turnout due to feelings of disenfranchisement or a lack of resources. These effects might be especially pronounced in cases of structural changes with long-term impacts on labor markets, such as those caused by automation. As shifts in political participation ultimately affect the alignment of new public policies with the citizens' preferences, it is important to understand how structural change due to automation interacts with political participation at the local level.

To address this question, this chapter adopts a local labor market approach that quantifies the exposure of US commuting zones to industrial robot adoption. We use this methodology to assess the impact of local robot exposure on county-level voter turnout

[1] A preprint version of this chapter is available as Chugunova, Keller, and Samila (2021). Structural Shocks and Political Participation in the US. Max Planck Institute for Innovation & Competition Research Paper No. 21-22.

in US federal elections from 2000 to 2016. We also take a comparative perspective, considering the local exposure to Chinese import competition – a major cause of structural transformation in US manufacturing during this period. The comparative analysis aims to determine if the effect of automation on political participation differs from other structural changes. Our findings confirm prior research showing negative effects of local exposure to both robots and Chinese imports on employment and income in U.S. local labor markets. However, we uncover contrasting effects on voter turnout. While we find significant negative effects of robot exposure on turnout in both Presidential and House of Representatives elections, our results indicate no impact or positive effects from Chinese import exposure in Presidential and House elections, respectively.

We investigate potential mechanisms behind these differential effects at the micro level. Using survey data on voter turnout, we confirm our main finding, showing that individuals more exposed to automation tend to participate less at presidential elections, unlike those exposed to Chinese imports. Moreover, we conduct an online survey experiment to examine potential motivations for turnout, presenting respondents with scenarios of job loss due to automation or trade. While both shocks are perceived to have considerable long-term impacts on workers, the experiment reveals that respondents see layoffs due to automation as more inevitable and beyond federal government intervention than those resulting from import competition. This suggests that individuals affected by automation might view voting as less effective than those exposed to import competition. At the same time, respondents exposed to the automation scenario agreed more strongly that layoffs lacked sufficient political attention. Our experiment thus highlights the perceived low value of voting and insufficient political attention in the context of automation as potential factors explaining the observed negative association between automation and voter turnout.

Our research adds nuance to the literature on voter behavior in times of economic hardship by showing that political participation is shaped not only by changes in income but also by the perceived efficacy of voting in particular contexts. This insight holds important implications for policy makers, especially in the context of labor market disruptions caused by automation. To prevent civic disengagement and enhance democratic participation, our results indicate the need for targeted strategies beyond traditional institutions and safety nets to address the unique challenges posed by technological change. This approach can help ensure that technological advances, while disruptive, take into account the needs of workers and citizens and do not undermine social cohesion.

Chapter II begins with the observation that, despite the general trend toward industrial automation over the past few decades, there are significant disparities in the adoption of automation technologies across firms, industries, and regions in high- and middle-income countries (Cheng et al., 2019; Brynjolfsson et al., 2023; Deng, Plümpe, & Stegmaier, 2023).[2] Understanding the drivers of automation technology adoption is crucial, as automation promises significant productivity gains while also carrying substantial labor market and distributional effects. To this end, this chapter examines the role of product market competition during the era of hyper-globalization in the 1990s and 2000s, a period characterized by intense global market integration and significant pressure on firms to reduce labor costs. Theory suggests that increased competition might either spur defensive innovation to cope with labor cost pressure or diminish investment due to declining market share. Compared to other investments, industrial robots offer higher labor substitutability, essential for cost reduction, yet involve substantial fixed costs of adoption. To clarify theoretical ambiguities and to assess the specific implications of competition in automation, it is essential to examine the relationship empirically.

We leverage a unique combination of administrative microdata from Portugal to study automation in a sample of manufacturing exporters during an episode of major trade liberalization. To measure firms' investments in automation equipment, we use detailed customs data that tracks imports of key automation equipment, in particular industrial robots and numerically controlled machinery. Our identification strategy exploits the comprehensive tariff liberalization between the European Union (EU) and Central and Eastern European Countries (CEECs) in the 1990s as an exogenous shock to market entry and competition, particularly affecting Portuguese exporters reliant on the EU market. More specifically, we build a Bartik-style instrument of firm-level exposure to tariff reductions by combining firm-product-level data on firms' export portfolios with product-level data on EU import tariffs. Our identifying assumption is that the extent of tariff reductions across products was exogenous to Portuguese firms and unrelated to Portuguese trade policy interests, since initial tariff levels reflected European Economic Community MFN tariffs set before Portugal's accession in 1986.

We provide robust evidence that the tariff liberalization increased competitive pres-

[2] A preprint version of this chapter is available as Bastos, Flach, and Keller (2023). Robotizing to compete? Firm-level evidence. Max Planck Institute for Innovation & Competition Research Paper No. 23-23.

sures and significantly affected firms' export performance. We find that more exposed firms experienced a sharp decline in exports to the EU, reduced product variety as well as export prices, likely reflecting a reduction in markups in the EU market. We also document lower employment growth among more exposed firms, resulting in substantial reductions in the total wage bill. Finally, we find that firms more exposed to product market competition on average reduced investments in automation, both at the intensive and extensive margin. However, when scrutinizing industries that are highly prone to automation, we observe that more productive firms respond to tariff reductions by increasing their automation investment in contrast to less productive firms. This finding suggests that in industries where automation is most prevalent, increased competition tends to discourage automation investment by less competitive firms while encouraging automation by industry leaders.

The contrasting result has important implications for how product market competition influences automation technology adoption in high-income countries. Our findings suggest that competition can act as a catalyst for increased automation among industry leaders while discouraging such investments in less competitive firms. Thereby, we add nuance to the debate on the impact of globalization on innovation and automation in manufacturing. The findings also offer a new explanation for the limited and concentrated diffusion of automation, highlighting how increasing competition may reinforce existing disparities in automation adoption among firms, industries, and regions.

Chapter III investigates the role of competition in labor markets for the adoption of automation technologies.[3] It takes as its starting point the growing evidence that the consolidation of manufacturing industries, together with the rise of "superstar" firms in the context of globalization, has increased employer concentration and amplified labor market power in many high- and middle-income countries in recent decades (De Loecker, Eeckhout, & Unger, 2020; Felix, 2021; Yeh, Macaluso, & Hershbein, 2022; Bighelli et al., 2023). As labor market power significantly affects firms' labor costs, it is important to understand how the trend in rising labor market power can affect the adoption of automation technologies. This chapter sheds light on this complex relationship by providing a theoretical framework and empirically testing model predictions in the context of US local labor markets.

The main contribution of this study is the insight that in firms with monopsony power,

[3] A preprint version of this chapter is available as Azar et al. (2023). Monopsony and Automation. Max Planck Institute for Innovation & Competition Research Paper No. 23-21.

automation can affect the total wage bill in two ways: by reducing the wage bill through reduced hiring, and by reducing the wages of the remaining workers due to the monopsonist's effect on local market wages. We formalize this intuition in a micro-founded model of the economy where firms internalize the wage effect of automation when choosing the share of tasks allocated to humans versus those automated by machines. In this model, technological change is modeled as an increase in the share of automatable tasks. Our model yields two important insights. First, if the equilibrium level of automation in a competitive economy is below the highest technically possible level of automation, introducing labor market power increases automation. Second, increases in the technological frontier of automation can lead to larger employment and wage reductions in local labor markets with high labor market power if the technological frontier is binding for monopsonistic firms but not for those in competitive labor markets.

To test the predictions of our model, we study the effect of improvements in industrial robot technology on employment and wages in US local labor markets over the period 1990 to 2015 and test how effects are moderated by differences in local labor market power. As in Chapter I, we calculate the exposure of local labor markets to industrial robots by combining information on the industry composition of employment in U.S. commuting zones with data on industry trends in industrial robot adoption in high-income countries. In addition, we consider the initial level of employer concentration in the local labor market as a proxy for the level of labor market power. Our analysis not only confirms that more exposed commuting zones experienced lower employment and wage growth, but also provides novel evidence that this effect was significantly more pronounced in areas with higher levels of employer concentration. This finding is consistent with our model predictions and offers first evidence for the potential influence of labor market power on robot adoption.

Our theoretical and empirical results show that imperfect competition in labor markets can increase firms' incentives to adopt automation technologies, leading to negative second-order effects on employment and wages. Thereby, we show concrete conditions under which firms could automate beyond a level that would be a optimal in competitive market. In doing so, we contribute novel insights to the debate on the causes of over-automation. This finding has first important policy implications. Our results suggest that the increase in the labor market power of U.S. manufacturing firms in recent decades may have led, in part, to excessive automation (Acemoglu & Restrepo, 2020b; Traina, 2022; Yeh, Macaluso, & Hershbein, 2022). However, the restricted access to firm-level data on the adoption of automation technologies in the U.S. context prevents us from demonstrating this mechanism at the micro level.

In **Chapter IV**, I take the analysis of labor market power and automation to the next level by systematically examining the relationship in firm-level data. Providing systematic evidence on this relationship is crucial because it helps to better understand how imperfect competition in labor markets can affect the adoption of automation technologies. Building on the model presented in Chapter III, I test the central prediction that firms with more labor market power have greater incentives to invest in automation. Testing this hypothesis poses two significant challenges. First, it requires a rare combination of data that allows measuring both firms' investment in automation and their labor market power, the latter of which is not directly observable. Second, it is necessary to identify contexts that allow for exogenous variation in labor market power in order to disentangle the inherent endogeneity of market power and automation investments. This chapter aims to address both of these challenges.

To overcome the first challenge, I use administrative micro-level data on manufacturing firms in Portugal from 2004 to 2020. These data provide not only measures of firms' automation investments, but also information on production inputs and outputs, which allows estimating labor market power. Specifically, I implement a production function estimation that allows computing firm-specific markdowns - the gap between the marginal product of labor and wages - as a function of output elasticities and revenue shares of inputs. I document considerable variation in estimated markdowns across firms, both within and across industries, suggesting imperfect competition in Portuguese manufacturing labor markets. The main analysis reveals a significant positive correlation between markdowns and each automation proxy. Specifically, machinery capital intensity and industrial robot imports show strong correlations in cross-sectional data, while machinery investment shows a similar pattern in panel data. These results provide initial evidence in support of the hypothesis of a positive relationship between labor market power and automation.

To further establish causality, I exploit the unexpected introduction of tolls on previously toll-free highways in Portugal in 2010. This event serves as an exogenous shock to commuting costs, thereby affecting the labor market power of local employers by reducing the mobility of workers living near the affected highways. Specifically, I incorporate this event into an instrumental variable framework. My analysis reveals a moderate positive effect of the toll introduction on markdowns. While I find partial evidence of a positive influence of markdowns on machinery investment, limited instrument strength and exogeneity do not allow for definitive conclusions from this case study.

This study presents new micro-level evidence of a positive relationship between labor market power and automation. The results suggest that imperfect competition in labor markets can affect technology adoption and increase automation in manufacturing, potentially leading to higher levels of automation than in a competitive labor market. This result has important policy implications. First, it implies that increasing market concentration could potentially accelerate automation trends. Second, it also suggests that one way for policymakers to protect workers from the effects of excessive automation is ensure that labor markets remain competitive, for example through policies that limit firms' wage-setting power and strengthen worker mobility. Overall, this chapter advances our understanding of the relationship between market power and technological change.

In conclusion, this thesis reflects my thought process and continual discovery of the complex phenomenon of automation. It has allowed me to deepen my personal thinking and contribute to bridging the gap of lacking micro-level evidence that I identified as a junior policy researcher. My work demonstrates how existing datasets can be used in innovative ways to answer emerging research questions. It also shows how academic research can contribute to policymaking when public administrations successfully integrate datasets across agencies and make them available to researchers.

This work sheds new light on the complex phenomenon of automation, yet our knowledge of it remains incomplete. Looking ahead, it provides us with a few research avenues to explore. My work was focused on evidence in the context of high-income countries, which is where the development and diffusion of automation technologies started. To recognize automation as a global phenomenon going forward, it will be necessary to dedicate specific attention to emerging economies. This could help improve our understanding of the role of automation in economic development.

Finally, my work also leads us to reflect upon the role of labor market power, not only for adoption incentives, but also for the pass-through of significant productivity gains from automation technologies to wages and workers. This seems particularly important in light of recent advances in automation technologies, such as generative AI, which automate workers' tasks but also show important complementarities with other tasks they perform. Understanding how workers who improve their productivity through the use of such tools can also benefit from long-term productivity gains will likely be another important area for future research. Such research could inform policies to ensure that automation technologies, while disrupting the world of work, remain technological marvels that contribute to shared prosperity.

1

Structural Shocks and Political Participation in the US

1.1 Introduction

Voter turnout is a key indicator of civic engagement, social connectedness, and trust as well as a critical nexus where economic phenomena intersect with the democratic process (Putnam, 2000; Adler & Goggin, 2005). In this light, understanding the dynamics of voter turnout is essential for grasping how individuals relate to broader societal and economic shifts. These relationships are especially pronounced in the context of structural changes such as globalization and automation, which not only redefine labor markets but also have profound distributional effects (D. Autor, Dorn, & Hanson, 2013; Acemoglu & Restrepo, 2020a). Such transformations can lead to significant income losses for certain demographic groups (Dauth, Findeisen, & Suedekum, 2014; Dauth et al., 2021). The resulting economic challenges are often at the root of changes in individual voting behavior, which in turn affects election outcomes and ultimately public policies (Colantone & Stanig, 2018; Anelli, Colantone, & Stanig, 2019; D. Autor, Dorn, Hanson, Majlesi, et al., 2020). This interplay underscores the notion that structural change is not simply an inevitable force, but is shaped by collective choices, and highlights the critical role of political participation in guiding these changes in ways that are consistent with the public interest and sustain the legitimacy of democracy (Lijphart, 1997; Horiuchi & Saito, 2009; Fowler, 2013, 2015; Grillo, 2019; D. Autor, 2022).

The distributional consequences of structural change can affect voter turnout, but the link between the two is complex and multifaceted, with contrasting possible outcomes: economic adversity could spur increased turnout as a form of grievance expression, or lead to reduced turnout due to feelings of disenfranchisement or lack of resources (e.g., Rosenstone, 1982). The academic consensus on how economic conditions influence voter turnout remains elusive, with empirical evidence yielding mixed results (Smets & van Ham, 2013; Cancela & Geys, 2016). Moreover, much of the existing research has focused on the immediate aftermath of income shocks, neglecting the long-term and spatially concentrated effects of labor market downturns caused by structural change (e.g., Charles & Stephens Jr, 2013; Jungkunz & Marx, 2022; Schafer et al., 2022; Bellettini et al., 2023).

To fill the gap in this critical area of research, we consider how the persistent effects of trade and automation on labor markets affect voter turnout over time. Addressing this question is important for several reasons. First, it allows for a more nuanced understanding of how economic policies and changes affect democratic engagement and social cohesion. Second, it provides insights into the mechanisms through which affected groups may become politically marginalized, potentially leading to cycles of inadequate representation and misaligned public policies. Such cycles risk exacerbating the very economic challenges these policies seek to address, underscoring the importance of aligning economic transformations with the democratic will and well-being of populations. By examining the impact of trade and automation, this research seeks to illuminate the intricate connections between structural change and electoral participation, and to provide a more informed understanding of how to navigate the challenges and opportunities presented by these significant economic shifts.

In this paper, we examine the effect of two major structural changes in the U.S. economy - the long-term labor market adjustment to industrial robots and Chinese imports - on voter turnout in federal elections across U.S. counties between 2000 and 2016.[1]

[1]This chapter is the result of a collaboration with Marina Chugunova and Sampsa Samila. A preprint version of this chapter is available as Chugunova, Keller, and Samila (2021). Structural Shocks and Political Participation in the US. Max Planck Institute for Innovation & Competition Research Paper No. 21-22.

We follow the methodology of Acemoglu and Restrepo (2020a) and D. Autor, Dorn, and Hanson (2013) to construct measures of local exposure to industrial robots as well as import competition from China. To establish the validity of our approach, we first estimate the causal effect of both structural shocks on employment and income using the same shift-share instrumental variable strategy. We confirm the established finding that both automation and import competition from China lead to lower employment growth and comparable declines in average household income at the level of local U.S. labor markets.[2] We then estimate the effect of commuting zone exposure to industrial robots and to Chinese imports on long-term changes in county-level voter turnout in both U.S. presidential and U.S. House of Representatives elections over two 8-year election cycles between 2000 and 2016.[3]

We document a significant negative association between commuting zone exposure to industrial robots and changes in county-level voter turnout in both types of federal elections. We find that a one standard deviation increase in robot exposure reduces presidential turnout by 1 percentage point, or that one robot per thousand workers reduces turnout by about 13 voters. Given the average increase in the U.S. stock of robots over the 8-year period, our estimates suggest that increasing exposure to robots reduced presidential turnout by about 1 million voters. In contrast, we find that exposure to rising imports from China has no effect on presidential turnout and a positive effect on turnout in U.S. House elections. The differential response of political participation to robots and Chinese import penetration is robust to controlling for differences in the net migration rate, swing state status, or the intensity of political campaigning at the county level.

Further analyses confirm this main result and shed light on the underlying mechanisms. Using individual-level data from the *General Social Survey*, we find that the decline in voter turnout is concentrated among those most at risk of automation. To explore the mechanisms behind the differential effects, we examine different motivations for absenteeism in an online survey experiment. While both shocks are perceived as equally important, respondents perceive layoffs due to automation as more inevitable and the federal government as less able to address them than in the import

[2] While the average decline in income is comparable between the two shocks, they are not identical. For example, the effect of trade competition was found to be more concentrated in manufacturing employment (Faber, Sarto, & Tabellini, 2019). See section 1.4 for a discussion of the potential differences and their impact on our results.

[3] The reference years of 2000, 2008, and 2016 cover critical elections in which two-term incumbents (Bill Clinton, George W. Bush, and Barack Obama, respectively) left office and long-term policy directions were set.

competition scenario. This result is consistent with the nature of the shock affecting the expected utility of voting. Finally, a complementary analysis of political campaigns confirms the link between lower voter turnout and lower attention to political parties. Regions exposed to automation are targeted by fewer and cheaper advertisements during political campaigns. We also document a mismatch. In regions affected by automation, political advertisements focus more on unemployment due to increased trade competition and less on social security issues. These latter findings may explain why political parties are reluctant to campaign on technology-related issues, and instead divert voters' attention to other political issues (Gallego & Kurer, 2022).

The contribution of our paper is threefold. First, we extend the literature on the political and social consequences of structural change (Feigenbaum & Hall, 2015; D. Autor, Dorn, Hanson, Majlesi, et al., 2020; Caprettini & Voth, 2020) by examining a new margin through which technological change affects its own long-run trajectory, voter turnout. Second, we contribute to the literature on the economic determinants of political participation (Smets & van Ham, 2013; Cancela & Geys, 2016; Markovich & White, 2022) by providing a causal analysis of the effect of two recent labor market shocks on political participation in the United States. Our framework allows us to show that the relationship between them is not uniform, i.e., negative income shocks do not always affect political participation in the same way. Third, we extend work on the underlying mechanisms that link structural economic change and individual political behavior and empirically test several of these mechanisms (for overview, Gallego & Kurer, 2022). We find that a more nuanced approach to political participation is needed. Namely, it is not only the change in income that matters for political participation, but also the reason for this change.

The rest of the paper proceeds as follows. In Section 1.2, we outline the empirical strategy for both the regional and the individual level analyses. In Section 1.3, we present the data and in Section 1.4 the results of regional- and individual-level analyses. In Section 1.5, we consider why the nature of the shock may matter for its effect on political participation and present the evidence from the survey experiment. Section 1.6 briefly discusses the potential role of political campaigning, and Section 1.7 concludes.

1.2 Empirical Strategy

1.2.1 Local-level Analysis

We apply a difference-in-differences framework pioneered by seminal studies on the local labor market effects of trade (D. Autor, Dorn, & Hanson, 2013) and automation (Acemoglu & Restrepo, 2020a). This approach captures the long-run general equilibrium adjustment to differential exposure to exogenous shocks to labor demand in US local labor markets and therefore considers changes in employment over periods of 7 years or more at the level of 722 continental US commuting zones (CZ).[4]

We follow this approach to identify the long-run effect of automation and Chinese import competition on political participation at US federal elections and estimate the following model:

$$\Delta log(Y_{j,c,t}) = \beta^r \begin{pmatrix}\text{US Exposure} \\ \text{to Robots}\end{pmatrix}_{c,t} + \beta^c \begin{pmatrix}\text{US Exposure to} \\ \text{Chinese Imports}\end{pmatrix}_{c,t} + \mathbf{X'}_{c,2000}\,\gamma + \mathbf{Z'}_{j,t}\,\delta + \epsilon_{j,c,t} \quad (1.1)$$

where, in our main result, $Y_{j,c,t}$ stands for the number of votes at US federal elections in county j in commuting zone c at time t. We estimate the model by stacking log differences over two 8-year periods: 2000-2008 and 2008-2016.[5] We control for unobserved period-specific regional trends by interacting census division with period indicators. Hence, our main regression identifies the coefficients β^r and β^c from variation in exposure to labor market shocks between CZs in a given time period and census division. Following Borusyak, Hull, and Jaravel (2022), we add lagged manufacturing shares interacted with period indicators to control for any unobserved shocks specific to the manufacturing sector overall in each period.[6]

[4]Commuting zones are groups of counties that constitute local labor markets in which workers seek employment to adjust to changes in labor demand (see Tolbert & Sizer, 1996)

[5]Each period covers two four-year terms of US Presidents and four two-year terms of the US House of Representatives. We consider the number of votes at the beginning and the end of each 8-year period.

[6]Borusyak, Hull, and Jaravel (2022) point out the need to control for the lagged manufacturing share in commuting zone employment when using the measure of commuting zone exposure to Chinese imports by D. Autor and Dorn (2013). Borusyak, Hull, and Jaravel (2022) argue that the sum of lagged manufacturing shares across industries used to build the exposure instrument is not constant across locations and periods and in most cases does not sum up to 1. As a consequence, regions with higher manufacturing shares are at risk of having systematically different values of the instrument, which can bias the estimate when these regions also show differences in unobservables. While D. Autor, Dorn, and Hanson (2013) control for the start-of-period manufacturing share of commuting zone employment, Borusyak, Hull, and Jaravel (2022) show that this is not enough to avoid leveraging non-experimental variation that stems from differences in the sum of shares across regions over time in addition to quasi-experimental variation in industry import shocks. This can only be achieved by accounting for the lagged manufacturing shares interacted with period indicators.

We also include $\mathbf{X'}_{c,2000}$, a vector of commuting-zone baseline characteristics in 2000, to allow for differential trends due to observable differences in demographics (age, education, gender and ethnic composition) or in the exposure to offshoring (share of routine employment, offshorability index) as in Faber, Sarto, and Tabellini (2019). In addition, we account for a series of potential contemporaneous confounds $\mathbf{Z'}_{j,t}$, such as the period-specific net migration rate, changes in the share of college-educated adults, the swing state status and the average spending on TV campaign ads per household in 2008 and 2016. At last, we also control for differential pre-trends in voting over the period 1992 to 2000.[7]

Exposure to robots: Following Acemoglu and Restrepo (2020a) we construct a shift-share measure of commuting zone exposure to industrial robots in each period, mapping changes in the stock of industrial robots per worker in 19 US industries into the 1990 employment structure of US commuting zones.[8] Accordingly, in each period for each commuting zone we compute the sum of changes in the stock of industrial robots R_i^{US} in an industry i relative to the total number of workers in an industry i in 1990, subtracting the growth of the robot stocks due to real output growth $g_{i,t:t+1}^{US}$ over the period, weighted by $l_{c,i,1990}$, the share of industry i in total employment in commuting zone c in 1990:

$$\begin{array}{c}\text{US Exposure to} \\ \text{Robots}_{c,t}\end{array} \equiv \sum_{i \in I} l_{c,i,1990} \left(\frac{R_{i,t+1}^{US} - R_{i,t}^{US}}{L_{i,1990}^{US}} - g_{i,t:t+1}^{US} \frac{R_{i,t}^{US}}{L_{i,1990}^{US}} \right) \tag{1.2}$$

When regressing the US exposure to robots on various measures of political participation, there are reasons to believe that the exposure measure could be correlated with the error term. For instance, it is possible that both the adoption of industrial robots and political participation are a function of unobserved changes in the US local labor market conditions, such as changes in the strength of unions. If unions are less able to organize workers and bargain for higher wages due to changes in legislation in certain states (e.g. right-to-work laws), firms could face lower incentives to introduce labor-saving technologies while workers are becoming less politically engaged. Therefore, we construct an instrumental variable as in Acemoglu and Restrepo (2020a) using changes in the penetration of robots in an industry i in five European countries ahead of the US in terms of the adoption of robot technology (Denmark,

[7]Note that our voting data only starts in 1992 and does not cover periods prior the China or robot shocks (e.g., the 1970s or 1980s), which could otherwise be used for placebo regressions.

[8]Our notation differs slightly from that of Acemoglu and Restrepo (2020a), where robots are denoted by the letter M. Instead, we use R for robots and M for imports from China.

Finland, France, Italy, and Sweden) and the lagged share of industry i in total employment in commuting zone c in 1970 to predict US adoption of robots only due to exogenous improvements in technology:

$$\begin{array}{c}\text{Exposure to}\\ \text{Robots}_{c,t:t+1}\end{array} \equiv \sum_{i \in I} l_{ci,1970} \, \frac{1}{5} \sum_{j \in EU5} \left(\frac{R^{EU5}_{i,t+1} - R^{EU5}_{i,t}}{L^{EU5}_{i,1990}} - g^{EU5}_{i,t:t+1} \frac{R^{EU5}_{i,t}}{L^{EU5}_{i,1990}} \right) \tag{1.3}$$

The identifying assumption of this strategy is that there are no differential shocks or trends affecting voting in commuting zones with greater exposure to robots relative to those with less exposure.

Exposure to Chinese imports: In addition, we construct a commuting zone exposure to Chinese imports for each period following D. Autor, Dorn, and Hanson (2013) as the sum of changes of merchandise imports from China to the US relative to the total number of workers in an industry i weighted by the share of each manufacturing industry i in total commuting zone employment in c at the beginning of each period:

$$\begin{array}{c}\text{US Exposure to Chinese}\\ \text{Imports}_{c,t:t+1}\end{array} \equiv \sum_{i \in I} l_{ci,t} \left(\frac{M^{CN-US}_{i,t+1} - M^{CN-US}_{i,t}}{L^{US}_{i,t}} \right) \tag{1.4}$$

Also this second explanatory variable could be correlated with the error term, for instance when an exogenous increase in income, e.g. the fracking boom, leads to higher demand for imported consumer products but also affects the likelihood of citizens to engage with politics. To mitigate the possible bias from omission and simultaneity, we construct an instrumental variable as in D. Autor, Dorn, and Hanson (2013) using imports of Chinese goods by eight high-income countries as well as lagged employment shares $l_{ci,t-1}$ in order to isolate the export supply shock stemming from China's accession to the WTO and its market-oriented reforms in the 2000s.[9]

$$\begin{array}{c}\text{Exposure to Chinese}\\ \text{Imports}_{c,t:t+1}\end{array} \equiv \sum_{i \in I} l_{ci,t-1} \left(\frac{M^{CN-OT}_{i,t+1} - M^{CN-OT}_{i,t}}{L^{US}_{i,t}} \right) \tag{1.5}$$

Section A.3 in the Appendix provides a detailed description of the data sources used to construct all measures of commuting zone exposure to robots and Chinese imports.

[9] These countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland.

1.2.2 Individual-level Analysis

To refine our main set of results and to test the relationship between the exposure to different labor market shocks and political participation at the individual level, we study microdata from the *General Social Survey* (GSS) on political behavior and attitudes and estimate the following regression model at the individual level:

$$\begin{gathered} GSS_i = \beta_1 \begin{array}{c}\text{Ind. exposure to}\\ \text{Robots}_{i,t}\end{array} + \beta_2 \begin{array}{c}\text{Ind. exposure to}\\ \text{Chinese Imports}_{i,t}\end{array} + \\ \beta_3 \begin{array}{c}\text{US exposure to}\\ \text{Robots}_{c,t-1:t}\end{array} + \beta_4 \begin{array}{c}\text{US exposure to Chinese}\\ \text{Imports}_{c,t-1:t}\end{array} + \alpha_{d,t} + \epsilon_i \end{gathered} \tag{1.6}$$

where, for each GSS survey question, GSS_i corresponds to the answer of a respondent i, in commuting zone c, in a census division d in year t. We estimate this regression using data from all nine biannual waves of the GSS from 2000 to 2016 and restrict the sample to individuals with age between 18 and 65. This yields a baseline sample of more than 12,000 individuals who provided information on their participation at the last presidential election.[10]

Individual exposure to robots: We develop a novel indicator to measure individual exposure to automation from 2000 to 2016, using data on occupational exposure to automation from Webb (2019), which assesses the semantic overlap of O*Net job task descriptions and titles and abstracts of robotics patents. However, correctly assigning the Webb automatability scores to individuals requires addressing the endogeneity of observed occupations, as highlighted by Anelli, Colantone, and Stanig (2019). Specifically, a worker's current occupation may be a response to displacement by automation. To mitigate this issue, we leverage GSS data from 1980 and 1989, preceding the automation surge, to construct a multinomial logit model. This model predicts occupational choices based on the vector of individual characteristics, denoted by $\mathbf{x}_i$, including age, education, gender, father's occupation, and regional background at age 16 (9000 observations, Pseudo-R2=0.1759). This framework enables us to project out-of-sample occupational choice probabilities for individuals between 2000 and 2016, yielding counterfactual scenarios less likely influenced by the automation trend. The accuracy of these out-of-sample predictions is demonstrated in Appendix Figures A.5 and A.6.

[10]The number of observations for each question varies across questions and is lower than the overall sample size, as some questions are not asked to all survey participants and not in every wave.

We calculate each individual's exposure to automation by aggregating the Webb (2019) automatability scores, denoted as θ_o. These scores, assigned at the 2-digit census occupation level, are weighted according to the predicted probability of an individual working in occupation o:

$$\text{Individual Exposure to Robots}_i = \sum_{o=1}^{14} \left(\hat{Pr}(Occ = o|\mathbf{x}_i) \times \theta_o \right) \tag{1.7}$$

It is important to note that the automatability scores from Webb (2019) are static, reflecting the state of technological capabilities at the time of observation, specifically as observed in patents in the late 2010s. Consequently, these scores do not account for the dynamic evolution of robotic capabilities over time.

Individual exposure to Chinese imports: We further quantify individual exposure to imports from China by analyzing the growth rate of these imports across manufacturing industry groups i over eight-year periods. A critical consideration is the endogeneity of an individual's observed industry, which may be influenced by structural changes induced by import competition. In other words, a worker's current industry might reflect a shift away from sectors more directly impacted by this competition. To address this, we employ again data from the General Social Survey from 1980 and 1989, prior to the China trade shock. We map the industry codes observed in the GSS to 19 broad industry groups, similar to those used in the IFR dataset on industrial robots. This dataset is used to estimate a multinomial logit model for predicting industry choice based on age, education, gender, father's occupation, and census region at the age of 16 (11,000 observations; Pseudo-R2= 0.1204). This methodology allows us to derive out-of-sample predictions for industry choice probabilities for workers between 2000 and 2016, generating a set of counterfactuals that are presumably less influenced by the China trade shock. Figures A.7, A.8 and A.9 in the Appendix show the out-of-sample prediction accuracy.

We calculate the exposure of individual i at time t to the Chinese import shock as the weighted sum of growth rates of imports from China to eight high-income countries in industry j since *t-8*. The weights are determined by the predicted choice probability to work in an industry j.

$$\text{Individual Exposure to Chinese Imports}_{i,t} = \sum_{j=1}^{19} \left(\hat{Pr}(Ind = j|\mathbf{x}_i) \times \frac{M^{j,t} - M^{j,t-8}}{M^{j,t-8}} \right) \tag{1.8}$$

1.3 Data

1.3.1 Political Participation

To study political participation at the county level, we use data from Dave Leip's Atlas of U.S. Elections (Leip, 2021) on the total number of votes in US presidential and House of Representative elections by county in years 2000, 2008 and 2016. This data source provides county level election results based on official reports for all states. With this data, we compute the log changes in the total number of votes as a measure of political participation at the county level. To control for the contemporaneous change in a county's underlying population of eligible voters that might explain differential growth in voting, we use US Census estimates for the total number of adult citizens (citizen voting age population, CVAP). This is our preferred measure of the voting population as it is available for counties in all US states and is unaffected by unobserved differences and changes in voter registration or the share of foreign residents.[11]

To account for potential changes in the underlying population structure of the county, which could be influenced by structural shocks, we analyze the log changes in the total number of votes while *controlling* for the citizen voting age population. This approach differs from measuring political participation as a share of cast votes from the citizen voting age population, ensuring that any observed effects are not solely a result of a change in the population of eligible voters. We report the qualitatively similar results of the analysis with the alternative measure of votes per citizen of voting age population in the Appendix.

For robustness, we also consider estimates of the total number of adult residents (voting age population, VAP) per county provided by the US Census. Yet, this measure comes with the disadvantage of hiding important regional differences in the share of foreign residents in the adult population.[12] Finally, we also consider the number of registered voters per county as provided by Leip (2021). Yet, this measure comes with the disadvantage of being affected by regional differences in voter registration practice as well as policy changes regarding voting registration. Apart from that, voter

[11] Data for the year 2000 comes from the decennial census. Data for years 2008 and 2016 are 5-year estimates over the period 2006 to 2010 and 2014 to 2018 based on the American Community Survey. Citizen voting age data is only available from year 2000 on.

[12] The share of non-US citizens in the adult population is highest in coastal and border regions, e.g. 49% in Los Angeles county in 2017, and has changed continuously over the past 20 years.

registration is not available for all states.[13] For these reasons, we use changes in the citizen voting age population as our preferred measure of contemporaneous changes in the underlying population of eligible voters.

1.3.2 Local Labor Market Outcomes

We compute local labor market variables in each commuting zone using 5% samples from the US Decennial Census for the years 1970, 1990 and 2000 as well as samples from the American Community Survey in 2006, 2007, and 2008 as well as 2014, 2015, and 2016 all provided by the *Integrated Public Use Microdata Series* (IPUMS). This data has the advantage of providing detailed information on individual characteristics (age, sex, education, ethnicity, birthplace) as well as their labor market situation (employment status, occupation, industry, income by source). Using the crosswalks by D. Autor and Dorn (2013), we can map geographies provided in the IPUMS data to 722 continental commuting zones.[14] This allows us to aggregate data at the commuting zone level and construct a rich set of labor market variables.

As outcomes, we compute the change in the log count in total, manufacturing and non-manufacturing employment. As Census data are collected for all individuals in a household, we also calculate changes in the dollar change in the average household income per adult in the commuting area, which is defined as the sum of the individual incomes of all working-age (16-64) household members divided by the number of household members in that age group.

As regression controls, we consider baseline demographic characteristics of commuting zones (log population, the share of men, the share of population above 65 years old, the share of the population with less than a college degree, the share of the population with some college or more, shares of Asian, Black, Hispanic, and White populations, and the share of women in the labor force), the industry composition (shares of employment in agriculture, mining, construction, manufacturing) and the exposure

[13] Dave Leip's Atlas does not provide full coverage in terms of voter registration data, since some states do either not have voter registration, e.g., North Dakota, or reported the number of voters inconsistently, e.g., Wisconsin, Florida, and Mississippi.

[14] The lowest geographic units in the IPUMS census data are either county groups (1970) or Public Use Microdata Areas (PUMA). Both of them are groups of counties that contain at least 250,000 (1970) or 100,000 people and often intersect with multiple commuting zones. Therefore, we employ the crosswalks used by D. Autor, Dorn, and Hanson (2013). We perform a probabilistic assignment of individual observations in the census data into multiple commuting zones based on crosswalks publicly available at https://www.ddorn.net/data.htm

to offshoring (share of routine jobs, average offshorability index) following D. Autor and Dorn (2013).

1.3.3 Other Contemporaneous Controls

Migration: Recent studies have pointed to the role of internal migration of workers to adjust to changing labor market conditions due to exposure to robots or rising imports from China (Faber, Sarto, & Tabellini, 2019; Greenland, Lopresti, & McHenry, 2019). To account for the potentially confounding factor of out-migration on changes in voter turnout, we use county-to-county migration counts from the SOI Migration Database. This data is constructed from annual tax return filings of the Internal Revenue Service (IRS). The IRS computes the total number of in- and out-migrating taxpayers by tracking changes in taxpayers' addresses reported between years since 1990.[15] For each county we compound in- and out-migration flows reported in the data over each 8-year period from 2000 to 2008 and from 2008 to 2016. To compute the net migration rate, we scale the net inflow of migrants per period by the total county population at the beginning of each period. County population estimates for the years 2000 and 2008 are taken from the US Census.

Political campaigning: A second potential confounding factor is localized political campaigning before elections that might be different by region and therefore affect the mobilization of voters.[16] To account for it, we use data on political television advertisements (hereafter "ads") from the Wesleyan Media Project (WMP, previously called the Wisconsin Advertisement Project). This database provides full coverage of political ads broadcasted in the year leading up to congressional (house and senate), gubernatorial, and presidential elections across all 210 US media markets in the years 2008 and 2016.[17] For each broadcast, the database provides detailed information on broadcasting time, ad length, TV channel, political affiliation as well as a large set of issue categories, for example, "taxes", "healthcare" or "gun control".[18] Importantly, the database provides cost estimates for each ad which allows us to estimate the total

[15]Following the migration literature, we use the number of reported tax exemptions on returns with address changes as a proxy for the number of migrating individuals (see Gross, 2003)

[16]As we discuss in Section 1.6, the party's decision to allocate resources to different areas might be endogenous and depend on the anticipated voter turnout.

[17]Media markets or "Designated Market Areas" are historical broadcasting regions in the US where residents receive the same radio and television signals. These areas are widely used for commercial research on media audiences in the US. Each media market has an exact mapping into US counties which is provided by Nielsen Media Research.

[18]Appendix Figure A.4 shows an illustrative example of the storyboards collected for each ad.

spending on political advertisement per media market in 2008 and 2016. We combine the WMP data with US Census data on the number of households per county to construct a measure of television campaigning intensity by dividing the total spending on political ads by the total number of households of all counties in a given media market area in 2008 or 2016.

1.4 Results

1.4.1 Local Labor Markets Effects of Automation and Trade

In the first step, we validate our data set by replicating established findings of the negative employment and income effect of exposure to robots and Chinese imports across US local labor markets. To compare our estimates more closely to the existing literature we construct all outcome variables as stacked differences over three time periods between 1993, 2000, 2007, and 2015 at the commuting zone level. We control for the full set of 1990 baseline commuting zone characteristics and find employment effects similar to those documented in Faber, Sarto, and Tabellini (2019). In Table A.3 we find that a standard deviation increase in the exposure to robots and Chinese imports reduced manufacturing employment growth by about 1 and 5 percentage points, respectively. We also find the employment effect of exposure to rising Chinese imports to be limited to manufacturing employment, while there seems to be a significant negative effect for increasing exposure to robots outside of manufacturing. Despite the differences in the extent of the employment effect, we can show that both shocks had a statistically comparable effect on the average annual household income per adult. Table A.4 shows that a standard deviation increase in the exposure to robots decreased the change in the average annual household income per adult by 571 dollars, while an equivalent increase in the exposure to Chinese imports reduced income by 762 dollars. Decomposing household income we can show that both shocks lead to reductions in the wage income of households as well as to increased reliance on social security and income from welfare programs. Across all our specifications the Kleibergen-Paap F-Statistic of the first stage is larger than the threshold value of 10 across which fulfills the requirement of instrument strength. Overall, Tables A.3 and A.4 confirm previous findings on the negative effect of both shocks on employment and the economic situation of households and working adults living in more exposed commuting zones.

Table 1.1: Impact of Robot Exposure and Chinese Imports on Voting at U.S. Federal Elections: County-Level Stacked Differences, 2000-2016 (2SLS)

	Δ log(votes) × 100			
	US President		US House of Representatives	
	(1)	(2)	(3)	(4)
US Exposure to Robots	-1.841***	-1.006***	-2.130***	-1.308**
	(0.384)	(0.265)	(0.669)	(0.584)
US Exposure to Chinese Imports	0.470	0.561	2.232*	1.846*
	(0.848)	(0.581)	(1.218)	(0.999)
Δ log(CVAP)		0.721***		0.690***
		(0.0440)		(0.0911)
Net in-migration rate		20.34***		40.10***
		(4.327)		(9.422)
Δ share of college educated		-27.60**		4.411
		(13.45)		(25.68)
Perennial swing state		1.266***		2.978***
		(0.488)		(0.836)
TV campaign ads, USD per HH		0.110***		0.164*
		(0.0232)		(0.0984)
Kleibergen-Paap F-Stat	31.99	33.01	28.32	29.49
R^2	0.65	0.84	0.44	0.57
Observations	6172	6136	5483	5432
Wald Test [R=C] p-Value	0.008	0.010	0.002	0.005
Region × Period	✓	✓	✓	✓
Lagged mfg. share × Period	✓	✓	✓	✓
Demographics	✓	✓	✓	✓
Routine Jobs & Offshorability	✓	✓	✓	✓
Pre-trend		✓		✓

Notes: The dependent variable is the change in the log count of votes multiplied by 100 (i.e. $[ln(y_{t+1}) - ln(y_t)] \times 100$). Differences are computed over 8-year election periods, from 2000 to 2008 and from 2008 to 2016. Explanatory variables are all standardized to have a mean of zero and a standard deviation of 1. CVAP stands for citizen voting age population. All specifications control for census division dummies interacted with period dummies, the 10-year lagged share of manufacturing in commuting zone employment interacted with period dummies, commuting zone demographic characteristics in 2000 (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, shares of Asian, Black, Hispanic and White population, and the share of women in the labor force) as well as the commuting zone share of routine jobs and the average offshorability index in 2000, following D. Autor and Dorn (2013). Regressions in column (2) and (4) also account for pre-trends controlling for the log change in votes between 1992 and 2000. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the commuting-zone level. Regressions are weighted by a county's citizen voting age population in 2000. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

1.4.2 Implications for Local Political Participation

In a second step, we use the local labor market framework to test the effect of both structural (and, as just demonstrated, income) shocks on county-level changes in political participation in federal elections between 2000, 2008, and 2016. In Table 1.1 we report the results of two-stage least squares regressions of both exposure measures on changes in the log number of voters at presidential elections. Controlling for baseline controls, we find that a standard deviation increase in the exposure to robots reduced the growth in the number of votes by 1.8 percentage points, while exposure to Chinese imports had a largely insignificant effect on voting. In specification (2), we control for the contemporaneous change in the underlying population of eligible voters in terms of the citizen voting age population, the net in-migration rate and changes in the share of college-educated adults. In addition, we control for the swing state status of each county as well as the difference in political campaigning intensity at the 2008 and 2016 elections. All controls significantly predict growth in voting and substantially reduce the effect size of robot exposure but without affecting the significance level. In this full specification, we estimate that a standard deviation increase in robot exposure reduced voting by 1 percentage point, while Chinese imports do not affect the growth in the number of votes at presidential elections in any specification. Wald tests at conventional significance levels consistently reject the null hypothesis that the difference between the estimated coefficients is zero. As a one standard deviation change in robot exposure corresponds to an increase of roughly 0.51 robots per thousand workers, our estimate implies that one more robot per thousand workers caused voting growth to fall by about 2 percentage points. This magnitude has to be compared with an average growth in the number of votes per 8-year election cycle of about 7.9 percent.

To corroborate this finding, we further study voting at US House of Representative elections between the same reference years. In Table 1.1, we find a more pronounced negative effect of robot exposure and a significantly positive effect of exposure to Chinese imports on voting at US House elections. In our full specification, we estimate that one standard deviation increase in exposure to robots leads to a -1.6 percentage point decrease and Chinese imports to a 2.2 percentage point increase at House of Representative elections.[19] These results broadly confirm differential voting response to comparable income shocks at the local labor market level. Our finding is also robust to using alternative measures for changes in the population of eligible voters (see Table

[19] This result is in line with the results of D. Autor, Dorn, Hanson, Majlesi, et al. (2020), who considered voter turnout at the general congressional elections between 2002 and 2012.

A.11).

To assess the magnitude and political significance of our finding, we run an additional regression using not changes in the number of votes, but in voter turnout as an outcome variable (see Table A.12). We compute voter turnout as the number of votes relative to the citizen voting age population and therefore do not control for changes in the eligible population as an independent variable. Similar to studies on the employment effect of both shocks (D. Autor, Dorn, & Hanson, 2013; Acemoglu & Restrepo, 2020a), looking at the outcome relative to a baseline population allows to translate the observed effects into individual equivalents (workers, or in our case voters). For both types of elections, we estimate the fully specified model and find that a standard deviation increase in the exposure to robots reduces voter turnout by about 0.5 percentage points, while increased exposure to Chinese imports has a statistically insignificant and at best positive effect on voter turnout. Our estimate implies that one more robot per thousand workers is associated with a 1 percentage point lower *voter turnout*. Given the average increase in the stock of robots of about 80,000 robots per electoral 8-year period, it can be estimated that automation has reduced turnout by about 1 million voters per 8-year period.[20] The results of Acemoglu and Restrepo (2020a) suggest that one more robot per thousand workers reduces employment by 6 workers. Our estimates suggest an even larger effect on political participation with one more robot per thousand workers reducing turnout by about 13 voters. This result suggests that the effect of automation on political participation goes beyond those people who are directly affected.

1.4.3 Evidence for Individual Political Participation

To elaborate on why the effect of automation on political participation potentially might go beyond those directly affected, we study micro-level data of the *General Social Survey* (GSS) for the years 2000 to 2016 (see Section 1.2.2 for details on the data and empirical strategy). It contains detailed information on the labor market situation of US residents as well as their political attitudes and beliefs. We build a measure of individual exposure to automation using data by Webb (2019) who gauges

[20] For the year 2000, we count 212 million US adult residents, 196 million adult citizen residents, 127 million employed workers and 105 million voters. The average national turnout at the presidential election was 53%. This means that for 1000 workers there were on average 1500 citizen residents and 803 voters. The reduction in voters due to one more robot per thousand workers is then equivalent to $13 \approx 803-(0.5367-0.01)\times 1500$.

Table 1.2: Individual Exposure to Robots and Chinese Imports and Political Participation: Pooled Cross-Sections, 2000-2016 (OLS)

	Heavy lifting	Forceful hand movement	Likely to lose job	Voted in last election	General trust
	(1)	(2)	(3)	(4)	(5)
Ind. Exposure to Robots	0.147***	0.100***	0.057***	-0.128***	-0.070***
	(0.025)	(0.026)	(0.013)	(0.014)	(0.015)
Ind. Exposure to Chinese Imports	0.067**	0.060	0.004	-0.034	-0.067**
	(0.030)	(0.037)	(0.027)	(0.023)	(0.028)
US Exposure to Robots	0.033*	0.041***	0.022***	-0.004	-0.040***
	(0.019)	(0.015)	(0.008)	(0.014)	(0.015)
US Exposure to Chinese Imports	-0.003	-0.006	0.000	0.000	0.015***
	(0.005)	(0.007)	(0.003)	(0.003)	(0.006)
Observations	3733	3734	5260	9163	5649
R2	0.17	0.11	0.06	0.15	0.13
Sample mean	0.45	0.48	0.09	0.71	0.39
Individual controls	Yes	Yes	Yes	Yes	Yes
Region × Year	Yes	Yes	Yes	Yes	Yes

Notes: Pooled sample consists of cross-sectional surveys from years 2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014 and 2016. All outcome variables are coded binary: (1) Respondent's work implies heavy lifting (2) R's work implies forceful hand movements (3) R believes job loss within next 12 months to be likely (4) R voted at last presidential election (5) R believes that people can be trusted in general. All specifications control for the following individual characteristics: age, years of schooling, gender and income. Standard errors are clustered at the commuting zone level. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

the exposure of an occupation to automation by measuring the overlap between the text of job task descriptions and the text of robotic patents. In addition, we compute a measure of individual exposure to imports from China as the growth in imports in each industry, weighted by the individual's probability of working in that industry. To be able to distinguish individual exposure to both shocks from the exposure from living in an exposed region, we add the two commuting zones measures of exposure to robots and Chinese imports over the past 8 years as well. Our main regressions are repeated cross-sections of biannual waves from the GSS between the years 2000 to 2016. We also control for confounding individual characteristics such as age, education, gender and income.

Table 1.2 documents how individual and regional exposure to the shocks affects the outcome variables of interest. First, in columns (1) and (2) we validate that the constructed measures of individual exposure to robots and Chinese imports are meaningful by confirming that more exposed individuals are also more likely to engage in manual work that involves forceful hand movements and heavy lifting. Next, column (3) shows that individuals that are more exposed to robots are also more likely to fear job loss in the next 12 months, which is in line with the labor market effects reported in Table A.3. For individuals exposed to Chinese imports, expectations of job loss do not seem to be affected on average. Column (4) presents the central result of this part of the analysis. It documents that a one standard deviation increase in an individual's exposure to robots reduced the likelihood of having voted in the past presidential election by 12 percent. Unlike individual exposure to robots, individual exposure to Chinese imports or regional effects do not appear to affect the likelihood of abstaining. The results of the GSS analysis suggest that people who are generally exposed to automation are less likely to cast their votes. The effect does not seem to be mediated by a potential change in economic conditions in the region. This confirms the differential effect on voter turnout in presidential elections at the county level, as reported in Table 1.1.

Although, as shown in Table A.4, the income effects of both shocks are comparable, the shocks are not identical. One documented difference is that the consequences of intensified trade with China are more confined to manufacturing employment, while an increase in automation generates negative employment spillovers outside manufacturing (Faber, Sarto, & Tabellini, 2019). Workers employed in different sectors might have different propensity to vote, which might explain the differential voter turnout following the two shocks that we observe. Yet, this difference is unlikely to explain the observed result. First, the parts of the difference between the affected groups are likely to be captured by the demographic characteristics that we control for. Secondly, even assuming the presence of a sector-specific determinant of voter turnout independent from established demographic determinants and specific to non-manufacturing employment (Smets & van Ham, 2013), the absence of an effect among those affected in the manufacturing sector and the negative effect observed in the mixed sample of those affected in both manufacturing and non-manufacturing employment suggests that those affected in non-manufacturing employment are the primary drivers of the significant effect observed. As it does not appear feasible, we proceed by considering what possible mechanisms trigger differential effects on political participation between the two structural changes by means of an online survey experiment.

1.5 Evidence from an Online Survey Experiment

1.5.1 Theoretical Considerations

Voting is the fundamental act of civic engagement in a democracy and has therefore received a lot of attention by scholars. Several theories attempted to answer why people turn out to polls and how they vote (see e.g., Dhillon & Peralta, 2002, for an overview of theories). From a rational voter perspective, citizens decide to vote if the utility of voting outweighs the utility of abstaining. Therefore, the differential effect of the two shocks on the voter turnout is because they deferentially affect the expected utility of the individual voters. The utility of voting is defined by its instrumental and expressive utilities (Brennan & Hamlin, 1998). Below we elaborate on some factors that may differ depending on the nature of the labor shock, hence, affecting the instrumental and expressive value.

The expressive value of voting typically includes factors that are not affected by the outcome of the vote: for instance, the satisfaction from fulfilling a civic duty, but also the utility of voting according to one's party affiliation (Fiorina, 1976). One may, therefore, assume that if a political party actively uses one of the shocks in its agenda, potential voters may gain utility from expressing support for the party in addition to the instrumental value.

The instrumental value appears to be more complex. As both of our shocks are labor shocks, we assume that the ideal outcome for a voter in response to the shock is preventing negative economic consequences. Several factors might affect the instrumental value of voting depending on the labor market shock. First, if a voter perceives one shock to be more important and to have larger consequences, she might expect higher instrumental benefits if the issue is addressed. Importantly, the perceptions of potential voters and not the *de facto* consequences of the shocks matter. Second, while the voters expect to benefit if the issue is addressed, voting in elections is a tool for influencing the government and governmental policies. Therefore if voters do not believe that the issue may be addressed through governmental action or policy they may expect less instrumental utility. Furthermore, going beyond the governmental ability to address the shocks, one might perceive one shock to be in general more inevitable and irreversible which may affect the willingness to vote. Third, if there is no candidate or political party that advocates an agenda to address the shock, voting may cast less instrumental utility. Additionally, the instrumental value of voting may be affected by global preferences such as time or risk preferences. For example, a present-biased voter may discount any utility that would come from addressing the issue in the future and not immediately. If the shocks trigger a shift in these preferences, they might translate into differential voting responses.

1.5.2 Design and Procedures

To consider what factors might contribute to the observed aggregate differences in political participation, we conducted an online survey experiment. In February-March 2021, we recruited 835 US residents via Prolific to take part in the study. Prolific is a platform similar to mTurk, but it offers the advantage of reaching more diverse and naive respondents (Peer et al., 2017). The respondents were on average 36 years old, about 60% of the respondents were males. We attempted to exclude students (0.6% of the total sample) who might not have labor market experience yet. We over-sampled industries that might be considered as affected by automation (manufacturing, mining, logistics and warehousing), which constitute ca. 30% of the sample. The respondents took on average less than 9 minutes (median 7,5 minutes) to answer the survey and were reimbursed with a flat payment of 1 GBP.

In our study, we followed the approach of Di Tella and Rodrik (2020). After answering basic demographic questions, respondents saw a piece of text formatted as a newspaper article (for example, see Fig 1.1). The article reported that a manufacturing plant announced layoffs. Depending on the treatment, the reason for the layoffs varied. We conducted three treatments: In the Automation treatment, the layoffs were due to the introduction of labor-saving technologies. In the Trade treatment, the layoffs were due to increased trade competition with other countries and in particular with China. Additionally, we ran a control treatment in which layoffs were due to restructuring and new managerial practices. In the last treatment, neither automation nor trade was mentioned.[21]

Under the text the respondents saw 3 comprehension questions. Two of the questions had to be answered correctly to proceed with the study. The questions referred to the information in the articles and ensured careful reading. After that, the respondents answered questions about their perceptions of the consequences of different scenarios (individual for unemployed workers and more general for the society as a whole),

[21] The texts of the news pieces from the Trade and Control conditions, as well as further survey materials can be found in the Appendix A.11.

Figure 1.1: Example of Vignette used in Online Survey Experiment

BUSINESS NEWS September 18, 2019

US Manufacturing Faces Headwinds

A view of the shop floor at the VBMC factory.

In the past month, many companies presented their new business strategies. One of the companies is VBMC, a large manufacturing company, which announced plans to phase out parts of their operations. They plan to invest in automation and other labour-saving technologies. A VBMC spokesman said: "To remain competitive, we have to offer competitive prices and introducing new technologies is the way forward. As a result of shutting down some of the production lines that become automated, we will become more efficient. However, in the course of these changes, about 900 good workers will lose their jobs. It is very regretful, but necessary to stay in business these days".

Many industries have been affected in recent years by developments in labour saving technologies and automation of processes. An employee of VBMC, who has been employed there for eighteen years, said the change would have devastating consequences for the workers. "Many will become unemployed and the rest might have to accept lower wages," he added.

Notes: This picture shows the mock newspaper article presented to survey participants in the "automation condition". Highlighted parts are added and varied depending on the treatment. Source: Authors' original writing based on Di Tella and Rodrik (2020).

desired actions by the government, voting and political attention to the issue, emotional responses towards different kinds of unemployment (following Granulo, Fuchs, & Puntoni, 2019), a version of the preference survey module of Falk et al. (2023) to consider time, risk, altruism, trust as well as locus of control.

Since we expect heterogeneities in responses along the lines of party affiliation, apart from the self-reported measure of political position, we elicited attitudes on the role of competition, government involvement and the role of luck in success in the US to validate if the self-reported measure was meaningful. Precise wording of questions as well as their sequence can be found in Appendix Table A.1.3.

1.5.3 Results

For most questions, respondents express their agreement or disagreement with the provided statements on a 7-point Likert scale that ranges from strongly disagree (1) to strongly agree (7) where 4 represents the indifference point. First, we conclude that all three suggested stories are equally believable as we do not detect a difference in how much the respondent can relate to the described event (Kruskal-Wallis H test, $\chi^2(2) = 2.721, p = 0.26$).

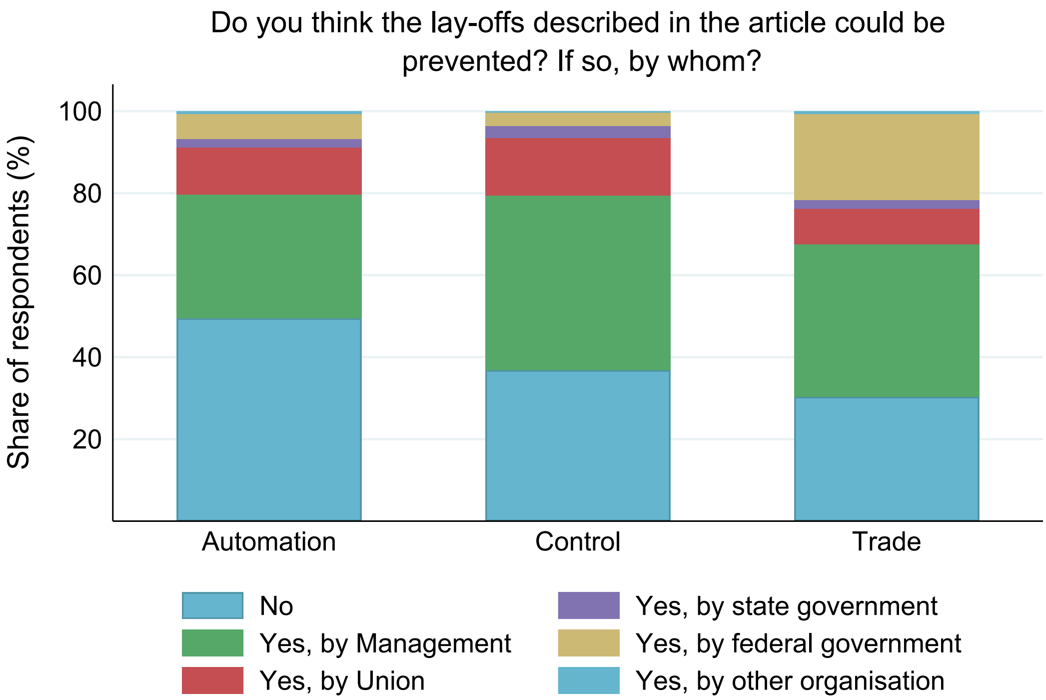
All three reasons for unemployment are perceived to be equally damaging both for individuals in the short term (ease of finding the next employment) as well as in the long term (long-lasting consequences of the shock, its effect on inequality and opportunities in the future).[22] Yet, the respondents perceive some consequences of the shocks differently. For instance, they believe that in the case of layoff due to automation, employees are less likely to find a position within the same occupation. Moreover, optimal search strategies seem to differ. While in all three scenarios, the respondents most often recommend to start searching for a new job directly (42% of respondents in Automation, 53% in Trade and 60% in Control), the share of respondents choosing this option is significantly lower in Automation than in the two other conditions (Automation and Control p=0.000, Automation and Trade p=0.007). However, in case of unemployment due to automation, the respondents more often recommend gaining additional qualifications or retraining into a new occupation before searching for a new job.[23] Taken together, while unemployment due to different shocks appears to affect the recommended job search strategy, we do not detect the differences in main variables that relate to the consequences of the shocks. Therefore, it appears unlikely that different perceptions of the consequences and importance of the shocks can drive the differential effect observed in the aggregate data.

As outlined above, the second factor that might affect the instrumental value of voting and thus the voter turnout is if the issue can be addressed and ultimately solved by the government. Our data suggests that the government is seen as less helpful in coping with automation as compared to trade shock. When asked who could have prevented the job loss, more respondents in the Trade condition highlighted the role of the federal government (21% in Trade vs 6% in Automation (p=0.000) and 3% in Control (p=0.000)). For the same question, the largest share of respondents stated that the job losses were inevitable (see Figure 1.2): 49.5% in the Automation treat-

[22] Unless otherwise specified, the statements are based on the results of the two-tailed t-tests. For robustness, we have replicated our analysis using OLS estimations and controlling for main demographic variables. The results remained qualitatively similar. Additionally, we account for multiple hypothesis testing and calculate sharpened q values by Benjamini, Krieger, and Yekutieli (2006) as implemented by Anderson (2008). The reader can find the mean scores as well as p-values of all of the t-tests and sharpened q values in the Supplementary Online Materials A.1.3. We report p values in the text, but the reported results persist if we consider sharpened q values.

[23] Additional qualifications: Automation 18%, Trade 13% and Control 11%, p=0.09 and p=0.01 for respective comparisons. Retraining into new occupation: Automation 28%, Trade 20% and Control (17%), p=0.04 and p=0.002.

Figure 1.2: Survey Results for Question regarding the Evitability of Shocks



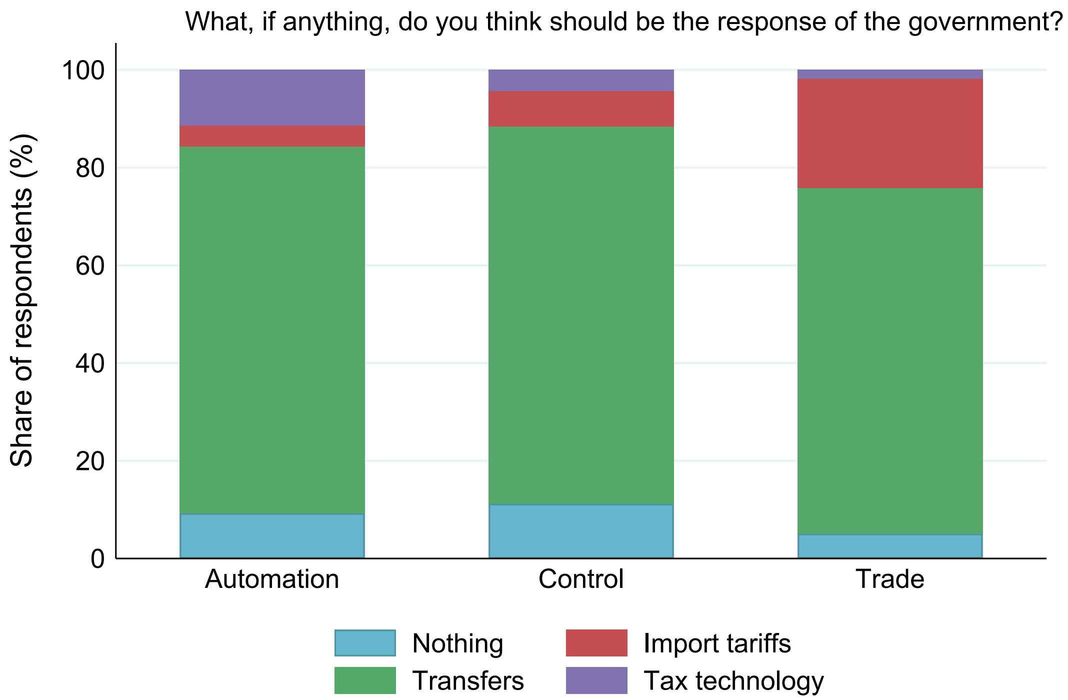
Notes: This figures shows shares of responses by treatment condition. Exact wording of the answer options: No, the lay-offs are inevitable; Yes, by the company management; Yes, by the union or other professional organisation; Yes, by the state government; Yes, by the federal government; Yes, by other organisation. Source: Authors' own calculations based on survey result.

ment as compared to 36.8% in Control (p=0.0025) and 30.3% in Trade (p=0.000). In a separate question if there is anything the society can do to prevent job losses due to technological advances and intensified trade, participants in all treatments were more likely to agree that technological unemployment represents a bigger challenge to society.[24] The average score is 3.32 for trade unemployment and 3.68 for technological one (p=0.000). While the respondents rather disagree with the grim statement, they are more pessimistic about automation.

Another question, that may lend additional support to the hypothesis that governmental involvement is perceived to be more useful in case of Trade as opposed to Automation or Control scenario, replicated the approach of Di Tella and Rodrik (2020) with slight adjustments to the answer options available to the respondents. The respondents were asked what should the government do in each scenario and could choose

[24]The question was asked separately for technological advances and intensified trade. Both questions were presented in all treatments at the very end of the survey.

Figure 1.3: Survey Results for Question regarding Preferred Government Response



Notes: This figures shows shares of responses by treatment condition. Exact wording of the answer options: Government should do nothing; Government should provide some financial assistance to workers who lose their jobs (e.g., unemployment compensation or training assistance); Government should restrict imports from overseas, by placing import tariffs on such imports for example; Government should impose higher taxes on labor-saving technology and regulate automation more strictly. Source: Authors' own calculations based on survey result.

one of the four options: nothing, administer direct transfers to affected parties, introduce import tariffs and introduce automation taxes. Three out of four options imply that the government needs to engage. The smallest share of respondents indicated that the government should do nothing in the Trade condition (only 5%) as compared to 9% in Automation (p=0.055) and 11% in Control (p=0.008) (see Figure 1.3). That is, government involvement is more demanded in the Trade condition.

Based on the survey responses, we conclude that government engagement may be seen as most helpful against the consequences of the trade shock. Additionally, the unemployment due to automation seems to be perceived as more inevitable in general.

We also asked several questions related to voting and political attention to the issues. In all treatments, the respondents overwhelmingly agree that voting in general is important with an average score of 6.3 points out of 7. Moreover, in all treatments, respondents tend to agree that it is important to draw the attention of the public and politicians to the issues. However, in the Automation condition respondents express stronger agreement (5.36) with the statement that not enough political attention is dedicated to the issue than in Trade (5.06, p=0.01). The Control condition falls in between.

As questions about voting and political attention might relate to ongoing political discussions in the US, we expected that the observed responses might depend on political attitudes of the respondents. Before exposing respondents to the treatment manipulation, we asked where would they place themselves on a 7-point scale between extremely liberal (1) and extremely conservative (7).[25] We intentionally chose not to mention specific political parties in order to avoid attitudes towards party leaders and rather focus on ideological positions. Additionally, we asked several questions that relate to one's ideological position (the role of the government, role of luck and effort in success and attitudes towards competition). The self-reported measure strongly and significantly correlates with responses to the ideological statements in the expected direction, which reconfirms that self-reported measure of political attitudes can be used to consider heterogeneities along the lines of political affiliation. On average our sample is slightly liberal (3.1 with 4 corresponding to "moderate") with no significant differences among treatments (Kruskal-Wallis test, $\chi^2(2) = 0.362, p = 0.83$).[26]

To consider the role of political affiliation, we run an OLS regression with answers to different statements as a dependent variable and the continuous measures of the political position and the treatment as well as the interaction of the two as independent variables. Additionally, we control for age, level of education, gender, if the respondent is white, if the respondent works in the affected industry (see the list above). While the political affiliation of the respondent does not significantly interact with treatment for questions on the importance and consequences of the shocks (both individual and societal), the interaction term of political attitudes and the Trade condition has large (ca. a third of a point) and significant coefficient on both questions related to political attention toward the shocks (see Table A.28). That is, more conservative respondents in the Trade condition tend to express stronger agreement with the statements that not enough political attention is dedicated to the problem and that it is

[25] About 1% of respondents answered "I do not know", they are excluded from this part of the analysis.

[26] Higher values stand for more conservative position and stronger agreement with the statement: *Competition is harmful. It brings out the worst in people*, Pearson's correlation= -0.3, p=0.000; *The government should take more responsibility to ensure that everyone is provided for*, Pearson's correlation=-0.6 p=0.000; *In the US, people become successful because they got lucky*, Pearson's correlation=-0.57, p=0.000

important to draw attention to it. In line with the argument that voting along own party preference may yield additional expressive utility, this results supports the idea that the more conservative voters may gain additional utility of expressive voting in the Trade condition.

In our survey responses we do not detect any differences in global preferences such as risk, trust and time preferences as well as altruism and locus of control. Also, contrary to some findings of Granulo, Fuchs, and Puntoni (2019), we do not find differences in emotional responses to different types of unemployment (see results of the t-tests in the Supplementary Online Materials A.1.3).

We additionally considered heterogeneity of responses by age, by being employed in the affected industry (manufacturing, transportation or warehousing, ca. 30% of the sample) and if the respondent is at risk of automation where the risk of automation score is calculated following the methodology used above for GSS respondents. This analysis did not provide additional insights into mechanisms behind the patterns documented with the regional data. Although each of the factors had significant coefficients for some variables, there are no notable interaction effects with treatment conditions.

To sum up, our survey evidence suggests that the automation shock is seen as more inevitable and governmental interventions to address it as less helpful. These two factors might have negatively affected the utility from voting and therefore led to lower voter turnout. On the contrary, in the case of Trade shock a more conservative groups of voters might have gained additional utility from expressing the party loyalty. From our survey it does not appear that one shock is perceived as more important than another.

1.6 Discussion of Political Campaigning

Decreased voter turnout may trigger a feedback loop of inadequate political representation if political parties ignore interests of those who abstain. If political parties expect a decrease in a voter turnout, they might, on one hand, attempt to capture the votes of the affected individuals and thus counteract the decrease in voter turnout by intensified political campaigning. On the other hand, they might reduce the intensity of political campaigning and focus on the interests of those who are more likely to vote. Our data allows to elaborate on how political parties react to the decrease in

Table 1.3: Impact of Robots and Chinese Imports on Political Advertising at US Presidential Elections: County-Level Analysis, 2000-2016 (2SLS)

	Spending on Political Ads / HH			
	Total	Jobs w/ China and Trade	Jobs w/o China or Trade	Social Security
Panel A:	(1)	(2)	(3)	(4)
US Exposure to Robots	-1.312***	0.0553***	-0.149*	-0.0142*
	(0.359)	(0.0114)	(0.0794)	(0.00850)
US Exposure to Chinese Imports	0.670	0.00120	0.110	0.0109
	(0.619)	(0.0101)	(0.104)	(0.0135)
Kleibergen-Paap F-Stat	32.17	32.17	32.17	32.17
Observations	6140	6140	6140	6140
Wald Test [R=C] p-Value	0.0011	0.0000	0.0151	0.0755
	Number of Political Ads			
	Total	Jobs w/ China and Trade	Jobs w/o China or Trade	Social Security
Panel B:	(5)	(6)	(7)	(8)
US Exposure to Robots	-1116.4*	89.15***	-85.69	-3.010
	(621.6)	(11.56)	(135.3)	(13.98)
US Exposure to Chinese Imports	810.4	3.197	87.35	23.46
	(808.1)	(14.89)	(130.7)	(22.40)
Kleibergen-Paap F-Stat	32.17	32.17	32.17	32.17
Observations	6140	6140	6140	6140
Wald Test [R=C] p-Value	0.0260	0.0000	0.258	0.262
Region × Period	✓	✓	✓	✓
Demographics	✓	✓	✓	✓
Lagged mfg. share × Period	✓	✓	✓	✓
Routine Jobs & Offshorability	✓	✓	✓	✓
Swing State	✓	✓	✓	✓

Notes: The dependent variables are the dollar value of spending on political ads per household (Panel A) and the total number of political ads in the designated market area a county belongs to in the election year in 2008 and 2016. All specifications include census division dummies interacted with a time period dummy as covariates, control for 2000 demographic characteristics of the commuting zone (as in Table 1.1), the 10-year lagged share of manufacturing employment interacted with a time period dummy as well as the share of routine jobs and the average offshorability index in 2000, following D. Autor and Dorn (2013). All specifications also control whether counties are situated in a "perennial" swing state (Colorado, Florida, Iowa, Michigan, Minnesota, Ohio, Nevada, New Hampshire, North Carolina, Pennsylvania , Virginia, Wisconsin). Explanatory variables are all standardized to have a mean of zero and a standard deviation of 1. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the commuting zone level. Regressions are weighted by a county's share in the national number of households in 2000. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

voter turnout.

As a source of data for political campaigning we use Wesleyan Media Project (see detailed description in Section 1.3). For each broadcast, the database provides detailed information on broadcasting time, ad length, TV channel, political affiliation as well as a large set of issue categories, for example, “taxes", “healthcare" or “gun control".[27] Therefore, we can consider both intensity of campaigning as well as issues the parties campaign on.

It appears political parties anticipate the decrease in voter turnout and in response reduce the number and budget for political ads in the affected regions. Table 1.3 reports that for the presidential campaign fewer and cheaper ads were shown in the regions affected by automation. There is no significant change in the number or costs of ads in the regions affected by Chinese imports. For those ads that were shown in the regions affected by automation, the topics appear to be ill-tailored: We document a significant increase in ads that mention jobs and trade, but a decrease in those mentioning jobs without connection to trade and social security issues, that – based on our survey experimental evidence – are of particular importance in case of automation.[28] This mismatch may be interpreted as a manifestation of a diversion hypothesis that suggests that political parties might divert voters into thinking that the cause of economic transformations that they experience as undesirable is international trade or immigration (Gallego & Kurer, 2022).

1.7 Conclusion

In this paper, we study how structural changes affect political participation via their impact on local labor markets. Answering a question put forward as one of the most pressing in the review of Gallego and Kurer (2022), we study the effect of the two largest structural changes to the economies of the past decades — long-run labor market adjustments to industrial robots and Chinese imports — on voter turnout in the US between 2000 and 2016. First, we confirm the established finding that both automation and import competition from China lead to comparable in magnitude declines in employment and average household income at the level of the local labor market.

[27] Appendix Figure A.4 shows an illustrative example of the story boards collected for each ad.

[28] Our ads data does not have a topic “automation" or comparable and therefore does not allow to construct a direct equivalent to the number of ads that mention jobs and China or trade. We compare this category to the number of ads that mention jobs and do not mention China or trade.

We document a significant negative relationship between commuting zone exposure to industrial robots and changes in county-level turnout at both types of federal elections. In contrast, the exposure to rising imports from China does not affect turnout at presidential elections and positively affects turnout at US House of Representative elections. In an online survey experiment we consider several potential driving factors. While both shocks are perceived to be equally important, respondents found layoffs due to automation to be more inevitable and the federal government to be less able to tackle it than in the import competition scenario.

By considering the effect of the two structural shocks we can show that the relationship between labor market conditions and political participation is not uniform, i.e. negative income shocks do not always affect political participation in the same way, which appears to be an implicit assumption in the literature on the economic determinants of political participation (Rosenstone, 1982; Charles & Stephens Jr, 2013; Burden & Wichowsky, 2014). It is not solely a change in economic conditions that matters but the reasons behind the shock and the role of the government in addressing it. With the message similar to Di Tella and Rodrik (2020) and Gallego and Kurer (2022), our results suggest that the reasons behind the income shocks are crucial for how a reduction in income affects political engagement.

One can argue that the differential effect of these particular shocks on the voter turnout is even more important to consider as they offer two alternative ways of reducing labor costs of production and policies aimed to slow the pace of one process may accelerate the other. For instance, to reduce labor costs one could either buy cheaper supplies abroad instead of producing them in the country or introduce labor-saving technologies and thus produce with less labor. As citizens who care about increased trade vote, politicians may be more likely to support their agenda and enact policies that impede trade and, consequently, encourage firms to invest more actively in labor-saving technologies, further disadvantaging those at risk of automation.

Further rigorous investigations are needed to consider whether *politicians* respond to structural shocks differently. Feigenbaum and Hall (2015) show that legislators in the US House of Representatives adjusted their roll-call behavior and voted in favor of more protectionist trade bills when their districts were more affected by Chinese import competition. This result suggests that legislators are sensitive to shocks to local labor markets. Yet, it remains unclear whether legislators tried to address the concerns of local workers or the interests of local company owners seeking trade protection. As Bartels (2009) demonstrates that US Senators tend to be more responsive to the interests of the most affluent constituents, it is possible that legislators only address local labor market shocks when the interests of workers and company owners align, which is more likely to be the case for import competition than for increased levels of automation. Differential responses by politicians may, therefore, be an important root to the differences in perceived government efficacy and might trigger the disparities in political participation levels that we document. Our evidence corroborates the concerns about the reinforcing feedback loop that is likely to ignore the interests of those who do not vote (Lijphart, 1997). Our results suggest that the ignored voices might belong to those affected by automation.

2

Robotizing to Compete

Firm-level Evidence

2.1 Introduction

The use of automation technologies has increased dramatically in recent decades, especially in high and middle-income countries. The widely accepted explanation for this development is that advances in engineering have radically improved the capabilities of these technologies, while lowering their relative prices. The ensuing automation of industrial production caused significant productivity growth, but had adverse consequences for the labor market prospects of low-skilled workers (Graetz & Michaels, 2018; Acemoglu & Restrepo, 2020a). In light of these impacts of automation technologies, it is important to understand the causes of their adoption. While differences in the relative price of labor and demographics provide a natural explanation for broad cross-country differences in automation (Acemoglu & Restrepo, 2022; Artuc, Bastos, & Rijkers, 2023), more recent studies based on micro-level data point to large differences in robot adoption across firms, industries and regions within countries (Cheng et al., 2019; Brynjolfsson et al., 2023; Deng, Plümpe, & Stegmaier, 2023).

How does product market competition impact firms' investments in automation technologies? Models of robot adoption commonly used in the literature suggest that a decrease in the market share of incumbents due to entry of new competitors hinders firms' ability to pay the large fixed cost of adopting automation technologies (Humlum, 2019; Koch, Manuylov, & Smolka, 2021). At the same time, foreign competition from both low- and high-wage countries may incentivize firms to engage in "defensive skill-biased innovation", increasing the sophistication of their products and production processes to make it harder to be imitated and leapfrogged by foreign competitors (Thoenig & Verdier, 2003). While previous research suggests that product market competition matters for firm-level investments in other innovation inputs and outputs, the direction and the magnitude of the effects differs across studies (Bloom et al., 2013; D. Autor, Dorn, Hanson, et al., 2020; Coelli, Moxnes, & Ulltveit-Moe, 2022, e.g.). Relative to other types of investment, robots are characterized by a significantly higher labor substitutability, which is vital for cost reduction, but they also involve substantial fixed costs of adoption (Acemoglu & Restrepo, 2020a; Bessen et al., 2023). Hence, the available evidence provides limited guidance on how firms' automation investments would react to increased competition.

In this paper, we study empirically the impact of product market competition on firms' investments in automation.[1] We bring together rich and comprehensive administrative micro data from Portugal, including employer-employee data, firm-level exports and imports, and firm-level imports of automation technologies. For causal identification, we use a large and so far unexploited tariff liberalization between the European Union (EU) and Central and Eastern European Countries (CEECs) in the 1990s. This event was a major shock for Portuguese exporters, who heavily depended on the European market. We find that firms more exposed to product market competition responded by reducing investments in automation on average, while only the most productive firms in highly automating industries exhibited a positive response. At the same time, the shock led to adjustments in several product and worker margins of the firm. Our results indicate that stronger competition leads to an increase in concentration both within and between Portuguese firms.

Our identification strategy leverages a previously unexploited source of variation in

[1] This chapter is the result of a collaboration with Paulo Bastos and Lisandra Flach. A preprint version of this chapter is available as Bastos, Flach, and Keller (2023). Robotizing to compete? Firm-level evidence. Max Planck Institute for Innovation & Competition Research Paper No. 23-23.

the degree of competition stemming from a large tariff liberalization between the EU and CEECs between 1993 and 2001. While the average tariff for industrial goods fell from 6.5 to 0 percent, some products experienced tariff reductions of up to 35 percentage points, substantially lowering the prices of goods from CEECs in the EU market. The liberalization had a significant impact on the degree of competition faced by Portuguese exporters, which were highly reliant on the EU market.[2] We measure the degree of exposure of Portuguese firms to this competition shock by combining firm-product-level data on the initial composition of firms' export portfolios with product-level data on EU tariffs with respect to CEECs. Our identifying assumption is that the variation in tariff reductions across products is exclusively determined by the EU's initial level of most-favored-nation tariff rates, which Portugal could not influence when joining the European Economic Community in 1986.

Our main outcome of interest – investments in automation equipment by Portuguese firms – is traceable via import statistics at the firm-product level. Using specific product codes in the harmonized system nomenclature, we are able to identify imports of automation equipment, including industrial robots and numerically controlled machinery. As there was little domestic supply of automation equipment in Portugal in the 1990s, firm-level imports are a reliable indicator of investments in automation. The data reveal a continuous increase in automation equipment imports and in the number of automation equipment importers during the 1990s, which provide large variation to estimate the causes of robot adoption.

We start the empirical analysis by illustrating the relevance of this negative shock on firm outcomes. To achieve this, we provide evidence of the significant impact of tariff liberalization on firms' export performance. Specifically, we document that more exposed firms experienced a sharp decline in total sales growth, driven by a sizable reduction in exports to the EU markets, while domestic and extra-EU sales remained unaffected. In addition, we find evidence for adjustment at the product margin: firms reduce the number of products exported to the EU, while exports to other destinations remain unaffected. Finally, we document a reduction in export prices for more exposed firms, which is likely to reflect a reduction in markups in the EU market. Thereby, we provide robust evidence for mounting competitive pressure resulting from the tariff liberalization. Reassuringly, we find no evidence of pre-trends and can show that our results are not driven by changes in exposure to competition from China in the EU

[2] In the year 1993, 80% of Portuguese manufacturing exports were destined for Western European countries.

market.

We extend the analysis of firm outcomes to the worker dimension, where we establish that firms respond to increased competitive pressures by lowering labor costs, thereby emphasizing the importance of the negative shock. We observe a notable decline in employment growth at more exposed firms, particularly among low-skilled workers. This reduction in employment growth is compounded by a decrease in work hours for incumbent workers, resulting in substantial reductions in the total wage bill, while hourly wages remain unaffected. These findings suggest that the tariff liberalization led firms to constrain new hires and adjust work hours for incumbent workers, indicating a strategic response that reduces labor costs and has the potential to enhance labor productivity.

In our main results, we show that greater exposure to the tariff liberalization is linked to reduced investments in automation. We find that a one-standard-deviation increase in exposure leads to a substantial 25 percent reduction in automation at the intensive margin, as well as a 3-percentage-point decrease in the likelihood of firms adopting automation at the extensive margin. Despite the apparent need for firms to curb labor cost in the face of intensified competitive pressure, this evidence indicates that, on average, heightened competition diminishes the incentive for automation. However, when scrutinizing more productive firms within industries that are highly prone to automation, we find evidence of heterogeneous treatment effects. Using differences in labor productivity across firms as a proxy, we observe that initially more productive firms respond by increasing their automation levels compared to less productive firms. This observation implies that within industries where automation is most prevalent, heightened competition tends to discourage substantial automation investments among less competitive firms while simultaneously fostering automation among the industry leaders.

The heterogeneous results among firms that we observe can be reconciled through the lens of models from the industrial organization literature. On the one hand, Schumpeterian models show that competition could reduce potential rents from innovation, leading to a decrease in innovation (Schumpeter, 1942). On the other hand, higher competition could reduce pre-innovation rents and increase pressure to overtake competitors (Arrow, 1972), implying a positive impact on innovation. Hence, the contrasting results we find may reflect firms' position as laggards or leaders. As initially more productive firms are the leaders in their industry, they have stronger incentives to innovate to escape competition, whereas the opposite holds for the laggards - decreased returns to innovation and profit margins lead less productive firms to decrease investments in innovation.[3]

Our paper contributes to the literature on trade and innovation (Shu & Steinwender, 2019). We exploit a novel source of variation in competition in foreign markets, the tariff liberalization between the EU and CEECs in the 1990s and provide new firm-level evidence for automation investments. By combining data on firms' ex-ante product portfolio with information on product-level tariff changes, we can compute firm-specific exposure to policy-induced changes in competition. This allows us to leverage variation in tariff exposure across firms within the same industry, offering a more precise approach compared to prior studies that primarily focused on tariff reductions or import competition at a more aggregated industry level (D. Autor, Dorn, Hanson, et al., 2020; C. Chen & Steinwender, 2021; Coelli, Moxnes, & Ulltveit-Moe, 2022). We also expand the literature by considering imports of automation equipment as part of process innovation and technology upgrading. While previous studies mainly focused on corporate research and development, technology adoption through imports of machinery are especially relevant to countries that may not be at the forefront of technology development, helping them to maintain competitiveness in the global market place (Hoekman & Javorcik, 2006; Lileeva & Trefler, 2010; Bustos, 2011). Finally, we study the effect of competition in the destination country of exports, while existing research has primarily focused on the impact of foreign competition on domestic markets.

Our paper also relates to the literature that studies the determinants of automation at the firm level. We contribute to this literature by empirically studying the role of competition in product markets, for which the literature has so far lacked a clear prediction. We show that competition has a heterogeneous impact on firm's automation depending on firms' initial competitiveness. This finding provides a novel explanation for the stark differences in automation adoption across firms within the same industries observed in recent micro-level studies (Brynjolfsson et al., 2023; Deng, Plümpe, & Stegmaier, 2023). So far, the heterogeneity of automation adoption has been ex-

[3] The model by Aghion et al. (2005) shows that differences in pre- and post-innovation rents determine the direction of responses to increased competition. Previous empirical studies reveal contrasting results of competition on innovation for different countries - for instance negative for US firms (D. Autor, Dorn, Hanson, et al., 2020) and positive for European firms (Bloom, Draca, & Van Reenen, 2016). As argued by D. Autor, Dorn, Hanson, et al. (2020), the negative impact of foreign competition on innovation they find for the US could be explained by the fact that US industries are further away from the technology frontier, whereas European industries investigated by Bloom, Draca, and Van Reenen (2016) are closer to the technology frontier. We show large heterogeneity within the same industry in a country.

plained by differences in factor markets conditions, such as changes in minimum wage, immigration, and labor and capital taxation (Acemoglu, Manera, & Restrepo, 2020; Danzer, Feuerbaum, & Gaessler, 2020; Fan, Hu, & Tang, 2021; Nain & Wang, 2021).

Finally, our paper also relates to the literature that investigates the impact of robot adoption on labour market outcomes. Several papers suggest that advanced automation technologies such as industrial robots and numerically controlled machinery increase the demand for skilled workers and may in this way contribute to an increase in wage inequality (D. H. Autor, Levy, & Murnane, 2003; Acemoglu & Autor, 2011; Michaels, Natraj, & Van Reenen, 2014; Akerman, Gaarder, & Mogstad, 2015; Acemoglu & Restrepo, 2020a; Koch, Manuylov, & Smolka, 2021). However, this is not necessarily the case: using firm-level data for Finnland, Hirvonen, Stenhammar, and Tuhkuri (2022) show that the adoption of advanced technologies increased employment without leading to skill-biased technological change. In our paper, firms that are more severely hit by the competition shock react by decreasing both investments in robots and employment, in particular of low-skilled workers. Hence, our results are not explained by a substitution between capital and labor, but could be rather a result from product-level reallocations within the firm, as we discuss in the paper.

The remainder of this manuscript is structured as follows: In Section 2.2, we provide background information on the tariff liberalization between the EU and CEECs in the 1990s. Section 2.3 presents the data used in this study, while Section 2.4 explains our empirical strategy. We summarize and discuss our findings in Section 2.5 and conclude with an outlook in Section 2.6.

2.2 Background

This section provides a description of the event of tariff liberalization between the EU and the CEECs in the 1990s. It emphasizes the characteristics that make this policy change exogenous from the perspective of the Portuguese economy, making it an ideal event to evaluate changes in competition faced by Portuguese exporters in the EU market. The following features characterized this period of tariff liberalization.[4]

[4] In terms of identification, one important advantage of this period, in comparison to the event of the Eastern European Enlargement in 2004, is the fact that the 2004 enlargement is characterized by a bundle of policy changes, including changes in non-tariff barriers and migration policies, as well as other changes in the environment, such as the rise of China after entry into the World Trade Organization in 2001 and its penetration in the EU market. In our period of analysis, we can be less concerned about these potential confounding factors that affect firms' competitiveness.

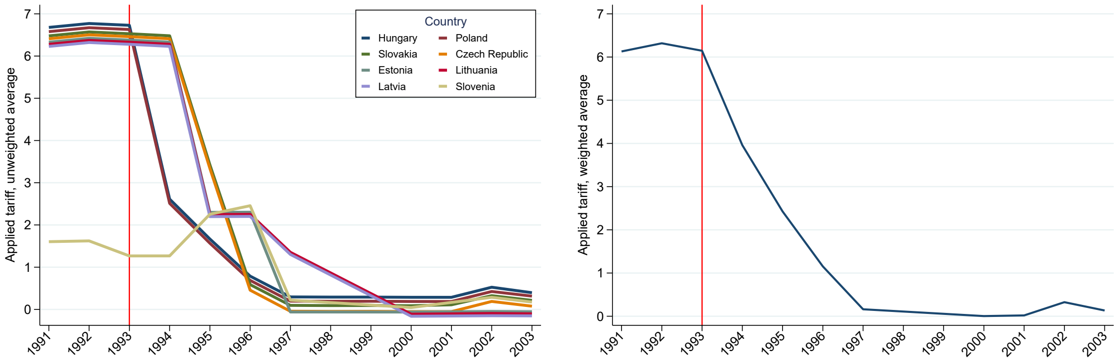
Association agreements and *de facto* customs union: Whereas much of the literature on the Eastern European Enlargment focuses on the formal accession of 10 new member countries to the EU in 2004, the process of economic integration started already in the 1990s. After the dissolution of the Soviet Union and the Council for Mutual Economic Assistance in 1991, the EU and the CEECs concluded a series of association agreements to strengthen economic and political ties and set up the legal framework for the later accession. The EU concluded association agreements with Hungary and Poland in 1991, with the Czechia and Slovakia in 1992, with Estonia, Latvia and Lithuania in 1993 and with Slovenia in 1995. The main part of these association agreements was a comprehensive liberalization of trade in goods and services.[5] While the EU had charged non-preferential Most-Favourite-Nation tariffs on imports from the CEECs before, the agreements set a time schedule for abolishing tariffs for industrial goods and substantially reducing tariffs for all remaining goods within the following years. Figure 2.1 shows that the large share of tariff changes happened in the beginning of the liberalization period between 1993 to 1998. By January 1, 2002, industrial tariffs had been abolished on both sides, creating a *de facto* customs union before many CEECs formally joined the EU in 2004. The EU's tariff liberalization with the CEECs had several implications for the Portuguese exporters, as we discuss below.

The EU's tariff liberalization with the CEECs in the 1990s boosted their firms' competitiveness in the EU market. Figure 2.1 shows that the average tariff for industrial goods fell from 6.5 to 0 percent between 1993 and 2001. During that period, some products experienced a tariff reduction of up to 70 percentage points. This tariff liberalization substantially lowered goods prices and facilitated market entry of exporters from the CEECs. Figure 2.2 illustrates that manufacturing exports from the CEECs increased 20 % yearly, and their share of total EU manufacturing imports rose from 1.5% to 9% from 1993 to 2004. The increasing market share of CEECs producers resulted in heightened competitive pressure on other exporters of low-value-added industrial goods to the EU market, including Portugal.

Relevance of the competition shock for Portuguese exporters: In the early 1990s, the EU market was of great importance to Portuguese manufacturing firms. Figure 2.3 indicates that the EU was the destination of over 80% of Portuguese manufacturing exports, accounting for more than 30% of total manufacturing output of Portuguese

[5] Beyond liberalizing trade, the agreements also set the basis for new institutions that facilitated political dialogue, financial co-operation and technical assistance for the restructuring of the Central and Eastern European economies. (see Commission of the European Econonic Communities, 1992).

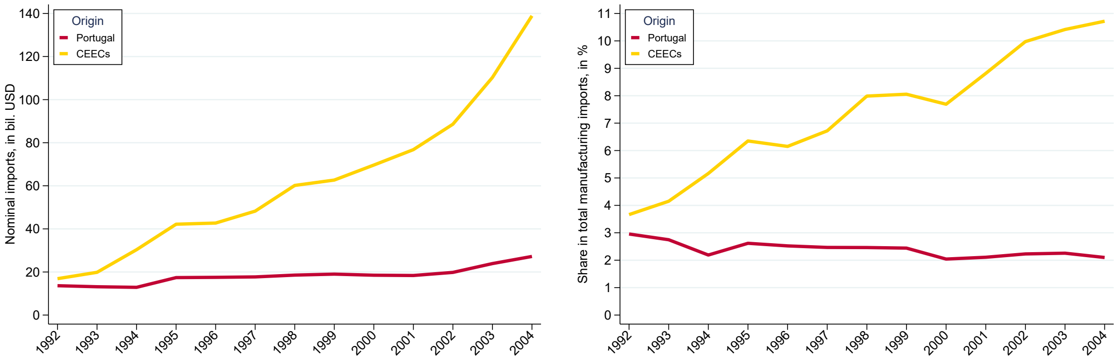
Figure 2.1: EU Import Tariffs towards CEECs (1991-2003)



(a) Average Applied Tariff By Country **(b)** Average Applied Tariff

Notes: Figure (a) depicts average applied tariffs for industrial products (HS Chapters 25 to 97). Figure (b) shows the average applied tariff for industrial products weighted by countries' exports to the EU in 1993. Source: Teti (2020), EUROSTAT.

Figure 2.2: EU Manufacturing Imports by Origin (1992-2004)

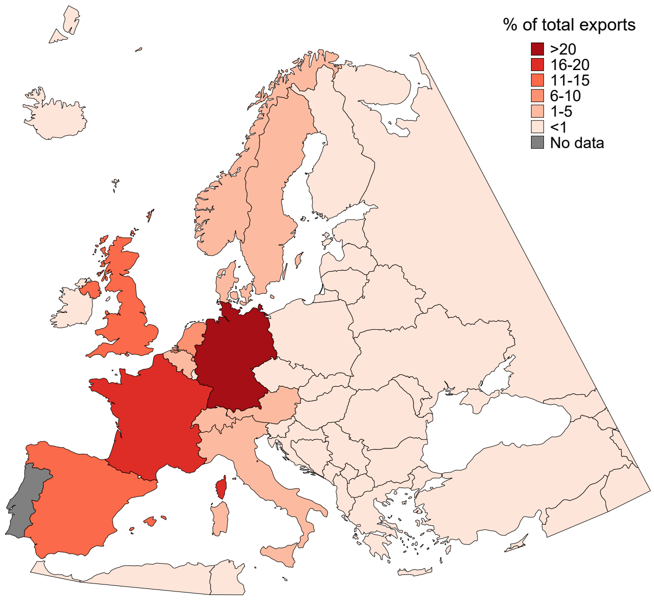


(a) Import Volumes **(b)** Share in EU Manufacturing Imports

Notes: Figures (a) and (b) show EU manufacturing imports by origin, in absolute values and percentage shares, respectively. Central and Eastern European Countries (CEECs) comprise Poland, Hungary, Czechia, Slovenia, Lithuania, Latvia, and Estland. Source: Author's calculations based on BACI International Trade Database.

firms. This reliance on the EU market made Portuguese firms vulnerable to economic fluctuations within the EU, as well as changes in EU trade policies. This implies that the rise of competition from the CEECs companies in the EU market was a significant competitive challenge for Portuguese exporters. The documents of the association agreements demonstrate that the Portuguese government made efforts to protect the domestic economy from increased competition, notably by incorporating exceptions

Figure 2.3: Destinations of Portuguese Manufacturing Exports in 1993



Notes: This figure shows the geographic distribution of Portuguese manufacturing exports across the Europe. Source: Author's calculations based on Commercio Internacional.

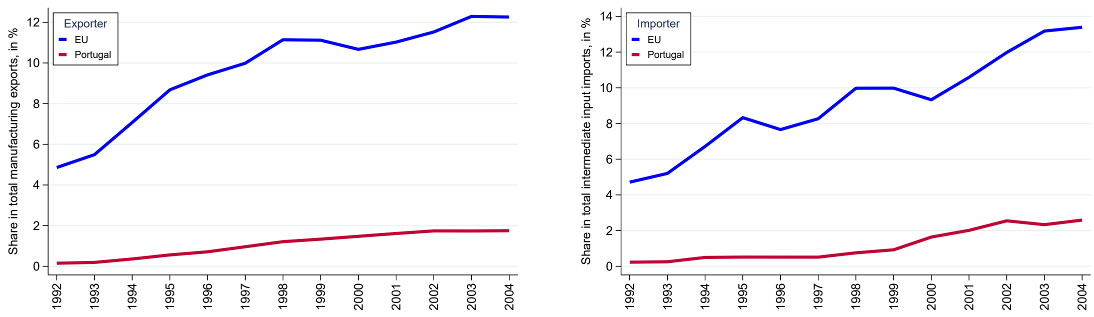
that postponed tariff liberalization and temporarily retained quantitative restrictions on certain goods for the Portuguese market.[6] However, the government was unable to protect local companies from competition with CEECs firms in the rest of the EU market.

As a result of these developments, Portugal's share in the EU market fell throughout the 1990s. Figure 2.2 illustrates that Portugal's share of EU manufacturing imports dropped from 3% in 1992 to 2% in 2004. Although Portuguese manufacturing imports kept growing in absolute terms, Portugal became less important as supplier of industrial goods to the EU market relative to its competitors from the CEECs.

Integration of Portugal and other EU countries with CEECs: At the same time, for reasons such as geographical location, the Portuguese economy integrated less strongly with the CEECs than the rest of the EU. Although Portuguese manufacturing exports to the CEECs grew steadily over the 1990s, Figure 2.4a shows that they still only accounted for about 2% of all Portuguese manufacturing exports in 2004. In contrast, CEECs had become an important destination for EU manufacturing exports

[6] See for instance Europe Agreement establishing an association between the European Communities and their Member States, of the one part, and the Republic of Poland, of the other, Protocol 5, Chapter II, Article 10.

Figure 2.4: Trade Integration with CEECs (1992-2004)



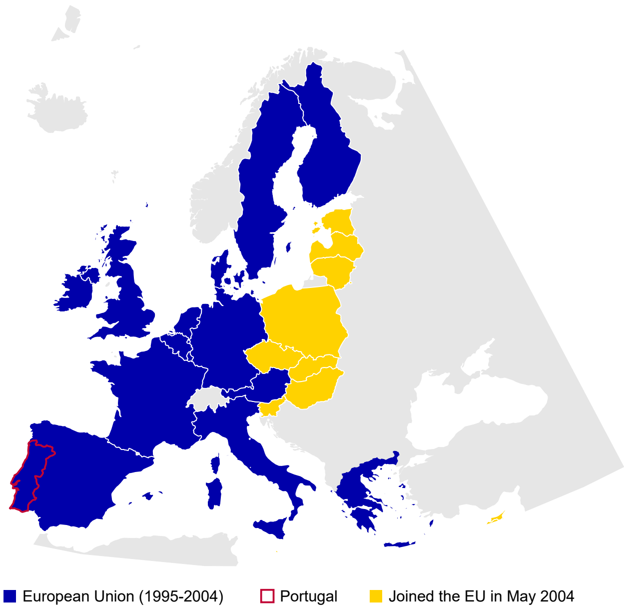
(a) Manufacturing exports to CEECs **(b)** Intermediate goods imports from CEECs

Notes: Figure (a) shows the percentage share of CEECs in total manufacturing exports for Portugal and the EU (excluding Portugal). Figure (b) depicts the percentage share of CEECs in intermediate input imports for Portugal and the EU (excluding Portugal), as classified by the OECD end-use categorization. Source: Author's calculations based on BACI International Trade Database.

receiving more than 12% of all EU manufacturing exports by 2004. Similarly, Portugal experienced relatively lower integration into value chains with the CEECs compared to the rest of the EU. According to Figure 2.4b, in 2004, Portugal's import share of intermediate goods from the CEECs was only 2.5%, whereas the rest of the EU had surpassed this figure by importing over 13%. By 2004, only 1% of all Portuguese manufacturing firms directly imported intermediate inputs from CEECs.

The rise of competition in the European export market was likely the most important channel through which the trade liberalization between the EU and the CEECs affected the Portuguese economy in the 1990s. This conclusion is also supported by Reis (2013) who relates the weak economic performance of Portugal in the late 1990s to the fierce competition in global markets for low value-added products that Portugal had specialized in. The historical evidence suggests that trade liberalization and the process of integration of the European Union were largely outside of the influence of the Portuguese government. As such, this period of tariff liberalization is a well-suited setting to study the effect of increasing competition in foreign markets on firms' technology investments.

Figure 2.5: Overview of the EU Eastern Enlargement in 2004



Notes: This figure illustrates countries by EU member status (1995-2004).

2.3 Data

2.3.1 Data Sources

To assess the impact of the tariff liberalization with CEECs on Portuguese firms, we combine tariff data with rich administrative data from the National Statistics Institute of Portugal (INE).

Tariff data: To proxy changes in competition in the context of the EU's tariff liberalization with CEECs, we leverage granular data on applied tariffs provided by Teti (2020). Specifically, this database provides information on applied tariffs of the EU for more than 5000 products at the HS 6-digit level. Its strength lies in its comprehensive tariff coverage based on a rigourous methodology that rectifies common issues such as misreporting and the resulting false tariff imputation, which results in large measurement error in other official tariff databases.[7] To assess the level of tariff protection for specific products, we calculate the average applied tariff imposed by the EU on the eight CEECs that joined the EU in 2004. This includes Poland, Hungary,

[7]Teti (2020) introduces a new database that is built using a new interpolation algorithm taking the misreporting into account.

Czechia, Slovakia, Latvia, Lithuania, Estonia, and Slovenia.[8]

Employer-employee data: We utilize data on the universe of firms and workers in Portugal from the dataset *Quadros de Pessoal (QP)* provided by INE. This database is the product of a high-quality compulsory census run by the Ministry of Employment covering the population of firms with wage earners in manufacturing and services. Each firm is required by law to provide information on an annual basis about its characteristics and those of each individual that comprises its workforce, ensuring high compliance with reporting. Firm-level information includes annual sales, number of employees, industry code, geographical location, date of constitution and share of capital that is foreign-owned. The set of worker characteristics includes wages, gender, age, schooling, date of starting, detailed occupation and hours worked. A worker may also be matched to the firm where she is employed. We use this data to build our controls and merge it to other administrative data-sets using a common firm identifier provided by INE.

Customs data: In addition, we use administrative data on firms' import and export transactions from the database *Estatísticas do Comércio Internacional (ECI)* provided by INE. This database is the country's official information source on imports and exports. It comprises all import and export transactions of firms, and provides detailed information on the product exported (imported) at the 8-digit level, the destination (source) market, and the value and quantity exported (imported). Export values reported in the data are free-on-board, thus excluding any duties or shipping charges, while import values include cost, insurance and freight (CIF). This data can be merged to the *Quadros de Pessoal* dataset using a common identifier. This feature allows us to identify firms that export among manufacturing firms, and hence are exposed to competition in the European market in the context of the tariff liberalization. Overall, we use the customs data to build our explanatory variable leveraging information on firms product portfolios, various outcome variables as well as control variables.

We leverage the customs data to measure firms' investments in industrial automation technology. Specifically, we trace firms' imports of industrial robots as well as numerically controlled machinery by means of detailed product codes listed in EU's

[8]While Cyprus and Malta were part of EU's 2004 enlargement, we do not considered them in this context as they had already established preferential trade relations with the EU in the early 1970s.

classification of goods, the Combined Nomenclature (CN).[9] Both industrial robots and numerically controlled machines have been used to automate many manual tasks in manufacturing, such as material processing (welding, grinding, turning, drilling, milling, etc.), object handling, or product assembly. As most automation technology is produced outside Portugal and must be imported, tracing investments in automation technology through imports is a good proxy for major automation investments in Portuguese manufacturing firms.

2.3.2 Description of Trends in Automation Equipment Imports

When looking at the imports of automation equipment and the adoption of such technologies by firms, we observe that Portugal underwent a process of increasing automation in the 1990s.[10] Figure 2.6a provides a compelling illustration of this evolution. Notably, it reveals a consistent upward trend in annual imports of automation equipment by manufacturing firms, with numerically controlled machinery imports nearly tripling from 1988 to the early 2000s. A similar trajectory is observed for industrial robots, which, starting from zero in 1988, surged to over 8 million EUR at the turn of the millennium. An important insight is that imports of numerically controlled machinery are in volumes by far the more important part of industrial automation.

Figure 2.6b shows that the overall increase in imports of automation equipment coincides with an increase in the number of importing firms, suggesting a diffusion of automation technology across firms. While the early observation period witnessed a rapid surge in the number of firms importing automation equipment, a notable turning point occurs in 1993, marked by a persistent slowdown in growth at the extensive margin. This intriguing trend shift is attributed to firms with fewer than 250 employees, which appear to decelerate their adoption post-1992. By 2003, over 800

[9]The Combined Nomenclature (CN) is the EU's eight-digit coding system, comprising the Harmonised System (HS) codes with further EU subdivisions. The nomenclature includes industrial robots categorized under the following codes: "84798950 - Multi-purpose industrial robots" (1987-1995) and "84795000 - Industrial Robots, not elsewhere classified" (since 1996). For a wide class of machine tools (4-digit headings 8456 to 8468), the Combined Nomenclature also distinguishes between "numerically controlled" and "other than numerically controlled" vintages or tools "for working with the hand". Similar to Acemoglu and Restrepo (2022), we leverage this distinction to trace further imports of automation equipment.

[10]Given the lack of domestic suppliers in the 90's, import data provide a good proxy for automation investments in Portugal. Moreover, firms in Portugal exhibit lower levels of investment in R&D and patent activity when compared to their counterparts in other EU countries. This highlights the importance of investing in technology adoption and automation as avenues to enhance the competitiveness for these firms.

manufacturing firms had imported automation equipment at least once, with small and medium-sized enterprises constituting the majority of adopters. Figure 2.7 provides further nuance to the general trend towards automation showing the share of adopters among the group of manufacturing exporters when broken up by 2-digit industries. While the median of diffusion lies at 7.4 percent in the furniture industry, adoption rates reach more than 30 percent for the top three industries (Machinery and equipment: 42%; Basic metals 36% and Motor vehicles: 35 %).

This initial examination of the data reveals a general trend towards increased automation adoption in Portuguese manufacturing, characterized by both higher volumes of imports and a growing number of firms adopting automation technology. This trend, however, exhibits variations in the pace of adoption over time and across different industries.

2.4 Empirical Strategy

2.4.1 Measuring Firm-level Exposure to Foreign Competition

To gauge the extent to which firms were exposed to increasing competition from Central and Eastern European firms in the EU market, we leverage information on the firms' initial export portfolio and information on product-specific reductions in EU tariffs vis-à-vis the CEECs. This information allows us to compute the firm-specific tariff reduction as the average tariff reduction weighted by the importance of each product in a firm's initial sales as given by

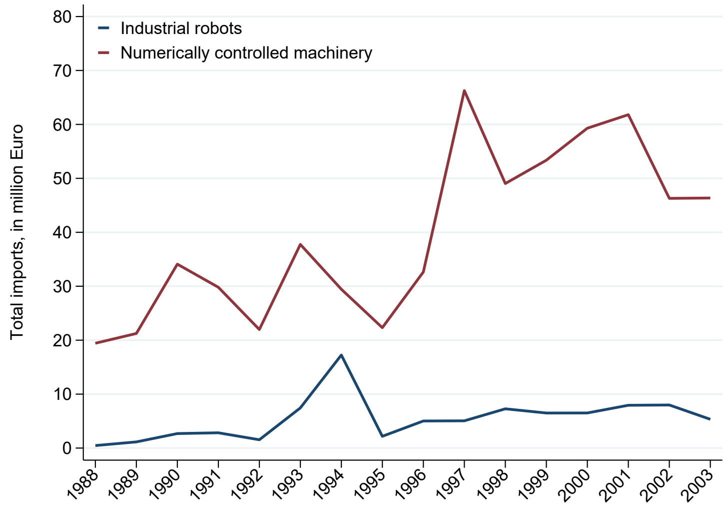
$$\Delta FC_i = -\sum_{p}^{1241} \phi_{i,p,1992} \times \Delta\tau_p \tag{2.1}$$

where the ϕ stands for the share of exports of the 4-digit product p to the EU in total sales of firm i in 1992 and $\Delta\tau$ is the difference between the applied tariff of the EU with respect to CEECs in 1992 and the zero tariff at the end of the liberalization.

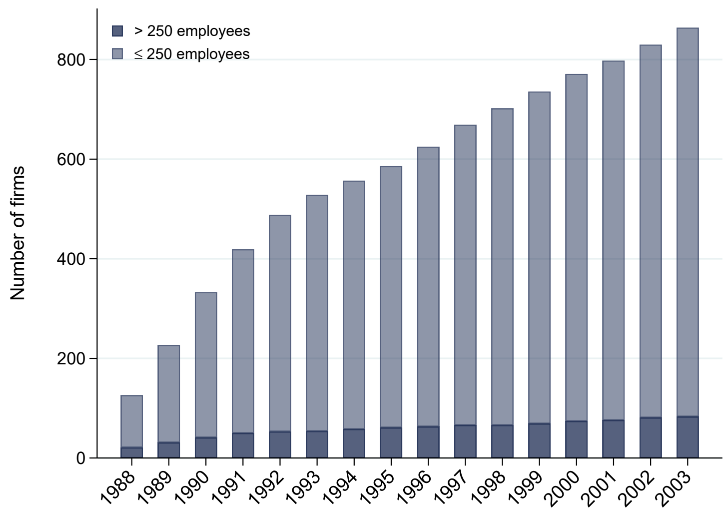
$$\phi_{i,p,1992} = \frac{X^{EU}_{i,p,1992}}{S_{i,1992}}$$

To ease the interpretation of coefficients in the regression analysis, we multiply the summation by -1. Thereby, we obtain an exposure measure which is larger for stronger

Figure 2.6: Automation Equipment Imports and Adopters (1988-2003)



(a) Total automation imports



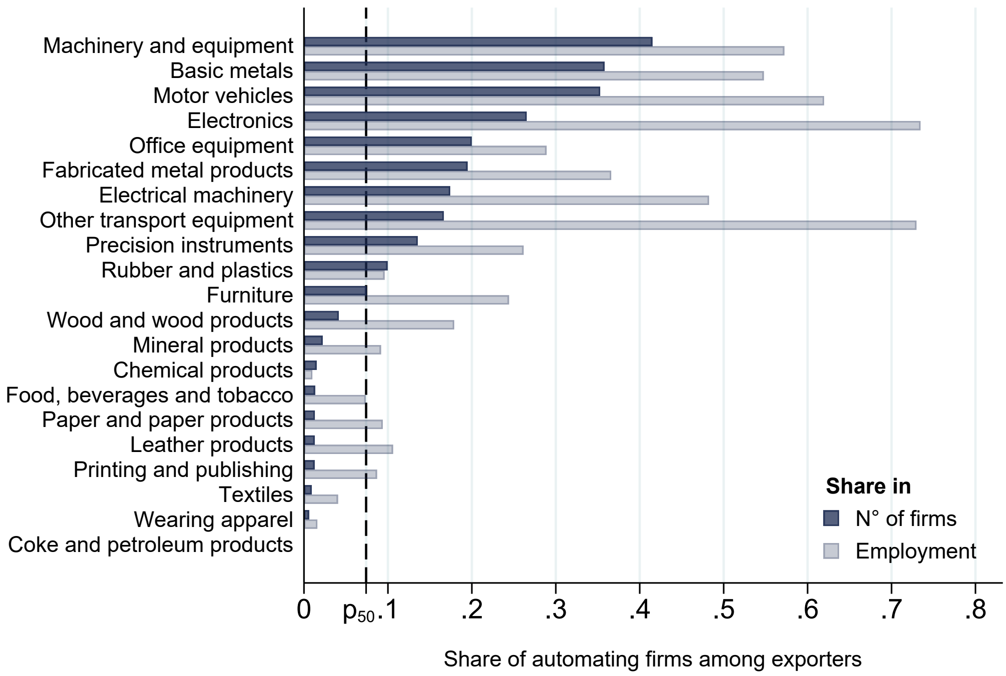
(b) Number of automation adopters

Notes: Figure (a) displays the total value of automation equipment imports by manufacturing firms, broken down by machinery type. Figure (b) shows the cumulative number of adopters, defined as firms that have imported automation equipment at least once, categorized by firm size. Source: Author's calculations from Commercio Internacional database.

reductions in tariffs.

An important advantage of the proposed measure is that it leverages variation in tariff reductions across products. Figure 2.8a and 2.8b show significant variation in tariff reductions across all 4-digit products. As each firm exports a different portfolio of

Figure 2.7: Diffusion within Industries (1988-1998)

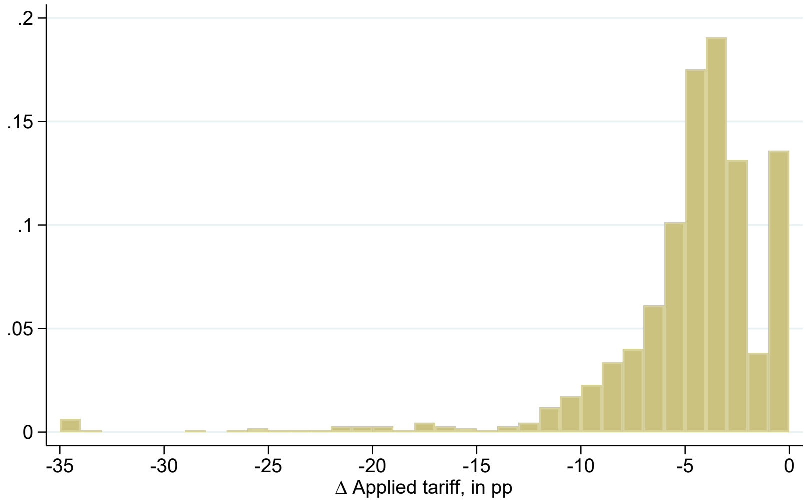


Notes: This figure shows the proportion of automating firms in both firm count and total employment within the 1992 manufacturing exporter cohort, broken down by 2-digit ISIC industries. 'Automating firms' are defined as manufacturing exporters active in 1992 having imported industrial robots and/or numerically controlled machinery at least once between 1988 and 1998. Source: Author's calculations from Commercio Internacional and Quadros de Pessoal data.

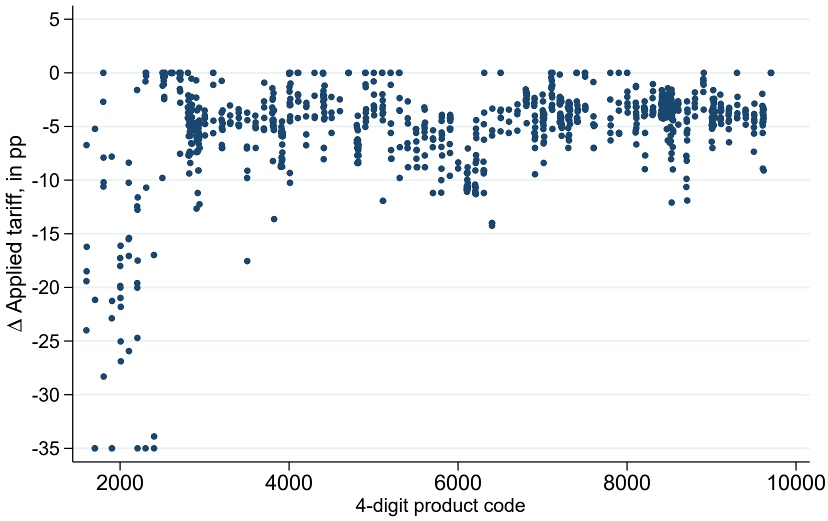
products, this variation in tariff reductions across products results in varying treatment intensity across firms – even within the same industry. This is an improvement over prior studies that leveraged tariff reductions or increasing import competition at the level of a firm's industry (e.g. D. Autor, Dorn, Hanson, et al., 2020; C. Chen & Steinwender, 2021) and allows for more stringent industry controls in our regression analysis. Figure 2.8b shows that tariff reductions varied widely across product classes and are not concentrated on specific goods.

Our identifying assumption is that the variation of tariff reductions across products is orthogonal to the competitiveness of Portuguese exporters and, consequently, unrelated to trends in the adoption of automation technology. If initial tariff barriers were strategically designed to shield firms specializing in non-competitive products, we would confound the extent of tariff reductions with unobserved differences in the competitiveness of firms. In such a scenario, we would anticipate a negative relationship between applied tariffs prior to liberalization and product-specific competi-

Figure 2.8: Product-level Variation in EU Tariff Reductions



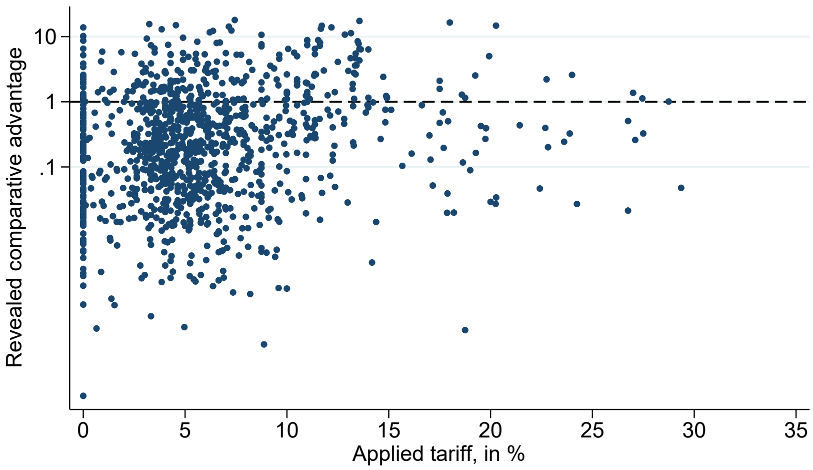
(a) Distribution of tariff reductions



(b) Tariff reductions across HS4 product classes

Notes: Figure (a) shows the distribution of absolute reductions in applied tariffs of the EU towards CEECs averaged at the 4-digit HS level without weighting for all non-agricultural products (HS Chapters 16 to 97). Figure (b) charts these reductions in applied tariffs for all 4-digit HS product classes. Source: Teti (2020).

Figure 2.9: EU Applied Tariffs and Portuguese Export Advantage in 1992



Notes: This figure plots the EU's applied tariffs towards CEECs for non-agricultural products in 1992, unweighted at the 4-digit HS level, against Portugal's revealed comparative advantage for each product i, computed as $RCA_i^{PRT} = (X_i^{PRT} / \sum_i X_i^{PRT})/(X_i^{WORLD} / \sum_i X_i^{WORLD})$, where X denotes exports. The graphs winsorizes outlier products with RCAs above 20. Source: Author's calculations based on BACI International Trade Database and Teti (2020).

tiveness indicators, such as the revealed comparative advantage (RCA).[11] Figure 2.9 depicts the relationship between EU tariffs and revealed comparative advantage of Portugal for each 4-digit product. Our analysis reveals no substantial association between EU tariffs and Portugal's RCA. This finding suggests that the tariff schedule of the EU's customs union was not aligned with Portugal's export strengths. Consequently, it supports our assumption that tariff reductions were equally important for both firms specializing in more and less competitive products.

2.4.2 Empirical Specification

To evaluate the importance of the tariff liberalization for the growth of Portuguese exporters, we start our analysis by estimating regressions in long differences:

$$\Delta\log(\mathrm{Y}_i) = \beta\Delta\mathrm{FC}_i + \mathbf{X}'_{i,1992}\gamma + \mathrm{industry}_j + \mathrm{region}_n + \varepsilon_i \tag{2.2}$$

where Y_i stands for different measures of firm performance, in particular sales, employment and export product characteristics. Specifically, we examine long differences

[11]Values above unity indicate a comparative advantage in a given product relative to the rest of the world.

in a measure of firm performance between 1992 and 1998, covering the year leading up to the liberalization and extending to the point when most of the goods trade with the CEECs was liberalized (see Figure 2.1b). We account for differential trends by controlling for firms' baseline characteristics in 1992 and including dummies for NUTSII regions and 2-digit ISIC industries.[12] In the main part of our analysis, we study the effect of increasing competition on automation by estimating the following equation:

$$\operatorname{asinh}(\mathrm{Y}_i) = \beta\,\Delta\mathrm{FC}_i + \mathbf{X}'_{i,1992}\gamma + \mathrm{industry}_j \times \mathrm{size\ bracket}_s + \mathrm{region}_n + \varepsilon_i \qquad (2.3)$$

where Y_i is the automation variable defined as the sum of imports of industrial robots and numerically controlled machinery by firm i between 1992 and 1998 scaled by the number of production workers in 1992. This measure of automation is close to the widely used concept of robot density, defined as the number of industrial robots per employees or hours worked (Graetz & Michaels, 2018). Looking at imports over the entire period of liberalization allows us to capture the firms' automation response to the full reduction in tariffs and without imposing restrictive timing assumptions. In our main analysis, we account for the skewed outcome distribution and the large share of zeros by appling an inverse hyperbolic sine transformation of the outcome variable.

In our main specification, we control for several baseline characteristics $\mathbf{X}'_{i,1992}$ that likely affect the propensity to adopt automation technology. First, we control for firm sales as larger firms tend to be more productive and are more likely to shoulder the fixed cost involved in automation adoption. Second, we account for differences in firm age as we expect younger firms to be more flexible in the re-organization of their production process. Third, we control for foreign ownership as this might affect access to foreign technology and knowledge. Finally, we include dummies for NUTS 2 regions as well as dummies for 2-digit ISIC industry by size bracket cells.[13] Thereby, we account for different trends in adoption and will only compare firms within the same industry and size class.

We also account for contemporaneous factors in trade that we expect to affect firms' incentives to automate. To account for potential improvements in market access for Portuguese firms exporting to CEECs, we include dummies that indicate whether firms were already exporting to CEECs in 1992 and whether they started exporting to CEECs over ther period until 1998. In addition, we want to ensure that both the tariff shock

[12] See Appendix Figure D.3 for more details on administrative regions in Portugal.

[13] We group firms into size brackets by number of employees in 1992 (10-49, 50-249, 250-499, 500-999 or ≥1000).

and firm-level automation are not confounded by rising competition from China in the EU in the decade leading up to China's accession to the the World Trade Organization in 2001. For this reason, we compute for each firm a measure of exposure to rising Chinese import penetration in 4-digit product markets in the EU, following Branstetter et al. (2019) which is analogous to our measure of exposure to the tariff liberalization.[14]

Finally, we control for the sum of product shares $\phi_{i,p}$ of each firm which corresponds to the share of exports to the EU in total sales. As most firms sell also products domestically or outside of the EU market, the sum of exposure shares is often smaller than unity. According to recent work on shift-share designs by Borusyak, Hull, and Jaravel (2022), such "incomplete shares" lead to biased estimates as they induce differences in the treatment intensity that do not come from exogenous variation in the shock and can potentially be correlated with the outcome variable. In our case, this could be a concern if firms with higher exposure to the EU export market are more productive and are also more likely to adopt advanced production technology. For this reason, we follow Borusyak, Hull, and Jaravel (2022) and correct for the non-random exposure of firms to the European export market by controlling for the sum of product shares $\phi_{i,p}$ of each firm in 1992.

2.5 Results

This section presents our main results. Section 2.5.1 documents that the exposure to tariff reductions reduced firms' sales growth highlighting the economic significance of the tariff liberalization for Portuguese exporters. Sections 2.5.2 and 2.5.3 explore different margins of adjustment showing that more exposed firms specialized in the most competitive products and significantly reduced their labor demand. Section 2.5.4 unpacks the effect of tariff reductions on automation, showing a negative average effect with strong heterogeneity by initial labor productivity and industry exposure to automation. Finally, Section 2.5.5 performs a variety of robustness checks.

[14]To compute a measure of firm-level exposure to Chinese import penetration in the European market, we average increases in Chinese import penetration across 4-digit product markets weighted by the importance of products p in a firm's total sales: $\Delta \mathrm{FC}_i^{China} = \sum_p^{1241} \frac{X_{i,p,1992}}{S_{i,1992}} \times \frac{IMP_{p,1998}^{China} - IMP_{p,1992}^{China}}{IMP_{p,1992}^{Total}}$.

2.5.1 Sales and Exports

Table 2.1 presents the results of long-difference regressions from 1992 to 1998, shedding light on the first-order impact of exposure to tariff reductions on firms' sales by destination. The estimation reveals that exposure to tariff reductions is associated with a substantial reduction in total sales, which is primarily driven by a decline in exports to the EU market, while domestic and extra-EU sales remain largely unaffected. Accordingly, the first column shows that a standard deviation increase in the exposure to tariff reductions is associated with a 20.5 percent decrease in total sales growth. Further unpacking total sales, columns (2) and (3) show that the sizable negative effect on total sales growths stems from a decline in foreign sales, while domestic sales do not exhibit any significant reduction. More specifically, columns (4) and (5) show that the negative effect on total exports can be attributed to exports to the EU market, while extra-EU exports are less affected. These results show that the tariff liberalization between the EU and CEECs had a significantly negative effect on the sales growth of Portuguese firms in the EU market and is highly suggestive of declining market shares due to increasing competition from CEECs. If declining market shares were indeed of economic relevance for Portuguese exporters, we would expect firms to adjust their export strategies and the organization of production in response, as demonstrated in the following section.

2.5.2 Export Strategies

Table 2.2 provides evidence that firms adjusted their export strategies in terms of the variety and prices of goods exported to the EU market. The first two columns report that a one-standard-deviation increase in exposure to tariff reductions resulted in a significant 23-percentage-point decrease in the growth in the number of product varieties exported to the EU. Remarkably, this effect does not extend to exports to destinations outside the EU.[15] Similarly, columns (3) and (4) reveal that firms decreased average product prices for EU exports by more than 2 percentage points, while prices for exports to other destinations remained unaffected. The reduction in prices could be driven by a reduction in the average quality of products exported to the EU. Indeed, column (5) shows that these adjustments were accompanied by a slight reduction in the quality of products exported to the EU, as defined by Khandelwal (2010). These

[15]The number of products is defined as the number of HS 8-digit products exported by the firm to a destination country.

Table 2.1: Effects of Exposure to Tariff Reductions on Sales by Destination: Long Differences, 1992-1998 (OLS)

	Δ log(Y) $\times$ 100 from 1992 to 1998				
	Total Sales	Domestic Sales	Total Exports	Intra-EU Exports	Extra-EU Exports
	(1)	(2)	(3)	(4)	(5)
Δ FC	-20.50***	-9.51	-11.92**	-13.41**	-10.01
	(6.60)	(27.96)	(4.90)	(6.33)	(9.57)
Observations	4,186	4,186	3,352	2,614	1,982
R-squared	0.07	0.12	0.05	0.14	0.02
Industry FE	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES

Notes: The dependent variable is the change in the log of a given sales variable between 1992 and 1998 multiplied by 100. The explanatory variable is normalized to have a mean of 0 and a standard deviation of 1. All regressions include dummies for 2-digit ISIC industries and NUTS2 regions and control for the sum of product shares. Standard errors are robust to heteroskedasticity and allow for clustering at the 3-digit industry-level (99 industries). Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

findings combined indicate that firms adapted their export strategy specifically for the EU market by price reductions and a focus on a narrower range of products. In contrast, their pricing and product mix strategies for exports to the rest of the world remained unchanged. This supports the hypothesis that increased competitive pressure in the EU market in the context of the tariff liberalization prompted significant changes in firms' strategies, in particular for sales to the EU.

2.5.3 Employment and Wages

Meanwhile, as shown in Table 2.3, tariff liberalization also had substantial ramifications for firms' production organization, particularly concerning labor demand. To establish this, we first look at the first two columns, which reveal that a one-standard-deviation increase in exposure to tariff reductions corresponds to a significant 7-percentage-point decrease in employment growth and a substantial 9-percentage-point reduction in wage bill growth. Delving deeper into the data, columns (4) and (5) provide insights into the specific effects on wages. Here, we show a drop of over 2 percentage points in monthly wages while hourly wages remain unchanged. This suggests a multifaceted response by firms to heightened competitive pressure. They

Table 2.2: Effects of Exposure to Tariff Reductions on Product Scope and Export Prices: Long Differences, 1992-1998 (OLS)

	Δlog(#Products)		Δlog(Price)		ΔQuality	
	Intra-EU	Extra-EU	Intra-EU	Extra-EU	Intra-EU	Extra-EU
	(1)	(2)	(3)	(4)	(5)	(6)
ΔFC	-0.236***	-0.006	-0.027**	0.013	-0.039*	0.017
	(0.021)	(0.025)	(0.010)	(0.020)	(0.021)	(0.020)
Observations	2614	1998	4588	3010	2089	1644
R-squared	0.14	0.02	0.02	0.02	0.02	0.02
Industry FE	YES	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES	YES

Notes: The explanatory variable is normalized to have a mean of 0 and a standard deviation of 1. All regressions include dummies for 2-digit ISIC industries and NUTS2 regions. Standard errors are robust to heteroskedasticity and allow for clustering at the 3-digit industry-level (99 industries). Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

adapt by both limiting new hires and reducing the work hours of incumbent workers, a strategy that has the potential to enhance labor productivity. These findings further corroborate the hypothesis that the tariff liberalization between the EU and CEECs induced significant competitive pressure, prompting firms to alter both strategy and the organization of production.[16]

2.5.4 Automation

The evidence so far suggests that firms reacted to increasing competition in the EU market by trying to curb labor costs and potentially increase productivity. Given firms' attempts to reduce labor costs, we could expect that they may strategically invest in technology capable of automating various aspects of their operations. Nevertheless, firms may also scale back investments in automation in response to the negative shock. This section provides empirical evidence using the exogenous tariff shock.

Table 2.4 presents our main result showing that firms more exposed to the tariff liberalization tend to automate less during the period of observation. Column (1) reports our baseline estimate indicating that a standard deviation increase in the exposure to tariff reductions decreases automation imports per production worker by about 57

[16]We present additional findings on employment and wage effects by skill type in Appendix Table B.8. It is important to note that Table 2.3 shows baseline effects without adjusting for firm characteristics. We find consistent effects in the fully specified model, as detailed in Appendix Table B.5.

Table 2.3: Effects of Exposure to Tariff Reductions on Employment and Wages: Long Differences, 1992-1998 (OLS)

	Δ log(x) × 100 from 1992 to 1998				
	Total employment	Total wage bill	Total work hours	Monthly wage	Hourly wage
	(1)	(2)	(3)	(4)	(5)
Δ FC	-7.27***	-9.82***	-9.44***	-2.45**	-0.39
	(2.66)	(3.27)	(2.80)	(1.00)	(0.81)
Observations	4,064	4,064	4,064	4,064	4,064
R-squared	0.04	0.03	0.03	0.03	0.02
Industry FE	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES

Notes: The dependent variable is the change in the log of a given employment or wage variables between 1992 and 1998 multiplied by 100. Explanatory variable is normalized to have a mean of 0 and a standard deviation of 1. All regressions include dummies for 2-digit ISIC industries and NUTS2 regions. Standard errors are robust to heteroskedasticity and allow for clustering at the 3-digit industry-level (99 industries). Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

percent. Column (2) shows that this estimate is robust to controlling for confounding firm characteristics such as sales, firm age and foreign ownership. Adding further contemporaneous controls for firms' exports to CEECs and Chinese import penetration in the EU market does not alter the estimate significantly. Once we introduce region and industry dummies, our main estimate observes a reduction by more than half. Yet, it still stands significant at 25 percent, shedding light on the impact of geographical and industry-specific factors.

In column (5), we further sharpen our analysis by incorporating industry-by-size bracket dummies. These more restrictive controls account for size-related adoption patterns across industries as revealed in Appendix Table B.3. Thereby, the model controls for the fact that firms of larger size in certain industries are potentially more suited for automation than others. In addition, this model only leverages variation in exposure to tariff reductions across firms within the same size class of a given industry. Despite this more stringent specification, the coefficient estimate experiences only a slight reduction to 23 percent. Contrary to our initial hypothesis that firms might increase automation to reduce labor costs, Table 2.4 therefore tells a different story: firms more exposed to the tariff liberalization, on average, engaged in less automation.

The stark negative association between exposure to tariff reductions and automation

Table 2.4: Effects of Exposure to Tariff Reductions on Automation Investment per Worker: 1992-1998 (OLS)

	asinh(Automation per worker) from 1992 to 1998				
	(1)	(2)	(3)	(4)	(5)
Δ FC	-0.57***	-0.57***	-0.57***	-0.25***	-0.23***
	(0.18)	(0.18)	(0.20)	(0.08)	(0.08)
Sales		0.00	0.00	0.01**	0.00
		(0.00)	(0.00)	(0.00)	(0.00)
Firm age		0.00	-0.00	0.00	-0.00
		(0.00)	(0.00)	(0.00)	(0.00)
Foreign ownership		0.46*	0.41*	0.17	-0.07
		(0.27)	(0.25)	(0.19)	(0.15)
Exporting to CEECs			0.17	0.20	0.11
			(0.12)	(0.13)	(0.14)
Export entry to CEECs			0.67***	0.49**	0.37**
			(0.24)	(0.19)	(0.18)
Δ FC^{China}			-0.02	-0.01	-0.02
			(0.06)	(0.03)	(0.04)
Observations	3,991	3,964	3,964	3,964	3,953
R-squared	0.03	0.03	0.04	0.18	0.23
Region FE	NO	NO	NO	YES	YES
Industry FE	NO	NO	NO	YES	YES
Industry x Size FE	NO	NO	NO	NO	YES

Notes: The dependent variable is the inverse hyperbolic sine of the sum of firm-level imports of industrial robots and numerically controlled machinery from 1992 to 1998, deflated to 1990 prices, and divided by the number of production workers in 1992. Explanatory variable is normalized to have a mean of 0 and a standard deviation of 1. Specification (4) include dummies for NUTS2 regions and 2-digit ISIC industries. Specification (5) includes a dummy variable for each 2-digit industry by employment size category (10-49,50-249,250-499, 500-999,≥1000). Standard errors are robust to heteroskedasticity and allow for clustering at the 3-digit industry-level (99 industries). Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table 2.5: Effects of Exposure to Tariff Reductions on Automation Adoption: 1992-1998 (OLS)

	Automation adoption from 1992 to 1998				
	(1)	(2)	(3)	(4)	(5)
Δ FC	-0.07***	-0.07***	-0.07***	-0.03***	-0.03***
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Sales		0.00	0.00	0.00**	0.00
		(0.00)	(0.00)	(0.00)	(0.00)
Firm age		0.00	0.00	0.00	-0.00
		(0.00)	(0.00)	(0.00)	(0.00)
Foreign ownership		0.06*	0.06*	0.03	0.00
		(0.03)	(0.03)	(0.03)	(0.02)
Exporting to CEECs			0.02	0.02	0.01
			(0.01)	(0.01)	(0.02)
Export entry to CEECs			0.08***	0.06***	0.05**
			(0.03)	(0.02)	(0.02)
Δ FC^{China}			-0.00	-0.00	-0.00
			(0.01)	(0.00)	(0.00)
Observations	3,991	3,964	3,964	3,964	3,953
R-squared	0.03	0.03	0.04	0.18	0.24
Region FE	NO	NO	NO	YES	YES
Industry FE	NO	NO	NO	YES	YES
Industry x Size FE	NO	NO	NO	NO	YES

Notes: The dependent variable is a dummy indicating whether the firm has imported industrial robots or numerically controlled machinery between 1992 and 1998. Explanatory variable is normalized to have a mean of 0 and a standard deviation of 1. Specification (4) include dummies for NUTS2 regions and 2-digit ISIC industries. Specification (5) includes a dummy variable for each 2-digit industry by employment size category (10-49,50-249,250-499, 500-999,≥1000). Standard errors are robust to heteroskedasticity and allow for clustering at the 3-digit industry-level (99 industries). Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

is also mirrored by the extensive margin of automation adoption. Table 2.5 shows estimation results of linear probability models using automation adoption between 1992 and 1998 as a binary outcome variable. The first column reports that standard deviation increase in exposure reduced the likelihood of automation adoption by 7 percentage points. When controlling for firms baseline characteristics, contemporaneous factors and as well as region and industry dummies, the estimate drops to 3 percentage points, but remains significant, even in the fully saturated model in column (5). This effect is sizable given the average adoption rate of 5.2 percent in our sample over the period of observation. As such, Tables 2.5 confirms our previous finding showing that the tariff liberalization also decreased automation at the extensive

Table 2.6: Heterogeneous Effects of Exposure to Tariff Reductions on Automation: 1992-1998 (OLS)

	asinh(Automation per worker)		Automation adoption	
	(1)	(2)	(3)	(4)
Δ FC	-0.60***	-0.24***	-0.07***	-0.03***
	(0.19)	(0.08)	(0.02)	(0.01)
Labor productivity	0.19	0.22	0.02	0.03
	(0.31)	(0.58)	(0.03)	(0.06)
Δ FC × labor prod.	0.58**	0.28*	0.06**	0.03
	(0.27)	(0.16)	(0.03)	(0.02)
Observations	3,991	3,953	3,991	3,953
R-squared	0.03	0.23	0.03	0.24
Firm characteristics	NO	YES	NO	YES
Contemporaneous controls	NO	YES	NO	YES
Region FE	NO	YES	NO	YES
Industry FE	NO	YES	NO	YES
Industry x Size FE	NO	YES	NO	YES

Notes: The dependent variable is the inverse hyperbolic sine of the sum of firm-level imports of industrial robots and numerically controlled machinery from 1992 to 1998, deflated to 1990 prices, and divided by the number of production workers in 1992. Explanatory variable is normalized to have a mean of 0 and a standard deviation of 1. Specifications (2) and (4) incorporate all control variables included in the fully specified model detailed in column (5) of Table 2.4. Standard errors are robust to heteroskedasticity and allow for clustering at the 3-digit industry-level (99 industries). Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

margin.

Building on the insights from Aghion et al. (2005) regarding the impact of the competitive position on firms' responses to competition, we further examine whether tariff reductions prompt varying automation strategies based on firms' initial competitiveness. Specifically, investing in cutting-edge automation technology might not help cope with the increased competition, and constitute a risky investment with uncertain payoff, if the competitive disadvantage of certain firms is too large. However, if firms are highly competitive and close to the technological frontier, we could expect that investing in automation might be within reach and sufficient to close the competitive gap. To test this hypothesis, we introduce an interaction term in equation 2.3 that includes firms' initial labor productivity (measured as sales per worker) as an indicator of competitiveness. Acknowledging the strong assumption of the linear nature of the moderating effect, this approach nevertheless enables a more detailed examination of the connection between automation and competition, offering insights into the role of firms' competitiveness.

Table 2.6 points into the direction of our hypothesis: the moderating influence of initial labor productivity on the impact of tariff reductions is positive. In the fully specified model, column (2) illustrates a statistically significant coefficient amounting to 28 percent. However, considering an interdecile range of 0.062 Million Euros per worker, this finding implies that transitioning from the 10th to the 90th decile would marginally mitigate the negative effect on automation, by a mere 1.7 percentage points, insufficient to reverse the underlying negative baseline effect of -24 percent. Columns (3) and (4) replicate this positive interaction when automation adoption is the dependent variable. Yet again, the magnitudes observed fail to reach substantial economic significance, as the negative impact on automation adoption is only dampened. Consequently, our preliminary conclusion is that initial competitiveness exhibits only a mild moderating role in this context.

In our final test, we explore the possibility that our current heterogeneity analysis might obscure distinctions among industries with varying inclinations towards automation. Given the noticeable disparities in adoption rates across industries, as shown in Table B.3, it is plausible that certain sectors could be inherently more conducive to automation adoption. Consequently, the moderating influence of initial productivity could vary across industries. To address this, we categorize industries based on their adoption rates, grouping those falling below the median of 7 percent as "low adoption industries," and categorizing the rest as "high adoption industries." We then conduct a refined heterogeneity analysis, introducing interactions with a dummy variable denoting industries with above-median adoption rates.

Our findings in Table 2.7 highlight a striking disparity: the positive interaction effect is significantly more pronounced for firms operating in high adoption industries. In the fully specified model, as demonstrated in column (2), the estimates for firms within high adoption industries suggest that transitioning from the 10th to the 90th decile would not only mitigate the negative effect on automation but do so by an impressive 140 percent, effectively reversing the initial negative baseline effect of -52 percent. Column (4) further reports a similar pattern, indicating that, at the extensive margin, a change in productivity spanning the interdecile range in high adoption industries yields a substantial positive impact, increasing the likelihood of automation by approximately 9 percent. These results imply that while the baseline effect remains negative, it is overturned for the most productive firms operating in indus-

Table 2.7: Heterogeneous Effects of Tariff Reductions on Automation by Sectoral Exposure: 1992-1998 (OLS)

	asinh(Automation per worker)		Automation adoption	
	(1)	(2)	(3)	(4)
Δ FC × Low	-0.44***	-0.21***	-0.05***	-0.02***
	(0.15)	(0.07)	(0.02)	(0.01)
Δ FC × High	-1.77***	-0.52**	-0.19***	-0.06*
	(0.48)	(0.24)	(0.05)	(0.03)
Labor productivity × Low	-0.83	0.04	-0.10*	0.01
	(0.50)	(0.45)	(0.06)	(0.05)
Labor productivity × High	28.12***	11.54***	3.19***	1.29***
	(5.82)	(4.14)	(0.62)	(0.43)
Δ FC × Labor prod. × Low	0.28	0.14	0.03	0.01
	(0.21)	(0.09)	(0.02)	(0.01)
Δ FC × Labor prod. × High	47.08***	22.67***	5.20***	2.49***
	(10.68)	(8.20)	(1.16)	(0.90)
Observations	3,991	3,953	4,186	4,150
R-squared	0.11	0.24	0.10	0.24
Firm characteristics	NO	YES	NO	YES
Contemporaneous controls	NO	YES	NO	YES
Region FE	NO	YES	NO	YES
Industry FE	NO	YES	NO	YES
Industry x Size FE	NO	YES	NO	YES

Notes: Explanatory variable is normalized to have a mean of 0 and a standard deviation of 1. Specifications (2) and (4) incorporate all control variables included in the fully specified model detailed in column (5) of Table 2.4. Standard errors are robust to heteroskedasticity and allow for clustering at the 3-digit industry-level (99 industries). Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

tries particularly exposed to automation. This finding bears potential implications for their survival and the overall concentration of industries in the long run.

In summary, our analysis reveals that, on average, rising competition deterred firms from automation. However, a noteworthy exception emerged: the most productive firms in industries prone to automation exhibited a positive response that offset the negative impact, resulting in increased automation among the top firms in highly automating industries. This suggests that within industries, heightened competition dissuades substantial automation investments among average firms, while primarily encouraging automation at the most productive firms. This phenomenon could potentially reinforce patterns favoring industry-leading "superstar" firms. Thereby, increased competition may lead to a scenario where top firms become more automated, further accentuating concentration within the industry.

2.5.5 Robustness

A potential threat to our identification strategy is the possibility that firms exposed to greater tariff reductions may have experienced lower export growth even before the treatment period. This scenario could arise if tariffs acted as protective measures for less competitive firms. In this case, more exposed firms would likely have automated less even in the absence of tariff liberalization, given their downward trend in export performance. In such a scenario, the impact of tariff reductions on automation would be confounded with the influence of low competitiveness, leading to an upward bias in our coefficient estimate.

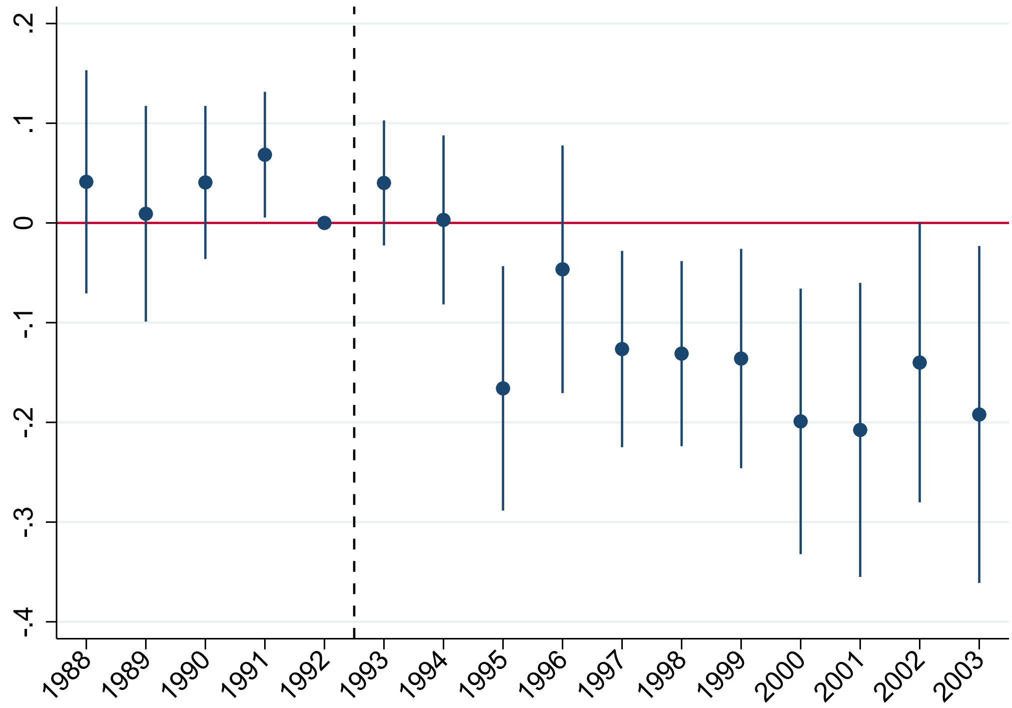
To address this concern, we extend the period of analysis and conduct an event study to investigate differences in exports between more and less exposed firms before and after the start of the tariff liberalization in 1992. Specifically, we estimate the following two-way linear fixed effects regression:

$$\log\left(Y_{i,t}\right) = \alpha + \sum_{k \neq 1992} \beta_k \left(\Delta FC_i \times 1_{t=k}\right) + \gamma_i + \delta_{j,t} + \Phi_i \times \delta_t + \varepsilon_{i,t} \tag{2.4}$$

where Y represents the total exports of firm i in year t, γ_i denotes firm-specific fixed effects that help account for time-invariant unobservable factors, while $\delta_{j,t}$ represents industry-by-year fixed effects to address contemporaneous factors that may confound the estimation. We further control for the sum of exposure shares Φ interacted with year dummies to obtain robust estimates following the methodology by Borusyak, Hull, and Jaravel (2022). We estimate the regression using data from 1988, which marks the start of our dataset, through 2003, one year prior to the Eastern enlargement of the EU.

Figure 2.10 depicts the coefficient estimates derived from Equation 2.4. It illustrates the absence of a differential trend in exports between firms more and less exposed to the tariff liberalization in the period leading up to tariff liberalization. This result supports the assumption that the treatment intensity was not correlated with prior export performance, serving as a proxy for firms' competitiveness. Furthermore, Figure 2.10 substantiates the impact of the tariff liberalization on exports showing persistent and statistically significant negative differences in exports from 1995 onwards. In 1998,

Figure 2.10: Dynamic Effects of Exposure to Tariff Reductions on Exports (1988-2003)



Notes: This figure plots regression coefficients β_k from Equation 2.4. The explanatory variable is normalized to have a mean of 0 and a standard deviation of 1. The plot reports 95% confidence intervals based on clustered standard errors at the 3-digit industry level.

firms that were a standard deviation more exposed to the tariff reductions had 12 percentage point lower export growth since 1992, which is in line with our estimate of 11.5 percentage points from Table 2.1. In sum, Figure 2.10 supports the assumption that the treatment intensity was uncorrelated with prior export performance, while confirming the persistently negative effect of the tariff liberalization on exports. We interpret this pattern as indicative of an exogenous increase in competition within the EU market, a pivotal assumption in our study.

Finally, our identification strategy could be threatened if more exposed firms had anticipated the increase in competition by investing in automation in advance. In this case, the negative coefficient in our main result could be due the fact that more exposed firms automate less because they had already automated in the pre-period. To address this potential concern we test how important automation investments prior to the tariff liberalization over the years 1988 to 1991 are in explaining automation

Table 2.8: Robustness of Effects of Tariff Reductions on Automation to Pre-trends: 1992-1998 (OLS)

	asinh(Automation per worker)		Automation adoption	
	(1)	(2)	(3)	(4)
Δ FC	-0.18***	-0.19***	-0.02***	-0.02***
	(0.06)	(0.06)	(0.01)	(0.01)
Labor productivity		0.48		0.05
		(0.59)		(0.07)
Δ FC × Labor prod.		0.23		0.02
		(0.17)		(0.02)
asinh(Automation per worker)$_{1988-1991}$	0.28***	0.28***		
	(0.04)	(0.04)		
Automation adoption$_{1988-1991}$			0.26***	0.26***
			(0.04)	(0.04)
Observations	3,953	3,953	3,953	3,953
R-squared	0.28	0.28	0.29	0.29
Firm characteristics	YES	YES	YES	YES
Contemp. controls	YES	YES	YES	YES
Region FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Industry x Size FE	YES	YES	YES	YES

Notes: Explanatory variable is normalized to have a mean of 0 and a standard deviation of 1. Specification (4) include dummies for NUTS2 regions and 2-digit ISIC industries. Specification (5) includes a dummy variable for each 2-digit industry by employment size category (10-49,50-249,250-499, 500-999,≥1000). Standard errors are robust to heteroskedasticity and allow for clustering at the 3-digit industry-level (99 industries). Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

in the main period of analysis.

In Table 2.8, we observe that while automation in the pre-period serves as a positive predictor for automation in the primary analysis period, factoring in pre-period automation only marginally reduces the effect estimate. Specifically, in column (1), the coefficient is -0.18, compared to -0.23 obtained in the fully saturated model in column (5) of Table 2.4, our primary result. Similarly, considering adoption in the pre-period trims the effect estimate at the extensive margin from -0.03 (as seen in column (5) of Table 2.5) to -0.02. Importantly, both effect estimates, at both the intensive and extensive margins, retain their statistical significance. At the same time, including the pre-trend eliminates the statistical significance of the interaction with labor productivity, which was already weakly significant and of modest size in Table 2.6. In summary, Table 2.8 reaffirms our primary finding even when accounting for anticipatory effects, bolstering the robustness of our results.

2.6 Conclusion

We bring together a rich set of administrative microdata, including employer-employee data and customs data, to construct a novel dataset on firm-level imports of automation technologies in Portugal. We exploit a large tariff liberalization between the EU and CEECs in the 1990s to investigate how increased product market competition affects firms' automation investments and performance. We first find that firms that are more exposed to the tariff liberalization experience significant reductions in sales, driven by exports to the EU, and adjust their export strategy by reducing the number of exported product varieties and lowering prices of exports to the EU. Second, we show that more exposed firms significantly reduce labor costs by hiring fewer employees and reducing workhours of incumbent workers. We then assess the consequences of increased competition on firm-level automation. In our setting, we find that a one-standard-deviation increase in exposure leads to a substantial 25 percent reduction in automation at the intensive margin, as well as a 3-percentage-point decrease in the likelihood of firms adopting automation at the extensive margin. Despite the apparent need for firms to curb labor costs in the face of increased competition, we find that heightened competition diminishes the incentive for automation. However, when scrutinizing firms within industries that are highly prone to automation, we observe that firms that are initially more productive respond by increasing their automation levels compared to less productive firms.

Our results have important implications for the economic development of a large set of middle-income countries for which the acquisition of advanced manufacturing tools presents an opportunity to catch up, particularly if they are not technology innovators themselves. Our study suggests that an increasingly competitive global market place decreases technology investments in automation equipment on average and increases incentives to invest only for the most productive firms. This can result in a technology adoption pattern that further favors the most productive firms, resulting in concentrated adoption by superstar firms and limited diffusion, hindering industrial catch-up efforts.

Future work could extend the empirical analysis by collecting data on other forms of automation, such as software development, which might have important implications for firms operating across all sectors of the economy. Whereas the use of industrial robots and numerically controlled machinery imports as proxies for automation has the important advantage of measurability, it narrows the focus of our study to a specific type of industrial automation in the manufacturing sector. This form of automation often comes with substantial fixed cost investments in hardware and requires a significant reorganization of the production process (Bessen et al., 2023). Other less costly and scalable forms of automation such as software automation (including generative artificial intelligence) are increasingly deployed to creative cognitive tasks across all sectors of the economy (Eloundou et al., 2023). Hence, the empirical analysis of the effect of competition on other forms of automation presents a promising avenue for future research.

3

Monopsony and Automation

3.1 Introduction

Over the last decades, firms in the United States have steadily increased their use of artificial intelligence and other forms of automation (Acemoglu & Restrepo, 2020a; Alekseeva et al., 2021; Zolas et al., 2021). At the same time, US labor markets have become increasingly concentrated, especially in manufacturing (Rinz, 2020; Benmelech, Bergman, & Kim, 2022). Both automation and labor market power may have contributed to increasing labor market inequality (Acemoglu & Restrepo, 2021; Yeh, Macaluso, & Hershbein, 2022). Yet, they might be intertwined, and both the level of automation and its effects on employment and wages could depend on the characteristics of the labor market, including the intensity of competition for workers.

In this paper, we study theoretically and empirically the interrelation between automation and labor market power.[1] We provide empirical evidence that labor market power can amplify the negative effects of automation on employment and wages. We also propose a theory that can help make sense of these empirical findings. If a firm is a wage-taker in the labor market – that is, it has no monopsony power – automating its processes would result in a reduction of its wage expenses due to hiring fewer workers. However, if a firm has monopsony power, the impact of automation on the firms' total wage bill consists of two components: the reduction in the wage bill due to fewer workers being hired, *and* the negative impact of automation on the wages of the remaining workers. That is, since the monopsonistic firm faces an upward-sloping labor supply, automating a marginal worker enables the firm to pay lower wages for the infra-marginal workers as well.

We build a model that formalizes these ideas. The model adds labor market power to the task-based theory of automation of Acemoglu and Restrepo (2018c). In this model, a firm must choose which tasks will be performed by humans, and which tasks it will automate with machines. There exists a threshold beyond which tasks cannot be automated with the existing technology. Technological change can be modeled in two ways: either an increase in productivity of labor or capital for their existing tasks, or an increase in the automation threshold, which allows more tasks to be automated. Labor market power arises as the result of jobs being differentiated, as in Berger, Herkenhoff, and Mongey (2022).

We first show that an increase in monopsony power leads to an increase in automation if we start from an equilibrium where the competitive level of automation is below the threshold of automatable tasks. We then examine whether higher labor market power amplifies or mitigates the effect of an increase in the automation threshold on employment. We show that the effect is ambiguous. On the one hand, if the automation threshold is binding in both the high and low labor market power economies, increasing the threshold would result in stronger reductions in employment in the economy with *lower* labor market power. On the other hand, if the threshold is not binding in the low labor market power economy, but it is binding in the high labor market power one, increasing the threshold would result in stronger reductions in employment in the economy with *higher* labor market power.[2] We show in numerical simulations that

[1]This chapter is the result of a collaboration with José Azar, Marina Chugunova, and Sampsa Samila. A preprint version of this chapter is available as Azar et al. (2023). Monopsony and Automation. Max Planck Institute for Innovation & Competition Research Paper No. 23-21.

[2]As we will show, it is not possible for the threshold to be binding in the low labor market power case, but not binding in the high labor market power case, because an increase in labor market power shifts the MPL/MPK curve to the right.

this effect tends to make the expected effect of automation on employment stronger when labor market power is high.

We test the predictions of our model in an empirical setting using data on robot adoption, US local labor market employment, wages, and concentration (Acemoglu & Restrepo, 2020a). We first replicate the main results of Acemoglu and Restrepo (2020a), and then explore the heterogeneity with respect to labor market concentration, measured by the Herfindahl-Hirschman index of employer concentration for each industry by commuting zone. This index serves as a proxy for the degree of labor market power within the local labor market. Our results show that commuting zones that are more exposed to industrial robots exhibit considerably larger reductions in both employment and wages when their labor markets demonstrate higher levels of concentration. This is consistent with the model predictions for the case when the automation threshold is binding in the high labor market power economy but not in the low one.

Our research contributes to several distinct strands of literature. First, we extend the recent work on the labor market effects of robots by introducing labor market power in the task-based framework of automation by Acemoglu and Restrepo (2018b) and by testing the implications empirically. We build on the canonical model allowing firms to possess wage-setting power due to upward-sloping labor supply curves and demonstrate that such wage-setting power can affect firms' equilibrium level of automation. We identify conditions under which firms could engage in excessive automation (Acemoglu & Restrepo, 2018a, 2018c) from the standpoint of a social planner. Thereby, we can revisit the assumption that firms take wages as given when deciding to automate (Acemoglu & Restrepo, 2020a; Koch, Manuylov, & Smolka, 2021; Bessen, Denk, & Meng, 2022; Adachi, Kawaguchi, & Saito, 2024). Empirically, we find that the negative impacts of industrial robots on employment and wage growth in US commuting zones are amplified in more concentrated local labor markets where firms hold more wage-setting power. This finding is important, considering that US labor markets show considerable variation in monopsony power (Azar, Marinescu, & Steinbaum, 2022; Berger, Herkenhoff, & Mongey, 2022; Yeh, Macaluso, & Hershbein, 2022).

Second, we contribute to a recent research on the determinants of automation (Danzer, Feuerbaum, & Gaessler, 2020; Dechezleprêtre et al., 2021; Fan, Hu, & Tang, 2021; Acemoglu & Restrepo, 2022) by showing that idiosyncratic differences in firms' labor market power can affect incentives to automate. The existing literature has predominantly focused on regional differences in labor markets like demographic change, migration, or minimum wage policies. We offer a novel explanation for the heterogeneity in robot adoption that has consistently been documented in recent microdata studies (Brynjolfsson et al., 2023; Deng, Plümpe, & Stegmaier, 2023).

Third, we further contribute to the literature on the wage and employment implications of monopsony (Robinson, 1933; Manning, 2021; Sokolova & Sorensen, 2021). While previous research has primarily concentrated on the direct effects of labor market power on wages and employment, our study extends this perspective. We show that labor market power can also indirectly influence labor markets through its impact on firms' adoption of automation technologies, thus influencing wage and employment growth.

Fourth, there has been a growing literature on the connection between automation and market concentration recently. Firooz, Liu, and Wang (2022) find empirical evidence suggesting that automation plays a role in augmenting sales concentration within US industries, without notable repercussions on employment concentration. Concurrently, Leduc and Liu (2022) posit that the prospect of workforce displacement due to automation can bolster employers' bargaining power, subsequently dampening real wage growth in a business cycle boom. We extend this nascent literature on automation and market concentration by shedding light on the reverse relationship: specifically, how initial differences in labor market power may impact the optimal level of automation, and its effects on labor market outcomes.

The paper is structured as follows: Section 3.2 presents the model and core findings, Section 3.3 discusses the empirical approach, Section 3.4 presents empirical results, and Section 3.5 concludes.

3.2 A Model of Task-Based Production and Monopsony

3.2.1 Households

Consider a representative household which derives utility from aggregate consumption C, which is a bundle of the different consumption goods produced by firms and disutility from labor. Its preferences over consumption and labor are represented by the following utility function:

$$U(C,L) = C - \frac{1}{\overline{\varphi}^{\frac{1}{\varphi}}} \frac{L^{1+\frac{1}{\varphi}}}{1+\frac{1}{\varphi}}, \tag{3.1}$$

where aggregate consumption C and labor L are bundles of firm-level consumption and labor, given by

$$C = \int_0^1 c_j dj, \tag{3.2}$$

$$L = \left[\int_0^1 l_j^{\frac{\theta+1}{\theta}} dj \right]^{\frac{\theta}{\theta+1}}. \tag{3.3}$$

Thus, all firms produce a homogeneous consumption good and there is perfect competition in the product market. However, jobs that firms offer are differentiated (with a constant-elasticity of substitution across jobs), which gives them some degree of monopsony power in the labor market.

The household has a fixed capital endowment K, which it rents out to the firms at an endogenous rate R. Capital is undifferentiated, and therefore firms are perfectly competitive in the capital market. The household supplies labor and capital l_j and k_j to firm j, and obtains profits π_j from firm j. The price of the consumption good is the numeraire. The household's budget constraint is

$$C = \int_0^1 w_j l_j dj + RK + \int_0^1 \pi_j dj. \tag{3.4}$$

The first-order condition with respect to l_j yields the inverse labor supply function to firm j which takes aggregate labor supply L as given:

$$w_j = \frac{1}{\varphi^{\frac{1}{\varphi}}} L^{\frac{1}{\varphi}} \left(\frac{l_j}{L} \right)^{\frac{1}{\theta}}. \tag{3.5}$$

We can rewrite this in terms of the wage index $W = \left[\int_0^1 w_j^{1+\theta} dj \right]^{\frac{1}{1+\theta}}$ as follows:

$$w_j = \left(\frac{l_j}{L} \right)^{\frac{1}{\theta}} W. \tag{3.6}$$

This is the inverse labor supply curve faced by firm j given aggregate labor L and the aggregate wage level W.

3.2.2 Firms

There is a continuum of firms with measure one, indexed by j. Firm j produces good c_j. Aggregate output for firm j is produced through a continuum of tasks, indexed by i:

$$y_j = \left(\int_0^1 y_j(i)^{\frac{\sigma-1}{\sigma}} di\right)^{\frac{\sigma}{\sigma-1}} \tag{3.7}$$

where $\sigma \in (0, \infty)$ is the elasticity of substitution between tasks. There is a threshold of automatable tasks I. Tasks $i > I$ can be produced with labor according to $y_j(i) = \gamma(i)l_j(i)$. Tasks $i \leq I$ can be produced with labor or capital: $y_j(i) = \eta(i)k_j(i)+\gamma(i)l_j(i)$. We assume that $\gamma(i)/\eta(i)$ is strictly increasing in i.

Wages are endogenous, and the firm is a monopsonist with respect to the wage paid to its own workers, and does not discriminate between workers. At the same time, it is a wage-taker with respect to the aggregate wage index W. The rate of return on capital R is also endogenous, and the firms are price-takers in the capital market.

The firm faces an upward-sloping labor supply curve $w_j(l_j)$ with constant elasticity θ. The overall amount of labor that the firm demands is the integral of the labor that it demands across tasks, that is $l_j = \int_0^1 l(i)di$. We also define $k_j = \int_0^1 k_j(i)di$.

3.2.3 Equilibrium and Comparative Statics

The profit maximization problem of firm j is

$$\max_{\{l(i),k(i)\}_{i\in[0,1]}} y_j - Rk_j - w_j(l_j)l_j. \tag{3.8}$$

There is a unique level of automation $\tilde{I}$ at which the firm would be indifferent between automating a task or have it done by humans. In the competitive case ($\theta = \infty$), that level of automation is given by

$$\frac{w_j}{R} = \frac{\gamma(\tilde{I})}{\eta(\tilde{I})}. \tag{3.9}$$

In the monopsonistic case ($\theta < \infty$), the automation level takes into account the extra cost due to the fact that hiring an additional worker increases wages for all existing workers as well

$$\frac{w_j(1+\frac{1}{\theta})}{R} = \frac{\gamma(\tilde{I})}{\eta(\tilde{I})}. \tag{3.10}$$

If $\tilde{I} > I$, the firm cannot produce all tasks up to $\tilde{I}$ with capital because some of the tasks below $\tilde{I}$ are not yet automatable. Thus, the equilibrium level of automation is $I^* = \min\left\{I, \tilde{I}\right\}$.

For tasks below the automation threshold I^*, the first-order condition with respect to $k_j(i)$ is

$$y_j(i) = \left[\frac{\eta(i)}{R}\right]^{\sigma} y_j. \tag{3.11}$$

For tasks above I^*, the first-order condition with respect to $l_j(i)$ is

$$y_j(i) = \left[\frac{\gamma(i)}{w_j(l_j)\left(1+\frac{1}{\theta}\right)}\right]^{\sigma} y_j. \tag{3.12}$$

We can solve each of these for y_j and replace it in the production function of firm j to obtain a production function in terms of aggregate labor and capital for the firm:

$$y_j = F(k_j, l_j) = \left[\left(\left(\int_0^{I^*} \eta(i)^{\sigma-1} di\right)^{\frac{1}{\sigma}} k_j^{\frac{\sigma-1}{\sigma}} + \left(\int_{I^*}^1 \gamma(i)^{\sigma-1} di\right)^{\frac{1}{\sigma}} l_j^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{3.13}$$

To simplify the expression, we define the productivity factors of capital and labor as $A_K = \left(\int_0^{I^*} \eta(i)^{\sigma-1} di\right)^{\frac{1}{\sigma-1}}$ and $A_L = \left(\int_{I^*}^1 \gamma(i)^{\sigma-1} di\right)^{\frac{1}{\sigma-1}}$ so that we can rewrite the production function as $y_j = F(k_j, l_j) = \left[(A_K k_j)^{\frac{\sigma-1}{\sigma}} + (A_L l_j)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$.

The marginal product of firm j's capital bundle is equal to the cost of capital R:

$$F_K(k_j, l_j) = A_K\left(\frac{y_j}{A_K k_j}\right)^{\frac{1}{\sigma}} = R \tag{3.14}$$

The marginal product of firm j's labor bundle is equal to the marginal cost of labor to the firm:

$$F_L(k_j, l_j) = A_L\left(\frac{y_j}{A_L l_j}\right)^{\frac{1}{\sigma}} = w_j(l_j) + w'(l_j)l_j = w_j(l_j)\left(1+\frac{1}{\theta}\right). \tag{3.15}$$

Imposing symmetry in the first-order condition for labor and combining it with the aggregate inverse labor supply $W = (L/\overline{\varphi})^{\frac{1}{\varphi}}$ yields a nonlinear equation in aggregate labor (conditional on a level of automation). Although the equation does not have a closed-form solution, we can use it to characterize the equilibrium conditional on the level of automation. Equilibrium employment conditional on the level of automation implies an MPL/MPK curve as a function of the level of automation i. The equilbrium level of automation is given by the intersection of this curve and the $\gamma(i)/\eta(i)$ curve, or the automation threshold if the latter is lower.

We can also show that automation increases (though not strictly) when labor market power is higher. This is because the schedule given by the equilibrium ratio of MPL and MPK conditional on a level of automation shifts to the right when labor market power increases. A shift to the right in the MPL/MPK schedule implies a higher intersection between this curve and the $\gamma(i)/\eta(i)$ curve, and implies a higher level of desired automation $\tilde{I}$. This is summarized by the following Proposition, and illustrated in Figure 3.1. If we start at point a in the figure, and shift the MPL/MPK curve to the right, equilibrium automation increases until $\tilde{I}$ hits the maximum possible level of automation, given by the threshold I. Further increases in market power would not increase automation, because $\tilde{I}$ would be above the threshold.

Proposition 3.2.1. *An equilibrium of the model exists and is characterized by the intersection between the $\gamma(i)/\eta(i)$ schedule and the $\frac{MPL}{MPK}(i)$ schedule which indicates the ratio of MPL and MPK conditional on the level of automation (ignoring the automation threshold). If the intersection of the two curves is below the automation threshold I, then the equilibrium level of automation I^* is given by $\tilde{I}$, i.e., the level of the intersection. If the intersection of the two curves is above the automation threshold, then the equilibrium level I^* is equal to the threshold I.*

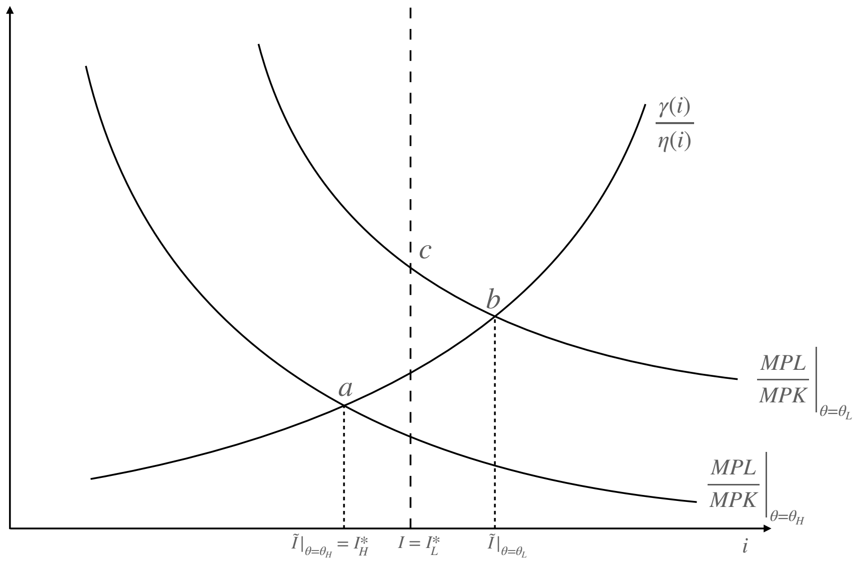
The equilibrium level of employment is characterized by the solution to the following equation in L at I^*:

$$A_L\left[1+\left(\frac{A_K K}{A_L L}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{1}{\sigma-1}} = \left(\frac{L}{\bar{\varphi}}\right)^{\frac{1}{\varphi}}\left(1+\frac{1}{\theta}\right). \tag{3.16}$$

If the equilibrium level of automation is below the threshold I, then an increase in labor market power $(1/\theta)$ increases automation. If the equilibrium level of automation is at the threshold I, then an increase in labor market power leaves automation unchanged.

We are also interested in the effect of technological progress, modeled as an increase in the set of automatable tasks, on employment and wages, and in particular in the heterogeneity of this effect by the level of labor market power. Consider two economies that are identical, except that in one of them labor market power is low (i.e., the

Figure 3.1: Equilibrium Automation under Low and High Levels of Labor Market Competition



Notes: This figure illustrates the determination of the equilibrium level of automation when the labor market power parameter is θ_H (less labor market power), and when it is θ_L (more labor market power). If labor market power is low, at $\theta = \theta_H$, the equilibrium level of automation is at point a, at the intersection of the MPL/MPK curve and the γ/η curve, which is below the automation threshold. If labor market power increases, so that $\theta = \theta_L$, the MPL/MPK curve shifts to the right, and the intersection is at point b. However, because tasks above I are not automatable, the equilibrium is in point c, at the intersection of the MPL/MPK curve and the vertical line that indicates automation level I. Thus, the equilibrium level of automation I^* is higher than in the low labor market power case.

elasticity of substitution parameter is high, $\theta = \theta_H$) and in the other labor market power is high (i.e., the elasticity of substitution parameter is low $\theta = \theta_L < \theta_H$). We can compare the response of employment and wages to an increase in the automation threshold I in these two economies.

The are three possible cases. (1) If the automation threshold is not binding for both the θ_L and θ_H economies, an increase in the threshold has no effect in either economy. (2) If the automation threshold is binding in both, a marginal increase in the automation threshold increases automation by the same amount in both. When this happens, it is possible for the effect of an increase in the automation threshold on employment and wages to be stronger in the more competitive economy. (3) It is possible that the automation threshold is not binding for the low labor market power economy, but is binding in the high labor market power economy (see Figure 3.1). In this case, an increase in the automation threshold has no effect on the equilibrium with low labor market power, that is, at point a, because the equilibrium is below the automation threshold. However, it does affect the equilibrium for the high labor market power economy, at point c, because it is at the threshold.

In the Appendix, we show that the effect of an increase in the automation threshold I on employment and wages can be negative or positive, depending on whether the (negative) displacement effect dominates the (positive) productivity effect (as in Acemoglu & Restrepo, 2018b). Regardless of the sign of the effect on employment and wages, if we are in case (2), the effect can be stronger (i.e., higher in absolute value) in the more competitive labor market, while in case (3) the effect can be stronger in the more monopsonistic labor market. The overall effect is therefore ambiguous. If the automation threshold has high variance, it is more likely that it will bind when labor market power is higher, and the mechanism in case (3) is more important. However, if the automation threshold does not vary across labor markets, the mechanism in case (2) is more important. To illustrate this, we provide a Monte-Carlo simulation of the expected marginal effect with a stochastic automation threshold in the following subsection.

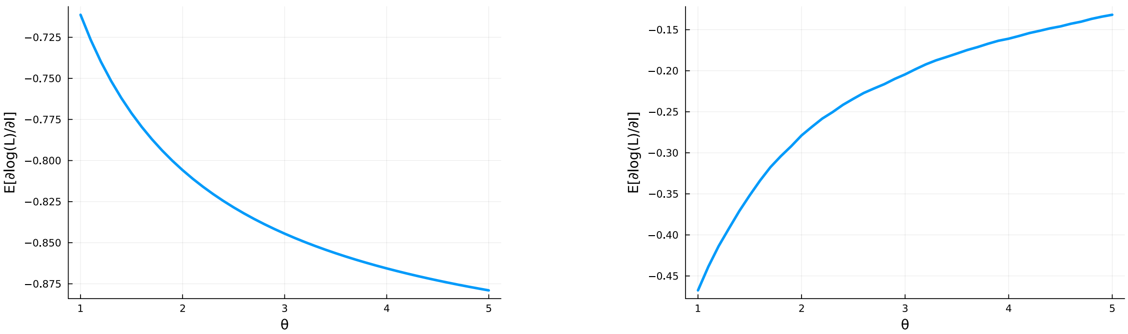
3.2.4 Simulation

We solve the model numerically for the following parameter values: $\sigma = 0.7$, $\varphi = 0.5$, $\overline{\varphi} = 1$, $K = 1$, $\eta(i) = 1$, $\gamma(i) = e^{Ai}$, with $A = 1$, and for a range of values for θ between 1 and 5. For each value of θ, we take 10,000 random draws for the automation threshold I. We do it first for a "low I dispersion case", with I uniformly distributed in the interval $[0.33, 0.331]$, in which case the threshold is always binding for this range of θ. We then run the simulation for a high I dispersion case, uniform over $[0.33, 0.45]$, which approximately covers the range of $\tilde{I}$ for our range of θ parameters.

For each draw, we calculate the derivative with respect to I (which can be zero if the threshold is non-binding), and take expectation across draws for each value of θ. The results are plotted in Figure 3.2.[3] In the low dispersion case, the mechanism described in case (2) dominates, and the expected effect of automation on employment is less negative when labor market power is higher. In the high dispersion case, the mechanism in case (3) dominates, and the expected effect of automation on employment (and therefore on wages as well) is more negative when labor market power is higher. As we argue above, the automation threshold is more likely to be binding when labor

[3]Note that in all cases, the wage effect goes in the same direction as the employment effect, due to increasing aggregate labor supply.

Figure 3.2: Simulated Average Effect of Automation Threshold on Log Employment as a Function of Labor Market Power



(a) Low I Dispersion **(b)** High I Dispersion

Notes: This figure shows the average marginal effect on log employment with respect to the automation threshold I. The model is solved numerically for the following parameter values: $\sigma = 0.7$, $\varphi = 0.5$, $\overline{\varphi} = 1$, $K = 1$, $\eta(i) = 1$, $\gamma(i) = e^{Ai}$, with $A = 1$, and for a range of values for θ between 1 and 5. For each value of θ, we take 10,000 random draws for the automation threshold I. In the low dispersion case, I is uniform in the interval $[0.33, 0.331]$, and in the high dispersion case it is uniform in the interval $[0.33, 0.45]$ (about the range of $\tilde{I}$ corresponding to our range of θs).

market power is higher.

This theoretical ambiguity implies that it is an empirical question whether labor market power amplifies or mitigates the labor market effects of automation. The next section describes our methodology to examine this question empirically.

3.3 Empirical Methodology

To test whether the effect of automation on employment and wages is stronger when labor market power is higher, we make use of the empirical framework presented by Acemoglu and Restrepo (2020a). This framework allows to study the long-run equilibrium adjustments of local labor markets in the United States in response to changes in labor demand driven by advancements in industrial robot technology.

3.3.1 Measuring Local Labor Market Exposure to Robots

Based on the study by Acemoglu and Restrepo (2020a), we measure the exposure to industrial robots in 722 continental US commuting zones over the period 1990 to 2015.[4] To approximate global advancements in industrial robot technology, we examine changes in the number of industrial robots per worker across 19 different industries in five European countries (Denmark, Finland, France, Italy, Sweden) that have been ahead of the US in adopting robot technology. For each industry i, we compute a measure of average robot penetration over the period from t_0 to t_1 as the average change in the stock of industrial robots relative to the total number of workers in that industry in 1990 subtracting the growth of robot stocks that is due to real output growth. This measure is given by

$$\mathrm{APR}^{EU5}_{i,(t_0,t_1)} = \sum_{j \in EU5} \frac{1}{5} \left(\frac{R_{j,i,t_1} - R_{j,i,t_0}}{L_{j,i,1990}} - g_{j,i,(t_0,t_1)} \frac{R_{j,i,t_0}}{L_{j,i,1990}} \right) \tag{3.17}$$

where $R_{j,i,t}$ is the number of robots in industry i in country j at time t, $g_{j,i,(t_0,t_1)}$ is the output growth rate of industry in country j between t_0 and t_1 and $L_{j,i,1990}$ is the total number of workers in industry i in country j in 1990.[5]

To obtain a measure of commuting zone exposure to robots, we finally multiply the industry-specific changes in average robot penetration in the five European countries by $l_{c,i,1970}$, the share of industry i in the total employment of commuting zone c in 1970.

$$\mathrm{Robots}_{c,(t_0,t_1)} = \sum_{i \in I} l_{c,i,1970} \times \mathrm{APR}^{EU5}_{i,(t_0,t_1)} \tag{3.18}$$

To compute the shares of industries in commuting zone employment, we make use of microdata from the decennial census of 1970 as in Acemoglu and Restrepo (2020a). We also use the microdata from the decennial censuses of 1990 and 2000 combined with microdata from the American Community Survey to compute outcomes variables in terms of employment, unemployment, non-participation as well as average wages for our main analysis.

The identifying assumption of the empirical strategy is that there are no differential shocks or trends affecting labor market outcomes in commuting zones with greater exposure to robots relative to those with less exposure.[6]

[4] Commuting zones are clusters of counties in which the majority of workers both live and work. This geography is typically used to delineate local labor markets (see Tolbert & Sizer, 1996).

[5] We use data on the industry-specific stocks of industrial robots from the International Federation of Robotic, while both output and employment data for industries in Europe comes from the EUKLEMS database.

[6] See Acemoglu and Restrepo, 2020a for a comprehensive check of the validity of the proposed measure of commuting zone exposure to robots.

3.3.2 Measuring Local Labor Market Concentration

We extend the empirical framework by Acemoglu and Restrepo (2020a) taking into account the competitiveness of local labor markets at the beginning of the observation period. We proxy the competitiveness of local labor markets with the degree of employer concentration within a commuting zone. A recent body of literature shows that measures of employer concentration reflect the extent to which firms face a more or less elastic labor supply curve in the local labor market (e.g. Berger, Herkenhoff, & Mongey, 2022). We therefore utilize the local employer concentration as a proxy for the labor supply elasticity (θ) in our model that describes the competitiveness of the local labor market. This allows us to explore how initial differences in local labor market competitiveness impact the effects of improvements in robot technology across different commuting zones.

We compute a measure of local labor market concentration for all 722 continental commuting zones in 1990 using data on county-by-industry establishment counts from the US Census *County Business Patterns*, county industry employment counts from Eckert et al. (2021) and a county-to-commuting zone crosswalk provided by David and Dorn (2013). In each commuting zone, we observe the number of establishments n in a 3-digit SIC industry i by employment bracket s in commuting zone c in 1990.[7] We take the mid-point m of an employment bracket s to approximate the actual employment size of establishments assigned to employment bracket s. We then compute employment shares and the Herfindahl-Hirschman index of employer concentration for each industry i in a commuting zone c as

$$HHI_{c,i} = \sum_{s=1}^{12} n_{c,i,s} \left(\frac{m_s}{L_{c,i}} \right)^2, \tag{3.19}$$

where L stands for the total employment of industry i in commuting zone c. As the level of analysis will eventually be at the commuting-zone level, we further aggregate the industry-by-commuting zone level HHIs to the commuting zone level. To calculate the average level of employer concentration for each commuting zone, we compute a weighted mean of all industry employer Herfindahl indices as

$$\overline{HHI_c} \equiv \sum_{i=1}^{395} l_{c,i} \times HHI_{c,i}, \tag{3.20}$$

where l is the share of industry i in total employment of the commuting zone c. As in Benmelech, Bergman, and Kim (2022), this average HHI at the level of the commuting

[7] County Business Patterns reports 12 employment brackets which are described in detail in Table C.1 in the Appendix.

zone represents the degree of employer concentration that the *average* worker faces in a given local labor market.[8]

3.3.3 Empirical Specifications

We explore the heterogeneous effect of local labor market exposure to robots on employment, unemployment and non-participation rates across labor markets with different initial employer concentration. We estimate the following model in three stacked differences over three periods from 1990 to 2000, 2000 to 2007 and 2007 to 2015:

$$\begin{aligned}\Delta \mathrm{y}_{c,(t_0,t_1)} = \beta_1 \text{ Robots}_{c,(t_0,t_1)} + \beta_2 \text{ Robots}_{c,(t_0,t_1)} \times \overline{\mathrm{HHI}}_{c,1990} + \beta_3 \overline{\mathrm{HHI}}_{c,1990} \\ + \mathbf{X}'_{c,1990}\,\gamma + \delta_t + \rho_j + \epsilon_{c,(t_0,t_1)}\end{aligned} \tag{3.21}$$

In our main specification, $y_{c,t}$ stands for the log number of private sector employees in commuting zone c in year t and $\overline{\mathrm{HHI}}_{c,1990}$ is the continuous measure of local labor market concentration of commuting zone c in 1990. The coefficient of interest is β_2 which captures the heterogeneous effect of robots on employment across commuting zones with different initial levels of local labor market concentration $\overline{\mathrm{HHI}}_c$. The sign of the coefficient β_2 allows us to infer whether the automation threshold is binding for monopsonists but not for competitive firms. If this was indeed the case, improvements in automation technology would lead to more negative employment effects in more concentrated labor markets. We keep $\overline{\mathrm{HHI}}_c$ fixed to initial levels in 1990 to avoid any endogeneity between increasing automation and *contemporaneous* changes in labor market concentration.

Following Acemoglu and Restrepo (2020a), we control for unobserved period-specific regional trends by including dummies for census divisions ρ_j and period indicators δ_t. Hence, our regression identifies the coefficients β_2 from variation in exposure to labor market shocks between commuting zones in a given time-period and census division and variation in the ex-ante local labor market concentration. We also include $\mathbf{X'}_{c,1990}$, a vector of commuting zone baseline characteristics in 1990, to allow for differential trends due to observable differences in demographics (age, education, gender and ethnic composition), industry shares (manufacturing, light-manufacturing) or in

[8]Figure C.1 in the Appendix displays the regional variation in labor market concentration across the 722 US commuting zones in 1990, attributing the value for each commuting zone to one out of seven equal-sized bins.

the exposure to Chinese import competition and offshoring (share of routine employment).

We also explore the heterogeneous effect of local labor market exposure to robots on wages across labor markets with different initial employer concentration. We compute for each commuting zone the average hourly, weekly and yearly wages of workers within 250 demographic cells defined by gender, education, age and race.[9] By looking at wages within defined demographics, we can control for changes in wages in the commuting zone that are driven by changes in the characteristics of the work force such as age.We estimate the following model at the demographic group by commuting zone level in two stacked differences over the periods from 1990 to 2000 and from 2000 to 2007:

$$\begin{aligned}\Delta \mathrm{y}_{c,d,(t_0,t_1)} = \beta_1 \,\mathrm{Robots}_{c,(t_0,t_1)} \;+\; \beta_2 \,\mathrm{Robots}_{c,(t_0,t_1)} \times \overline{\mathrm{HHI}}_{c,1990} + \;\beta_3 \,\overline{\mathrm{HHI}}_{c,1990} \\ +\; \mathbf{X}'_{c,1990}\,\gamma \;+\; \sigma_d \;+\; \delta_t \;+\; \rho_j \;+\; \epsilon_{c,d,(t_0,t_1)}\end{aligned} \tag{3.22}$$

where y stands for the log average wage of workers in a demographic cell d in commuting zone c and year t. In addition to the dummies for census divisions ρ_j, the period indicators δ_t, the commuting zone characteristics in 1990 $\mathbf{X}'_{c,1990}$, we also include a dummy for each demographic cell that corrects for differential long-run trends in wages across the different demographics. Again, we are interested in the coefficient of the interaction term β_2 which reflects the heterogeneous effect of robots on average wages across commuting zones with differential initial levels of labor market concentration.

3.4 Results

In our empirical results, we first document the negative effect of robot exposure on commuting zone employment consistent with Acemoglu and Restrepo (2020a) and reveal that the negative employment effect is substantially more pronounced in initially more concentrated labor markets. Next, we find heterogeneous effects of robots on measures labor force participation. Last, we document that labor market concentration also moderates the negative effect of robots on average wages.

[9]See Appendix C.2.2 for more details on the computation of average wages.

3.4.1 Employment

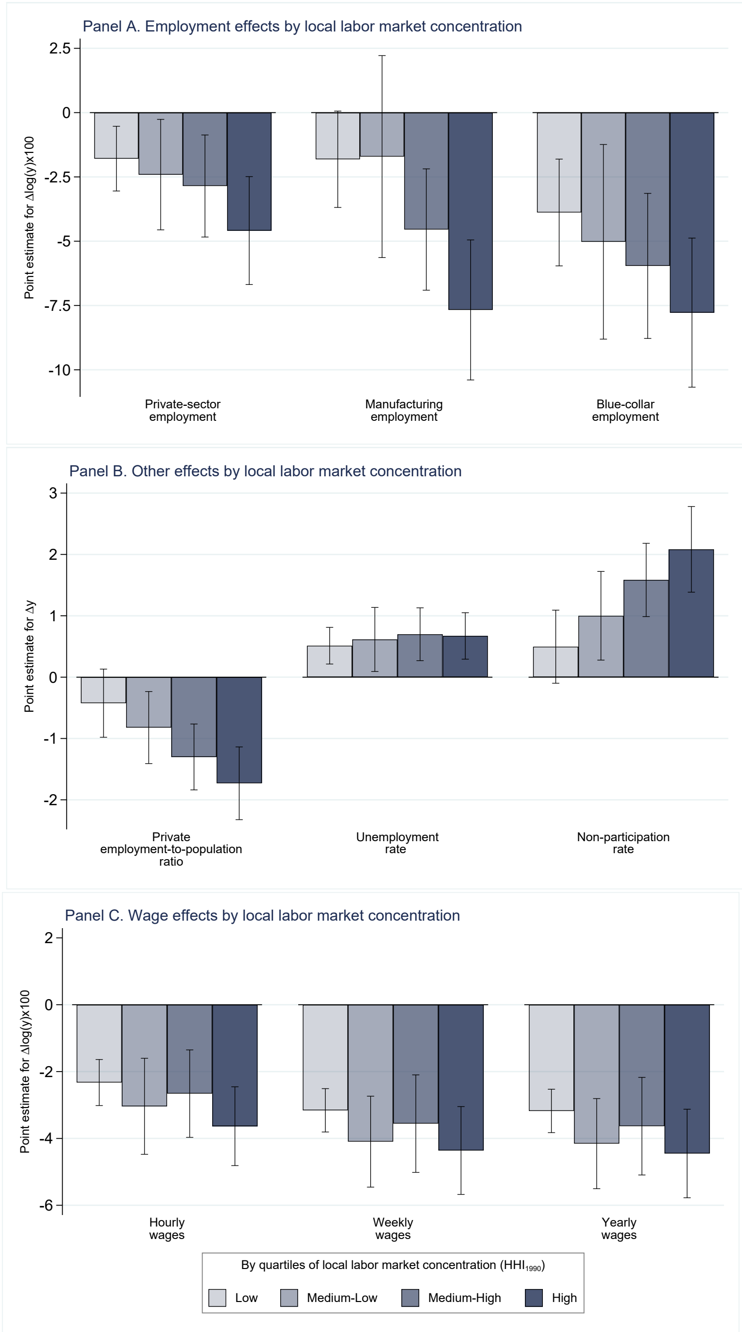
Consistent with previous evidence by Acemoglu and Restrepo (2020a) and Faber, Sarto, and Tabellini (2022), column (1) in Panel A of Table 3.1 shows that an increase of commuting zone exposure of 1 robot per thousand workers decreases total employment by about 2 percent. However, column (2) reveals significant heterogeneity in the effect by initial levels of labor market concentration in 1990. It shows that the coefficient of the interaction of robot exposure and the continuous variable of local labor market concentration in 1990 is significantly negative and sizable in magnitude. The estimates in column (2) imply that the effect of robots on total employment is about 60% stronger in commuting zones at the 75th percentile of labor market concentration distribution ($\overline{\text{HHI}}_{1990}^{75th} = 0.44$) compared to commuting zones at the 25th percentile ($\overline{\text{HHI}}_{1990}^{25th}$=0.22). We can also observe the strong moderating effect of labor market concentration when looking at manufacturing and blue-collar occupation reported in columns (4) and (6) which are arguably most exposed to industrial robots.

We further corroborate the relationship estimating the mean effects of robots in commuting zones in different quartiles of the distribution of labor market concentration in 1990.[10] Panel A in Figure 3.3 shows the point estimates by concentration quartile and confirms the previous finding of consistently stronger effects in commuting zones in the upper quartiles of the concentration distribution for total employment as well as for manufacturing and blue-collar employment.

The combined evidence suggests that improvements in automation technology seem to affect employment more negatively in more concentrated local labor markets. While there is no data on robot adoption across commuting zones allowing us to test mechanisms directly, the obtained results are in line with case 3 presented in Section 3.2.3. The observed pattern suggests that firms in more concentrated labor markets are bound by the automation threshold and are more likely to automate as automation technology improves, amplifying the effect on employment. On the other hand, firms in less concentrated labor markets are less likely to be bound and do therefore react less as automation technology improves.

[10]We order commuting zones by the level of labor market concentration in 1990 and group them into 4 bins that each contain one quarter of the total US population in 1990.

Figure 3.3: Local Labor Market Effects of Exposure to Robots by Local Labor Market Concentration



Notes: The figure displays coefficient estimates of the impact of robots on labor market outcomes for each quartile of commuting zones based on the employment-weighted distribution of labor market concentration in 1990. For each outcome variable, we estimate a single regression model. The displayed coefficients are obtained from the interaction of quartile dummies with the main explanatory variable: exposure to robots. The capped lines indicate 95% confidence intervals. All estimates in Panel A and B are from specifications that include the full set of controls from Table 3.1. All estimates in Panel C are from specifications that include the full set of controls from Table 3.2.

3.4.2 Labor Force Participation

Next, we explore how lower employment growth due to robots might lead to higher unemployment rates and non-participation in the labor force in more concentrated regions. Column (1) in Panel B of Table 3.1 shows that the decrease in employment in the first part of the analysis translates into a lower employment to population ratio. We find that an increase of exposure by 1 robot per thousand workers reduced the share of employed individuals in the population of working age adults by 0.6 percent. This negative effect is again significantly more pronounced in more concentrated labor markets.

Yet, column (4) shows that the positive effect of robots on unemployment rates is not significantly different in more versus less concentrated labor markets. Column (6) shows that the reduction in the employment to population ratio due to robots leads to higher non-participation rates in more concentrated labor markets, thus providing explanation to absence of the differential effect on unemployment. This interesting pattern is consistent with recent evidence by Dodini et al. (2023) showing that more concentrated labor markets provide workers with fewer outside options which leads to higher non-participation rates and larger earnings declines for workers after involuntary job separation. Panel B in Figure 3.3 illustrates that the effect of robots on employment and non-participation rates is systematically more pronounced in commuting zones in the upper quartiles of the concentration distribution.

3.4.3 Wages

Finally, we find that local labor market concentration also moderates the effect of robots on average wages within demographic cells across commuting zones. Table 3.2 reports the estimates following the model specification of equation 3.22 with demographic cell fixed effects. Consistent with the results in Acemoglu and Restrepo (2020a), we find in column (1) that an increase in exposure to robots by 1 robot per thousand workers decreases average hourly wages by more than 2 percent. Again, we find that this average effect masks significant heterogeneity along the dimension of labor market concentration. Estimates in column (2) imply that effect of robots on average hourly wages is 35 percent larger in commuting zones at the 75th percentile relative to commuting zones in the 25th percentile of local labor market concentration. This pattern is also true for average weekly and yearly wages. Panel C in Figure 3.3 corroborates again a systematic pattern showing that the mean effect on wages

Table 3.1: Local Labor Market Concentration and the Effect of Robot Exposure on Employment and Labor Force Participation: Stacked Differences, 1990-2015 (Reduced Form)

	Panel A. Change in log(employment) × 100					
	Total employment		Manufacturing employment		Blue-collar employment	
	(1)	(2)	(3)	(4)	(5)	(6)
Robots	-2.253***	-1.240	-2.832***	-0.556	-4.598***	-2.979**
	(0.494)	(0.778)	(0.659)	(1.338)	(0.772)	(1.251)
Robots × $\overline{\text{HHI}}$		-12.855**		-29.001***		-20.061***
		(4.829)		(7.956)		(6.678)
$\overline{\text{HHI}}$		0.561		-0.229		6.506
		(4.779)		(7.407)		(6.215)
Observations	2166	2166	2166	2166	2166	2166
R-squared	0.44	0.44	0.37	0.38	0.42	0.43
	Panel B. Percentage point change in rate					
	Employment to population ratio		Unemployment rate		Non-participation rate	
	(1)	(2)	(3)	(4)	(5)	(6)
Robots	-0.684***	-0.125	0.554***	0.505***	0.815***	0.144
	(0.117)	(0.329)	(0.130)	(0.148)	(0.143)	(0.339)
Robots × $\overline{\text{HHI}}$		-6.729***		0.559		8.130***
		(1.977)		(0.585)		(2.113)
$\overline{\text{HHI}}$		4.630***		-0.776		-4.975***
		(1.281)		(0.518)		(1.294)
Observations	2166	2166	2166	2166	2166	2166
R-squared	0.30	0.34	0.22	0.22	0.51	0.55
Demographics	✓	✓	✓	✓	✓	✓
Industry Shares	✓	✓	✓	✓	✓	✓
Trade Exposure	✓	✓	✓	✓	✓	✓
Census Divisions	✓	✓	✓	✓	✓	✓
Period FE	✓	✓	✓	✓	✓	✓

Notes: $\overline{\text{HHI}}$ denotes the employer concentration index in 1990, as defined by Equation 3.20. All specifications control for the following commuting zone characteristics in 1990: demographic characteristics of commuting zones in 1990 (log population; the share of females; the share of the population over 65 years old; the shares of the population with no college, some college, college or professional degree, and masters or doctoral degree; and shares of Asian, Black, Hispanic and White population), the shares of employment in manufacturing and light manufacturing and the female share of manufacturing employment in 1990, as well as the exposure to Chinese imports and the share of employment in routine jobs in 1990. Regressions also control for census division and period dummies. Regressions are weighted by commuting zone population in 1990. Standard errors are clustered at the state level. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table 3.2: Local Labor Market Concentration and the Effect of Robot Exposure on Wages: Stacked Differences, 1990-2007 (Reduced Form)

	Change in log wages × 100					
	Hourly Wages		Weekly Wages		Yearly Wages	
	(1)	(2)	(3)	(4)	(5)	(6)
Robots	-2.553***	-2.132***	-3.379***	-3.018***	-3.416***	-3.031***
	(0.341)	(0.354)	(0.334)	(0.311)	(0.331)	(0.308)
Robots × $\overline{\text{HHI}}$		-5.224**		-4.513*		-4.796*
		(2.372)		(2.509)		(2.546)
$\overline{\text{HHI}}$		-2.634		-2.746		-2.653
		(2.847)		(2.958)		(2.935)
Observations	158254	158254	156402	156402	156402	156402
R-squared	0.21	0.21	0.26	0.26	0.26	0.26
Demographics	✓	✓	✓	✓	✓	✓
Industry Shares	✓	✓	✓	✓	✓	✓
Trade Exposure	✓	✓	✓	✓	✓	✓
Census Divisions	✓	✓	✓	✓	✓	✓
Period FE	✓	✓	✓	✓	✓	✓

Notes: $\overline{\text{HHI}}$ denotes the employer concentration index in 1990, as defined by Equation 3.20. We estimate regressions at the demographic cell × commuting zone level where we define demographic cells by age, gender, education and race. The outcome variables are log changes in the average wage by demographic cell multiplied by 100. All specifications include a dummy for each demographic cell and control for the following commuting zone characteristics: demographic characteristics in 1990 (log population; the share of females; the share of the population over 65 years old; the shares of the population with no college, some college, college or professional degree, and masters or doctoral degree; and the shares of the Asian, Black, Hispanic and White population), the shares of employment in manufacturing and light manufacturing and the female share of manufacturing employment in 1990, as well as the exposure to Chinese imports and the share of employment in routine jobs in 1990. Regressions also control for census division and period dummies. Regressions are weighted by commuting zone population in 1990. Standard errors are clustered at the state level. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

tends to stronger among commuting zones in the upper quartiles of the concentration distribution.

3.5 Conclusion

The extent to which employers exercise monopsony power in labor markets has wide-ranging implications for workers, firms and labor markets. In this paper, we argue that labor market power can in fact drive excessive demand for automation as automation at firms with labor market power affects the total wage bill in two ways: it reduces the wage bill as fewer workers are being hired, *and* it reduces the wages of the remaining workers. Therefore, if monopsony power is high enough, the firm could have an incentive to automate with a technology that is less efficient than the workers it replaces and still obtain net cost efficiencies through the reduction in the wages of the remaining employees.

We formalize this idea by incorporating labor market power from the differentiated jobs model by Berger, Herkenhoff, and Mongey (2022) into the task-based theory of automation of Acemoglu and Restrepo (2018c). When the labor market is competitive, some automatable tasks are not automated because it is still more cost-effective for them to be done by humans. However, it may be privately optimal for the firm to automate them under monopsony, precisely in order to exploit its monopsony power. For this reason, marginal increases in automatable tasks may not reduce labor demand when the labor market is competitive, while reducing it in the case of a monopsonistic labor market. On the other hand, when the automation threshold is binding in both high and low labor market power economies, it is ambiguous whether labor market power amplifies or mitigates the effect on automation.

We examine this question in the empirical setting of Acemoglu and Restrepo (2020a), studying industrial automation in the US. We replicate their results and explore the heterogeneity with respect to labor market concentration, measured by Herfindahl-Hirschman index of employer concentration for each industry. We show that automation is associated with considerably larger reductions in employment and wages in more concentrated labor markets. This provides first evidence that labor market power affects firms' automation decisions.

One policy implication of our model is that minimum wage policies could decrease the incentive to automate in monopsonistic labor markets where the minimum wage is binding. As minimum wages prevent the monopsonist to pay below the wage floor, the policy flattens the marginal cost of labor curve of the monopsonist. In this way, the minimum wage alleviates the incentive to automate beyond what the competitive firm would do. Therefore, perhaps surprisingly, minimum wage policies could reduce the level of automation in monopsonistic labor markets.

Our paper raises a number of questions that require further research. First, there is a need for a more thorough examination of the relationship between labor market power and automation. This would require more detailed data at the local industry or firm level. Second, we have focused on automation of production tasks by industrial robots. Future research may broaden the focus and consider technologies that are increasingly automating non-production tasks outside of manufacturing.

4

Labor Market Power and Automation

Firm-level Evidence

4.1 Introduction

In recent decades, manufacturing firms have undergone profound changes toward more automated production processes, driven largely by the need to manage labor costs and address labor shortages (Danzer, Feuerbaum, & Gaessler, 2020; Dechezleprêtre et al., 2021; Acemoglu & Restrepo, 2022). At the same time, manufacturing has undergone significant consolidation, resulting in dominant "superstar" firms and higher employer concentration. This change has increased labor market power and helped firms contain labor costs (De Loecker, Eeckhout, & Unger, 2020; Felix, 2021; Yeh, Macaluso, & Hershbein, 2022; Bighelli et al., 2023). Both trends toward automation and labor market power have raised concerns about their impact on income inequality and labor market dynamics. However, the potential impact of rising labor market power on firms' incentives to adopt automation technologies remains largely unexplored due to a lack of robust empirical evidence. Filling this gap is crucial because, firms adjusting automation in response to labor market power may lead to either excessive or insufficient automation, with important distributional implications.

Theoretical models in labor economics currently lack a clear perspective on the impact of labor market monopsony on automation. Central to monopsony theory is the concept of finitely elastic labor supply for individual firms, which allows them to set wages below the marginal productivity of workers and maintain lower average labor costs. This suggests that firms with significant labor market power may have lower incentives to automate. However, a recent model developed in Azar et al. (2023) challenges this notion, positing that monopsonistic firms, internalizing the wage effects of their labor demand, might actually exhibit a higher propensity to automate, since automating marginal workers allows them to lower wages for the rest of the workforce. These contrasting views underscore how labor market frictions can lead to deviations in automation levels from those in a perfectly competitive labor market. Given the theoretical ambiguities, there is an urgent need for empirical research to provide clear evidence and a deeper understanding of these dynamics, which is essential for understanding the implications of increasing market concentration for labor markets and technological change.

This paper aims to fill this gap by investigating the impact of labor market power on the degree of automation in manufacturing firms. I use a unique set of administrative microdata from Portugal, a country that has been extensively studied in the areas of labor market frictions, rent sharing, and labor market power (Card, Cardoso, & Kline, 2016; Card et al., 2018). The firm-level dataset is characterized by consistently providing detailed information on inputs, outputs, investments, and imports of industrial robots for the universe of Portuguese manufacturing firms over the period 2004 to 2020. The dataset allows for a precise quantification of labor market power through markdown estimation - calculating the gap between labor's marginal revenue product and wages - using a production function approach. The estimation results reveal significant variation in labor market power across and within Portuguese manufacturing industries, and provide novel evidence of a robust positive relationship between markdowns and various measures of firm-level automation, including the use of industrial robots. This empirical investigation offers a novel perspective on how imperfect competition in labor markets can shape technology adoption in manufacturing.

To estimate firm-specific markdowns, I use a method developed by Yeh, Macaluso, and Hershbein (2022) that has been shown to robustly estimate labor market power in U.S. manufacturing plants. This method is based on the key insight that product markups and input markdowns can be identified and estimated separately if at least one other observable input is flexible and free of monopsony power. In this case, the wedge between the marginal revenue product and the cost of the flexible input reflects only product markups. This allows us to identify labor markdowns as the ratio of the labor wedge to the flexible input wedge. This insight is crucial to my study, as it allows consistent estimation of markdowns in terms of revenue shares and output elasticities of inputs using standard panel data on firms' inputs and outputs. To derive output elasticities, I implement a non-parametric production function estimation using a proxy variable approach, as described in Yeh, Macaluso, and Hershbein (2022).

The analysis reveals significant variation in labor market power within Portuguese manufacturing firms, suggesting that labor markets in Portuguese manufacturing are far from perfectly competitive. On average, the marginal revenue product of labor in these firms is 18 percent above the wage, implying that workers receive about 85 percent of the value they generate. I find significant variation, with an interquartile range of 40 percent, both across and within industries. Cross-sectional data reveal a strong positive correlation between markdowns and automation, as measured by both the machine-to-worker ratio and, more specifically, imports of industrial robots. Moreover, panel regressions with firm fixed effects show that a 10 percent increase in markdowns is associated with a 1.6 percent increase in machinery investment in the following year. Taken together, these results suggest that higher labor market power is associated with increased automation investment in Portuguese manufacturing.

To identify the causal effect of labor market power on automation, I further exploit the unexpected introduction of tolls on previously toll-free highways in 2010. This event provides a quasi-experimental variation in the labor market power of local employers by increasing commuting costs and consequently reducing the mobility and outside options of workers living near affected highways. markdown combines dynamic treatment effects in an instrumental variable framework. The results partially confirm the positive relationship between markdowns and machinery investment. However, they also reveal limitations in instrument strength and exogeneity that limit the ability of the case study to draw robust conclusions.

The results of this study have important policy implications. First, they imply that increasing market concentration may accelerate automation trends. Second, they suggest that one way for policymakers to protect workers from the effects of excessive automation is to ensure that labor markets remain competitive, for example through policies that limit firms' wage-setting power or increase worker mobility.

This paper contributes to three strands of research. First, it advances the literature on automation and labor markets by empirically examining the relationship between automation and labor market power at the firm level. I substantiate the task-based model of automation by Azar et al. (2023), which posits that monopsonistic firms have stronger incentives to automate as they internalize higher marginal cost of labor compared to firms in perfectly competitive labor markets. I empirically test this hypothesis using microdata and show that higher markdowns are correlated with increased investment in machinery and equipment in manufacturing firms. This evidence has important implications for economic theories on automation and labor markets that predominantly assume firms as wage-takers (Acemoglu & Restrepo, 2018b; Koch, Manuylov, & Smolka, 2021; Bessen, Denk, & Meng, 2022; Adachi, Kawaguchi, & Saito, 2024).

Second, this research extends the literature on labor market monopsony (Robinson, 1933; Manning, 2021; Sokolova & Sorensen, 2021) by shedding light on how labor market power may affect non-labor market outcomes in terms of firms' technology adoption. It builds on and goes beyond findings by Traina (2022) of a positive correlation between capital intensity and labor wedges in U.S. manufacturing plants by demonstrating that labor market power is a significant predictor of robot adoption. Moreover, I confirm the cross-sectional evidence that higher markdowns predict an increase in subsequent machinery investment in a panel data setting and use quasi-experimental variation to establish causal identification. In doing so, this study also contributes to recent research investigating the extent of rent sharing and wage inequality in the Portuguese labor market by providing novel markdown estimates for Portuguese manufacturing firms (Card, Cardoso, & Kline, 2016; Félix & Portugal, 2016; Card et al., 2018; Garin & Silvério, 2024; Martins & Melo, 2024).

Third, this paper contributes to the literature on the determinants of automation by demonstrating how firm-specific differences in labor market power are related to increased automation. This finding adds a new dimension to existing firm-level studies that have predominantly focused on differences in the relative cost of labor due to factors such as minimum wages (Fan, Hu, & Tang, 2021), labor market reforms (Dechezleprêtre et al., 2021), or labor scarcity (Danzer, Feuerbaum, & Gaessler, 2020; Benmelech & Zator, 2022). Variations in labor market power across local labor markets may also help explain the observed heterogeneity in robot adoption within industries across regions, as indicated by recent microdata (Leigh & Kraft, 2018; Brynjolfsson et al., 2023). Finally, the results relate to the broader debate on how market structure can distort firms' incentives to innovate, highlighting the importance of firms' labor market power in this context (Acemoglu, 2023).

The paper is organized as follows: Section 4.2 presents the theoretical framework and the markdown estimation procedure, Section 4.3 describes the data sources and construction, Section 4.4 presents the main results, Section 4.5 implements the instrumental variable approach for testing robustness, and Section 4.6 concludes.

4.2 Theoretical Framework and Markdown Estimation

To study the link between labor market power and automation in firms, it is essential to understand how labor market power can be quantified. This section first reviews how the literature conceptualizes labor market power as a consequence of finite labor supply elasticities. Subsequently, it introduces the approach by Yeh, Macaluso, and Hershbein (2022) for quantifying labor market power in terms of markdowns, which are directly linked to finite labor supply elasticities. The section concludes with a summary of the markdown estimation procedure by Yeh, Macaluso, and Hershbein (2022), which will be applied in this study.

4.2.1 Conceptualizing Labor Market Power

The modern literature on labor market monopsony suggests that labor market power of firms mainly arises from finitely elastic labor supply curves (see Manning, 2013, 2021). This idea reflects the observation that an employer can reduce wages without losing all its workers, as would be the case in a perfectly competitive market with infinitely elastic labor supply. Such finite labor supply elasticities can arise from various factors like high search costs, limited information on outside options, low worker mobility, or firm-specific human capital (Card, 2022). Regardless of the specific source of friction, the literature argues that finite labor supply elasticities endow firms with labor market power, commonly defined as a firm's ability to compensate workers below their marginal revenue product (Robinson, 1933). This gap between workers' marginal productivity and their wages is known as the markdown, and is directly linked to the finite labor supply elasticity. This relationship becomes evident when considering a firm's profit maximization problem, as follows:

$$\max_{l \geq 0} \; R(l) - w(l)l \tag{4.1}$$

where $R(l) \equiv rev(l; \mathbf{X}^*_{-l}(l))$ denotes a revenue function where all inputs, except for labor l, are evaluated at their optimum.

Assuming a differentiable wage schedule given by the inverse labor supply function $w(l) = l^{\frac{1}{\varepsilon}}$, we can derive and rearrange the first order condition as:

$$\begin{aligned} R'(l*) &= w'(l*)l * + w(l*) \\ R'(l*) &= w(l*)\left[1 + \frac{w'(l*)l*}{w(l*)}\right] \\ \nu = \frac{R'(l*)}{w(l*)} &= 1 + \frac{1}{\varepsilon} \end{aligned} \tag{4.2}$$

where $\frac{1}{\varepsilon}$ is the inverse labor supply elasticity. Equation 4.2 establishes a direct relationship between the firm-level labor supply elasticity and the markdown. It demonstrates that in perfectly competitive markets with infinite labor supply elasticities, the right-hand side approaches unity, indicating no discrepancy between marginal productivity and wages. However, as elasticity becomes finite and diminishes, this gap broadens, leading to markdowns above unity.[1] Consequently, the labor supply elasticity can be inferred directly from the magnitude of the markdown.

Consistent with the recent monopsony literature, finite labor supply elasticities are also the key parameter that Azar et al. (2023) use to model the implications of labor market power for automation. Azar et al. (2023) argue that firms with finitely elastic labor supply internalize the impact of automation on wages of remaining workers, consequently increasing the automation of their production tasks. This arises because, unlike firms in perfectly competitive labor markets that are wage-takers with constant marginal labor costs, those in imperfectly competitive markets can lower wages by reducing labor demand. This means that monopsonists face an upward-sloping marginal labor cost curve and, consequently, higher marginal costs than their competitive counterparts.

To empirically study the impact of labor market power on firms' automation, it appears natural to use firm-specific labor supply elasticities as measure of monopsony power. However, the direct measurement of these elasticities is challenging without

[1]In this paper, I follow the convention of using unity, rather than zero, as the benchmark value of markdowns to indicate the absence of labor market power and perfect alignment between workers' marginal productivity and their wages.

exogenous or experimental variation in wages (Ransom & Sims, 2010; K.-M. Chen et al., 2020). While feasible in specific contexts, estimating these elasticities across a broad range of firms and industries is difficult. Recent methodological advancements, however, have improved the measurement of markdowns from detailed firm-level balance sheet data (Brooks et al., 2021; Berger, Herkenhoff, & Mongey, 2022; Deb et al., 2022; Traina, 2022; Mertens, 2023). Given their direct relationship with firm-level labor supply elasticity, markdowns present a practical alternative to measure the labor market power of firms.

4.2.2 Deriving and Estimating Markdowns

To quantify markdowns, I adopt the methodology of Yeh, Macaluso, and Hershbein (2022), which combines theoretical insights from the monopsony literature with production function estimation techniques from the industrial organization literature. The distinct advantage of this approach is that it allows one to separately identify markups in the output market and markdowns in the labor market, thereby avoiding the conflation of the two sources of market power in measurement. Building on the insight by Hall, Blanchard, and Hubbard (1986), Yeh, Macaluso, and Hershbein (2022) first derive an expression of product markups as the wedge between the output elasticity and the revenue share of a "flexible" input, defined as an input free form monopsony power or adjustment costs.[2] Assuming that at least one flexible input exists, they then derive an expression of the markdown as follows:

$$\nu_{it} = \frac{\theta^l_{it}}{\alpha^l_{it}} \cdot \mu^{-1}_{it} \tag{4.3}$$

The expression shows that the ratio of the output elasticity of labor θ^l and labor's revenue share α^l are a product of the markup μ and the markdown ν of firm i at time t. In the spirit of Hall, Blanchard, and Hubbard (1986), the ratio partially captures the markup. However, it also encapsulates the markdown, due to monopsony in the labor market. This implies that with a known markup, such as one derived from the wedge for the flexible input, the markdown can be separately identified by multiplying the ratio of labor's output elasticity and its revenue share with the inverse of the markup, as given in Equation 4.3. Implementing this insight empirically requires data on firms'

[2] Appendix D.1 provides the detailed derivation of markups and markdowns in the framework of Yeh, Macaluso, and Hershbein (2022).

inputs and revenues as well as firm-specific output elasticities. While revenue shares can be computed from firm-level data on inputs and outputs, output elasticities cannot be observed directly.

To estimate output elasticities, which indicate the responsiveness of output to changes in a particular input, I adopt the production function approach outlined by Yeh, Macaluso, and Hershbein (2022). The key insight is that output elasticities can be derived by taking the partial derivative of a firm's production function with respect to a specific input, provided the production function parameters are known.[3] The central task, therefore, is to estimate the parameters of the production function, defining how firms combine inputs to produce output. To this end, I implement the approach by Yeh, Macaluso, and Hershbein (2022) in the following setting:

$$y_{it} = f\left(\mathbf{x}_{it}; \boldsymbol{\beta}\right) + \omega_{it} + \varepsilon_{it} \tag{4.4}$$

where y_{it} is the log of observed output, $\mathbf{x}_{it}$ a vector of log inputs, $f\left(\mathbf{x}it; \boldsymbol{\beta}\right)$ the log-transformed production function, ω_{it} the firm-specific idiosyncratic productivity in year t, and ε_{it} the measurement error.

Estimating the production function parameters $\boldsymbol{\beta}$ faces the well-known endogeneity problem of simultaneity or transmission (Marschak & Andrews, 1944; Griliches & Mairesse, 1995). The issue arises from the firm-year-specific productivity ω_{it} which simultaneously influences both a firm's choice of inputs and its output, yet remains unobservable to the econometrician. In this context, employing a simple least squares regression of output on inputs, without accounting for the unobserved productivity, would result in a correlation between inputs and the error term. This would violate the exogeneity requirement of Ordinary Least Squares (OLS) estimation, resulting in biased and inconsistent parameter estimates.

To address the endogeneity problem, I implement a proxy variable method, as in Yeh, Macaluso, and Hershbein (2022), building on established production function estimation methodologies by Olley and Pakes (1996), Levinsohn and Petrin (2003), Loecker and Warzynski (2012) and Ackerberg, Caves, and Frazer (2015). This approach mitigates the endogeneity arising from simultaneity by using lagged inputs as instruments orthogonal to productivity shocks in period t and flexible material inputs to construct a proxy for unobserved productivity shocks.

[3] A detailed derivation of markups and markdowns as a function of revenue shares and elasticities can be found in Appendix D.1.

The mechanics of the proxy-variable methodology can be summarized in short as follows: First, it is necessary to obtain estimates $\hat{\varphi}_{it}$ of log output free from measurement error $\hat{\varepsilon}_{it}$. This is achieved by running a regression of log output on a second-order polynomial of inputs $\mathbf{x}_{it}$, including year fixed effects:

$$y_{it} = \phi(\mathbf{x}_{it}) + \delta_t + \varepsilon_{it}. \tag{4.5}$$

Second, productivity can then be constructed as $\omega_{it}(\boldsymbol{\beta}) = \hat{\varphi}_{it} - f(\mathbf{x}_{it}; \boldsymbol{\beta})$. Assuming that productivity follows a Markov process, innovations to productivity ξ_{it} can then be identified as the residuals from a third-order polynomial regression of productivity on its lagged values, given by:

$$\omega_{it}(\boldsymbol{\beta}) = \rho_1 \omega_{it-1}(\boldsymbol{\beta}) + \rho_2 \omega_{it-1}^2(\boldsymbol{\beta}) + \rho_3 \omega_{it-1}^3(\boldsymbol{\beta}) + \xi_{it}. \tag{4.6}$$

Third, having estimated productivity and its innovations, production function parameters $\hat{\boldsymbol{\beta}}$ are estimated by optimizing a Generalized Method of Moments (GMM) system. This optimization is based on the moment condition that, in expectation, innovations are orthogonal to the instrument vector $\mathbf{z}_{it}$ of lagged inputs:

$$\mathbb{E}(\xi_{it}(\boldsymbol{\beta}) \cdot \mathbf{z}_{it}) = \mathbf{0}_{Z\times 1}. \tag{4.7}$$

This process involves minimizing a quadratic loss function using numerical optimization, with parameters estimated separately for each industry.[4]

Once the production function parameters $\hat{\boldsymbol{\beta}}$ have been estimated, output elasticities for material inputs and labor are determined by taking the first-order derivative of the production function, specified as a translog function. Combining output elasticities with revenue shares of materials and labor allows to compute the markdown defined in Equation 4.3.

The approach by Yeh, Macaluso, and Hershbein (2022) has various advantages. First, this method stays neutral regarding the specific source of labor market power, requiring only that labor supply elasticities are finite. Therefore, it can encompass a wide range of labor market power settings. Second, the approach allows for the separate identification of markdowns and markups, effectively disentangling market power in both product and labor markets. This is important when studying the relationship of

[4] See Appendix D.2 for a detailed description of the production function estimation procedure of Yeh, Macaluso, and Hershbein (2022).

markdowns and automation. Third, it offers a measure of labor market power that can be computed for a wide range of firms and industries, assuming data on their inputs and outputs is available. These reasons make the approach by Yeh, Macaluso, and Hershbein (2022) an ideal choice to derive measures of labor market power in the context of this study.

This section has discussed how the literature derives labor market power from finite labor supply elasticities and shown their direct relationship with markdowns as well as their relevance in the model of automation in Azar et al. (2023). I have outlined a method for measuring markdowns across many firms, based on revenue shares and output elasticities, following the approach Yeh, Macaluso, and Hershbein (2022). This sets the stage for employing this methodology to calculate markdowns, which requires data on firms' inputs and outputs — a topic I will delve into in the following section.

4.3 Data

In this section, I introduce the microdata used to investigate the relationship between labor market power and automation. Key to this analysis is detailed firm-level panel data on production inputs and output, essential for calculating markdowns as defined in Equation 4.2. This calculation relies on data about revenue shares and output elasticity estimates from production function estimations. Moreover, a comprehensive analysis requires detailed data on firms' automation investments.

To address these requirements, I use the following administrative datasets from the National Institute of Statistics of Portugal (INE): Integrated Business Accounts (*Sistema de Contas Integradas das Empresas*, SCIE), and International Trade Register (*Comercio Internacional*, CI). In this section, I will introduce these data sources, discuss sample restrictions, and detail variable construction. Finally, I will present results of the markdown estimation and provide descriptive statistics related to automation.

4.3.1 Data Sources

The primary dataset used in this study is the *Integrated Business Accounts* dataset, an exhaustive annual firm-level census covering all non-financial firms in Portugal since

2004.[5] Its suitability stems from several key attributes. Firstly, the dataset provides universal coverage and reliable measurement. It builds on financial statements that firms are required to report annually to public authorities, including the Ministry of Finance, Ministry of Justice, the Central Bank, and the National Institute of Statistics, for accounting, tax, and statistical purposes. The mandatory reporting adheres to national accounting standards and is carried out systematically through a single interface, the Simplified Corporate Information (Informação Empresarial Simplificada, IES) system. This mitigates concerns related to both sample selection and measurement error or non-response. Secondly, the dataset offers a wealth of firm-level information that is crucial for production function estimation. In particular, I leverage data on inputs and output, including fixed tangible assets, payroll, intermediate consumption, energy expenses, and output.[6] Lastly, the dataset provides detailed data on investment by asset type, particularly in machinery and equipment, which serves as a proxy for automation investments, further underscoring its value for this analysis.

Beyond the firm census, I leverage data from the *International Trade Register*, a detailed dataset capturing all import and export transactions of Portuguese firms at the 8-digit product level, sourced from customs records. Importantly, it allows the detailed tracing of automation equipment imports, particularly industrial robots, as a proxy for industrial automation.[7] The key advantage of these administrative datasets is the ability to link firm census and customs data using a common firm identifier from INE.

For the purpose of this analysis, I focus on incorporated businesses in manufacturing, with complete data in production variables. Although the firm census is comprehensive, encompassing over 19.4 million observations from nearly 3.3 million firms between 2004 to 2020, I restrict the data for the following reasons. First, I focus on firms in the manufacturing sector. This sector has been leading the adoption of automation technologies, in particular industrial robotics, for many decades and is marked by spatially concentrated production and significant consolidation in recent years. This environment makes it an ideal case for studying the interplay between automation and labor market power. Secondly, I restrict the sample to incorporated businesses

[5]The dataset covers all sectors with the exception of financial and insurance companies, local and central public administrations, private households with employed persons, and international organizations and other non-resident institutions.

[6]I supplement the *Integrated Business Accounts* data with information on energy expenses from the *Annual Survey on Industrial Production* (IAPI) for the years 2004 and 2005.

[7]Industrial robots are classified under the 8-digit product code "84795000-Industrial robots, not elsewhere specified or included".

Table 4.1: Overview of Successive Sample Restrictions: 2004-2020

Sample Restriction	Number of Firm-Year Observations	Total Number of Firms	Turnover	Employment	Machinery Investment
Full Population	19,466,452	3,324,381	100.0	100.0	100.0
Manufacturing	1,319,187	186,041	24.2	19.8	27.4
Incorp. Businesses	704,167	83,081	23.7	18.3	27.3
Non-Missing Data	491,262	46,749	21.9	16.8	25.5

Notes: This table provides the number of firm-year observations and distinct firms as well as the percent share of turnover, employment and machinery investment in each sample as compared to the raw administrative dataset. 'Full Population' corresponds to the complete sample of the *Integrated Business Accounts* dataset over the period 2004 to 2020. 'Manufacturing' refers the sub-population of firms in industries classified under Section D in Revision 3 and Section C in Revision 4 of the International Standard Industrial Classification. 'Incorporated Firms' refers to the subset of manufacturing firms that fall under the legal category of 'soc' (sociedad). 'Non-Missing Data' refers to the sub-sample of incorporated manufacturing firms with non-missing and non-zero data across all production variables, including labor, capital, intermediate consumption, energy, and output.

with at least one employee, thereby excluding self-employed workers and sole proprietors. This exclusion is based on the rationale that self-employed workers, serving as both employer and employee, do not fall under typical labor market power dynamics. Moreover, these entities are not subject to mandatory reporting, leading to limited data availability, particularly on inputs and outputs beyond turnover and employment, for most of these entities in the dataset. Finally, the sample is limited to firms that have non-missing and non-zero data across all production variables, which is a prerequisite for implementing the markdown estimation discussed in Section D.2. Table 4.1 outlines these successive sample restrictions, resulting in a non-balanced panel comprising 490,000 observations from over 46,000 firms between 2004 to 2020, suitable for markdown estimation.

Having delimited the sample of analysis, I construct production variables as follows: capital is defined as the net book value of fixed tangible assets; labor, as annual payroll; material consumption, as intermediate consumption excluding energy; and energy expenses, as the costs of electricity, fuel, and other liquids.[8] Output is measured by sales adjusted for inventory changes. As in Yeh, Macaluso, and Hershbein (2022), I deflate these variables to their 2010 Euro values using output, capital, and intermediate input price deflators for Portuguese industries from the EUKLEMS database (Stehrer et al., 2019). To moderate outliers, I winsorize the extreme values at both the

[8]Following the definition for material inputs by Yeh, Macaluso, and Hershbein (2022), the variable intermediate consumption also includes contract work.

Table 4.2: Descriptive Statistics for Markdown Estimation Sample

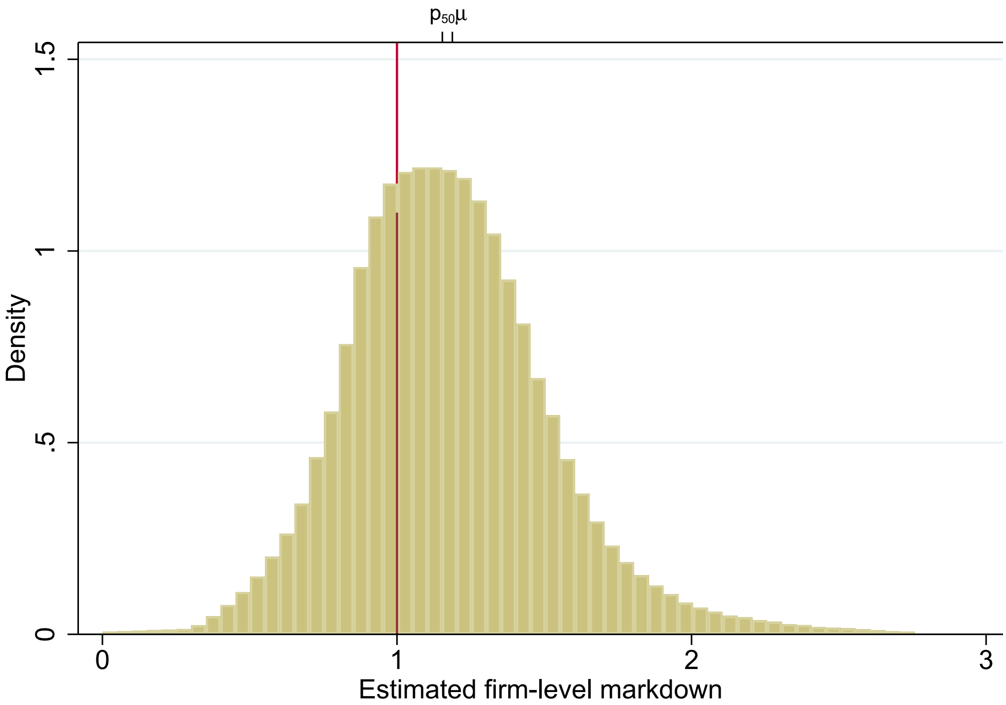
Variable	Mean	SD	Q1	Q3	Min	Max
Production Variables						
Output (€)	2,014,577	15,025,554	115,899	899,658	325	3,694,711,552
Payroll (€)	295,298	1,136,612	33,315	213,077	75	153,613,216
Fixed Tangible Assets (€)	662,455	3,690,980	14,636	288,144	1	429,105,280
Material Consumption (€)	1,382,574	12,632,881	46,636	489,877	86	3,319,239,168
Energy Expenses (€)	60,367	370,909	4,324	28,798	3	44,188,864
Other Firm Characteristics						
Firm Age (Years)	18	14	7	25	0	250
Number of Employees	22	63	4	19	1	5,641
Annual Wage (€)	10,803	7,233	7,635	12,581	46	917,153
Local Employment Share						
2-digit Industry	0.016	0.066	0.001	0.008	0.000	1.000
3-digit Industry	0.045	0.135	0.001	0.023	0.000	1.000
5-digit Industry	0.096	0.217	0.003	0.058	0.000	1.000
Machinery Investment (€)	66,267	656,700	0	11,255	0	89,267,347
Market Power Estimates						
Markup	1.127	0.140	1.035	1.195	0.327	8.208
Markdown	1.179	0.348	0.947	1.377	0.000	2.734
Observations	381,571					

Notes: Data consists of firm-year observations from 2005 to 2020. Monetary values of production variables are adjusted to 2010 Euro prices. 'Output' denotes sales net of changes in inventory. 'Payroll' encompasses remuneration of employees and corporate bodies. 'Fixed Tangible Assets' refer to the reported net book value of fixed tangible assets at the end of each year. 'Material Consumption' stands for intermediate consumption excluding energy expenses. 'Energy Expenses' cover electricity, fuel, and other liquids. 'Annual Wage' is calculated as payroll divided by employment. 'Machinery Investment' refers to reported investment in machinery and equipment. 'Local Employment Share' indicates a firm's portion of industry employment in its NUTS III region, categorized into 2, 3, or 5-digit industries according to the Portuguese industry classification, consistent with the International Standard Industrial Classification (ISIC). 'Markups' and 'Markdowns' are estimated as described in Appendix D.2. Source: Authors' own calculations from Integrated Business Accounts data in 2004-2020.

bottom and top 0.5 percentile for each 2-digit industry. After estimating markdowns with the algorithm by Yeh, Macaluso, and Hershbein (2022), I further eliminate markdown outliers exceeding the top 0.5 percentile and those falling below zero. The final sample, comprising over 380,000 observations from 2005 to 2020, is described with summary statistics in Table 4.2.[9]

[9]The production function estimation algorithm calculates parameters (β) using productivity innovations (ξ), which are obtained as residuals from a Markov process that models productivity (ω) as a function of its first-order lag. Consequently, the initial year for each firm in the dataset lacks both the first lag of productivity (ω) and a residual (ξ). Therefore, the estimation sample is restricted to observations from the year after a firm's initial appearance in the dataset, resulting in parameter estimation solely for the period starting in 2005 and a reduction in the total number of observations.

Figure 4.1: Distribution of Estimated Markdowns in Portuguese Manufacturing



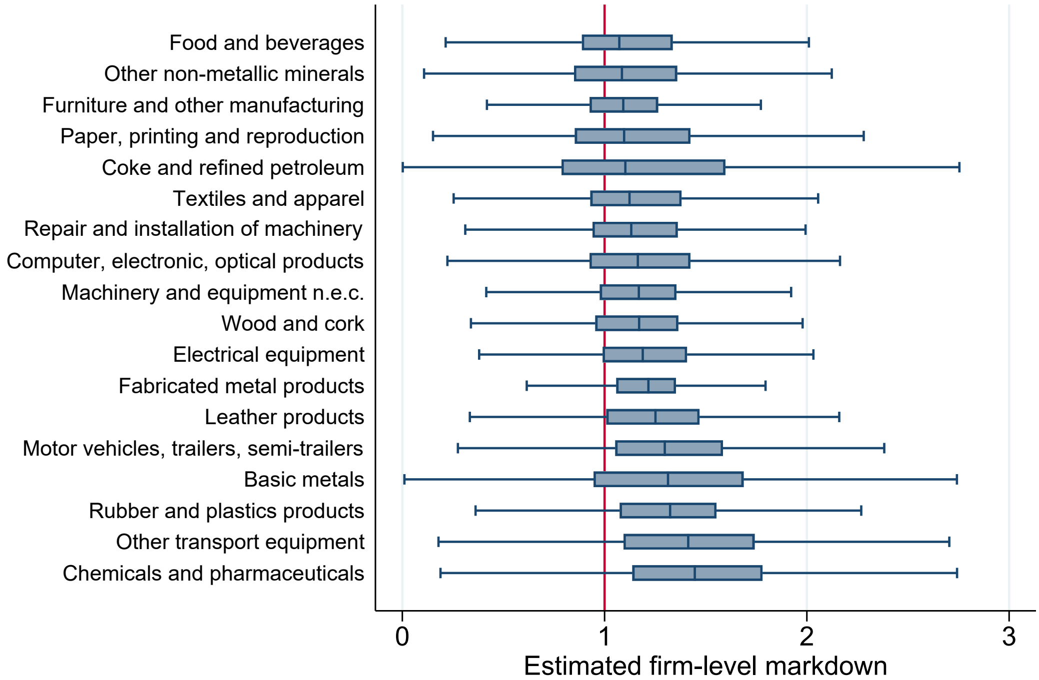
Notes: This histogram shows the distribution of markdowns estimated from 2005 to 2020, as per Equation 4.2 and following the methodology detailed in Section D.2. Source: Authors' own calculations from Integrated Business Accounts data in 2005-2020.

4.3.2 Markdowns in Portuguese Manufacturing

The markdown estimation results, displayed in Figures 4.1 and 4.2, highlight substantial variation in labor market power across firms in the Portuguese manufacturing sector. The histogram of firm-level markdowns, depicted in Figure 4.1, shows that most firms set markdowns above unity, with an average of 1.17. This implies that workers receive 84 cents per marginal Euro produced at the average firm. The distribution is slightly right-skewed with a median of 1.15 and an interquartile range of 0.43, pointing to a significant degree of labor market power among specific firms.[10] Although these estimates appear substantial, they are slightly lower than markdowns reported in earlier studies, such as Félix and Portugal (2016) for Portuguese manufacturing

[10]Interestingly, some firms exhibit markdowns less than unity, a phenomenon aligned with recent findings suggesting rent-sharing due to workers' bargaining power, as discussed in Mertens (2023) and Yeh, Macaluso, and Hershbein (2022).

Figure 4.2: Distribution of Estimated Markdowns by Manufacturing Industry



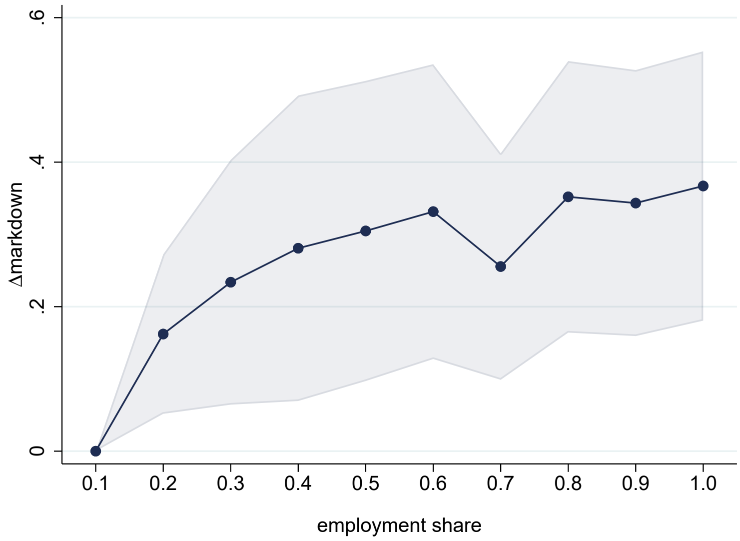
Notes: The figure presents box plots of estimated firm-level markdowns by industry group for the period 2005-2020. Industries are arranged in ascending order of their median markdown. Each box spans the interquartile range, from the 25th to the 75th percentile, encapsulating the middle 50% of the data. Whiskers extend to the smallest and largest values within 1.5 standard deviations from the lower and upper quartiles, respectively. Observations beyond this range, representing extreme values, are not included in the figure. Source: Authors' own calculations from Integrated Business Accounts data in 2005-2020.

firms and Yeh, Macaluso, and Hershbein (2022) for U.S. manufacturing plants.[11] At the same time, my results indicate slightly higher labor market power relative to the average labor supply elasticity reported in other European studies, as documented in the meta-analysis by Sokolova and Sorensen (2021), aligning well with the broader literature.

Further analysis indicates notable differences in labor market power across and within industries. As delineated in Figure 4.2, low-tech sectors with numerous firms, including "Food and beverages" and "Other non-metallic minerals," tend to have relatively low median markdowns, generally below 1.10. In contrast, more concentrated industries such as "Other transport equipment" and "Chemical and pharmaceutical prod-

[11] Félix and Portugal (2016) find an average labor supply elasticity of 3.27 at Portuguese manufacturing firms, equating to a mean markdown of 1.31, while Yeh, Macaluso, and Hershbein (2022) report a mean markdown of 1.53 for U.S. manufacturing plants.

Figure 4.3: Markdowns and Local Labor Market Shares



Notes: The figure shows point estimates and 95 percent confidence intervals from an OLS regression of firm-specific markdowns on indicators for employment share deciles, controlling for indicators of firm age, as well as industry, region and year fixed effects. The baseline for comparison is the smallest size group. Each size indicator, such as "0.1", represents firms with employment shares in the corresponding range (e.g., s ∈ (0, 0.1]). Other indicators follow the same principle. Following Yeh, Macaluso, and Hershbein (2022), the regression applies employment weights. Standard errors are clustered by industry. Source: Authors' own calculations from Integrated Business Accounts data in 2005-2020.

ucts" consistently exhibit higher median markdowns, exceeding 1.40.[12] This pattern indicates that structural industry differences may contribute to the overall variability in labor market power within the manufacturing sector, as initially observed in Figure 4.1. At the same time, the considerable dispersion of markdown estimates across firms within industries, highlighted by the substantial standard deviations in Table D.1, underscores the influence of firm-specific factors. These findings emphasize the need to account for both industry heterogeneity and firm-specific characteristics in subsequent analyses of labor market power and automation.

To examine the connection between estimated markdowns and potential sources of labor market power, I briefly explore how markdowns correlate with a firm's employment share in the local labor market. I calculate each firm's share of employment within its industry-region and create an indicator for each share decile.[13] Following Yeh, Macaluso, and Hershbein (2022), I employ a non-parametric regression to deter-

[12]See Appendix Table D.1 for related statistics.

[13]The local labor market is defined as a 5-digit industry within a NUTS III region, with firms assigned based on the municipality of the headquarters' location. Refer to Appendix Figure x for information on Portugal's administrative regions.

mine the average markdown for each employment share decile, as follows:

$$\nu_{it} = \alpha + \sum_{d=1}^{S} \beta_d^{share} \cdot \mathbf{1}_{s_{it} \in S_d} + \mathbf{X}'_{it}\gamma + \varepsilon_{it}, \tag{4.8}$$

where $\mathbf{X}_{it}$ includes industry, region, and year fixed effects, along with dummies for eight age brackets, following the methodology of Yeh, Macaluso, and Hershbein (2022).[14] The results, illustrated in Figure 4.3, show that markdowns increase with a firm's share in the local labor market. Firms with the highest employment shares have markdowns roughly 35% higher than the smallest firms, on average.[15] This finding supports the notion that higher markdowns in Portuguese manufacturing are associated with monopsonistic environments, where employers likely face less elastic labor supply (Berger, Herkenhoff, & Mongey, 2022).

In sum, the descriptive analysis reveals considerable variation in labor market power, as reflected by estimated markdowns, among Portuguese manufacturing firms both within and across industries. Additionally, I find that these markdowns correlate with the firms' significance as employers in local labor markets, aligning with the concept of local labor market monopsony as a source of labor market power. These findings underscore the suitability of the Portuguese context, marked by imperfect competition in its manufacturing labor markets, to examine the relationship between labor market power and automation, which will be explored in the next section.

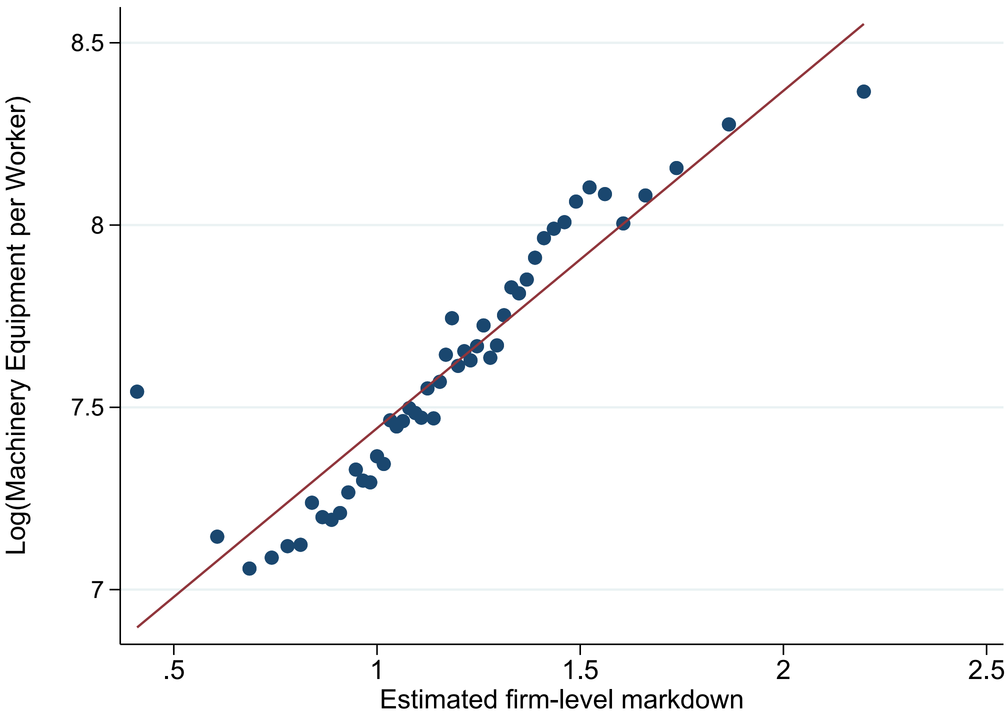
4.4 Results

This section presents the main results. First, Section 4.4.1 offers preliminary cross-sectional evidence, showing a positive correlation between estimated markdowns and firm-level automation, as measured by machinery equipment per worker and robot adoption. Second, Section 4.4.2 presents results from panel regressions that exploit year-on-year changes within firms, demonstrating that an increase in labor market power is associated with higher subsequent investment in machinery and equipment.

[14] Following Yeh, Macaluso, and Hershbein (2022), I include indicators for age groups: 0–2 years, 3–4, 5–6, 7–8, 9–10, 11–12, 13–15, and 16+ years.

[15] See Appendix Figure D.2 for estimates based on alternative local labor market definitions. In more broadly defined markets, precision decreases due to a lower number of firms with shares above 0.1. Yet, the pattern of higher markdowns in firms with shares above 0.1 is confirmed. Interestingly, the relationship isn't strictly monotonic in more broadly defined markets with markdowns peaking for firms in the middle of the share distribution.

Figure 4.4: Markdowns and Machinery Equipment per Worker (2006-2009)



Notes: The figure presents a binned scatter plot with 50 bins of equal weight, controlling for 2-digit industry industry and year fixed effects (slope = 0.923; N=83,760). This visualization is based on data on the net book value of machinery equipment per worker, available for the years 2006 to 2009. Source: Authors' own calculations from Integrated Business Accounts data.

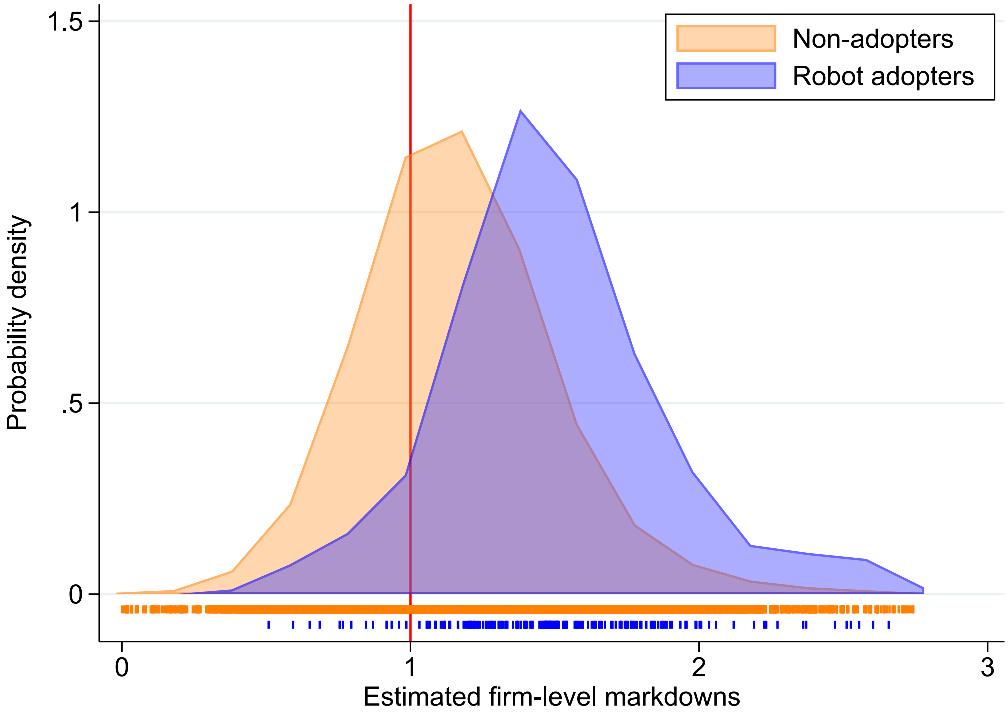
4.4.1 Cross-sectional Evidence on Markdowns and Automation

The administrative microdata offers several variables related to industrial automation. From 2006 to 2009, firms reported the net book value of machinery and equipment, which can serve as a proxy for automation in the broader sense of mechanized production.[16] I refine this measure by normalizing the stock of machinery and equipment by total firm employment. This approach yields greater precision compared to broader capital intensity measures based on fixed tangible assets, which encompass non-automation-related items like land and buildings. Moreover, the machinery stock metric is sufficiently inclusive to capture various automation forms and is widely reported, with over 90% of firms in the final sample recording a positive machinery equipment stock. This ensures ample variation for analysis.

Preliminary analysis indicates a positive correlation between labor market power and

[16] It should be noted that the stock of 'machinery and equipment' does not encompass tools used by workers; these are classified under a separate balance sheet item in the administrative data.

Figure 4.5: Comparing Markdown Distributions of Robot Adopters and Non-Adopters



Notes: This figure shows kernel density plots of the distribution of markdowns of manufacturing firms in 2010. Robot adopters are defined as firms that imported at least 2,500 Euro worth of industrial robots between 2010 and 2020. Source: Authors' own calculations from Integrated Business Accounts and International Trade Register data.

automation. The cross-sectional bin scatter plot, depicted in Figure 4.4, illustrates this relationship by correlating markdowns with the log of machinery equipment per worker, while controlling for 2-digit industry and year fixed effects. The figure includes a fitted line derived from an OLS regression of the residualized variables, showing that a one-unit increase in markdown corresponds to a more than 90% increase in machinery equipment per worker, controlling for industry and year. This finding is consistent with Traina (2022) who observed a positive correlation for capital intensity and markdowns at U.S. manufacturing plants, offering preliminary descriptive evidence of the positive association of labor market power and automation. Yet, the pattern observed so far does not clarify the direction of causality nor confirm if the pattern persists with more specific automation technologies.

To address these concerns, I leverage additional administrative data on industrial robots, a leading technology highlighted in recent research on the labor market impacts of automation (Graetz & Michaels, 2018; Acemoglu & Restrepo, 2020a). Considering most industrial robot production occurs outside Portugal, mainly by a few global manufacturers, I trace the adoption of industrial robots in Portuguese manufacturing through direct imports reported in the International Trade Register dataset.[17] Following Acemoglu, Koster, and Ozgen (2023), I create a dummy variable for robot adoption, identifying firms that imported more than 2,500 Euros worth of industrial robots from 2010 to 2020. This period was characterized by a significant uptick in the number of robot importers in Portuguese manufacturing, as documented in Appendix Figure D.1. Comparing markdowns across robot adopters and non-adopters at the start of the decade provides a first test of the relationship between labor market power and subsequent automation.

A detailed examination of the data also indicates a positive link between labor market power and the likelihood of future robot adoption. The kernel density plots of markdown distributions in 2010, depicted in Figure 4.5, reveal that potential robot adopters already exhibited higher markdowns before their actual adoption. To mitigate potential biases from industry heterogeneity and firm-specific factors, conduct a regression analysis using the Poisson pseudo-maximum likelihood (PPML) method.[18] Results in Table 4.3 affirm that higher markdowns in 2010 increase the probability of subsequent industrial robot adoption, even after adjusting for industry-by-size bracket fixed effects and firm size controls. This evidence refines the positive correlation between markdowns and machinery per worker observed in Figure 4.4, employing a more specific automation measure and adding a temporal dimension to the analysis.

4.4.2 Panel Data Evidence on Markdowns and Automation

To address the issue of time-invariant omitted variables, I exploit the panel dimension of the administrative data. Specifically, I leverage data on investment in machinery and equipment from the *Integrated Business Accounts* dataset, which is available for every year from 2005 to 2020. While robot import data offers valuable insights into a specific automation technology adopted by a small fraction firms, the advantage of the machinery investment data lies in the consistent annual reporting by most firms

[17] Leone (2023) reports that 10 multinational enterprises account for 90% of sales of industrial robots, most of them located in Japan, South Korea, Switzerland or Germany. The method of measuring industrial automation through industrial robot imports is also employed in other recent firm-level studies (e.g. Bonfiglioli et al., 2020; Dixon, Hong, & Wu, 2021).

[18] The PPML method is particularly effective for managing zero-inflation in outcome variables, a key aspect due to the limited number of robot adopters in the data, totaling only 205 in the estimation sample.

Table 4.3: Markdowns and Robot Adoption: 2010-2020 (PPML)

	Robot adoption			
	(1)	(2)	(3)	(4)
log(markdown)	3.350***	2.924***	1.843***	0.530*
	(0.521)	(0.446)	(0.373)	(0.311)
log(output)				0.144
				(0.157)
log(employment)				0.661***
				(0.238)
log(capital intensity)				0.434***
				(0.092)
Observations	25,185	25,185	17,601	17,601
Pseudo R-squared	0.07	0.20	0.26	0.32
Industry FE	NO	YES	YES	YES
Industry × Size FE	NO	NO	YES	YES

Notes: Dependent variable: dummy for firm's imports of industrial robots of more than 2,500 Euros (2010-2020). Controls: Specification (2) includes 2-digit industry dummies. Specification (3) adds dummies for 2-digit industry-size bracket pairs, grouping firms by number of employees in 2010 (1-9, 10-249, or ≥250). Specification (4) adds the log of output, employment and capital intensity in 2010, respectively. Capital intensity stands for the ratio of fixed tangible assets per worker. All four specifications use the same sample. In Specifications (3) and (4), industry-size cells without robot adoption between 2010-2020 are absorbed by fixed effects and automatically excluded, resulting in fewer observations. Standard errors in parentheses are clustered at the 3-digit industry level. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

over 15 years, providing the necessary variation to exploit year-on-year changes for robust within-firm analysis. To this end, I estimate the following regression equation:

$$Y_{i,t} = \alpha_i + \beta \ \nu_{i,t-1} + \mathbf{X}_{i,t-1} + \gamma_{j,t} + \delta_{r,t} + \varepsilon_{i,t} \tag{4.9}$$

where investment in machinery (Y) for firm i in year t is regressed on the first lag of the estimated firm-level markdown (ν) and firm controls, including firm-, industry-year and region-year fixed effects. I impose a lag structure to avoid a potential mechanical correlation between investment and markdowns, which are partly calculated using

Table 4.4: Markdowns and Investment in Machinery: Panel Regressions, 2005-2020 (OLS)

	asinh(investment in machinery$_t$)				
	(1)	(2)	(3)	(4)	(5)
log(markdown$_{t-1}$)	0.939***	0.921***	0.908***	0.883***	0.164***
	(0.049)	(0.048)	(0.047)	(0.046)	(0.040)
log(employment$_{t-1}$)				0.924***	0.004
				(0.044)	(0.044)
log(capital intensity$_{t-1}$)				0.065***	-0.036**
				(0.017)	(0.016)
log(output$_{t-1}$)					1.252***
					(0.041)
Observations	335,146	335,133	334,875	334,875	334,875
R-squared	0.58	0.58	0.58	0.58	0.59
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Industry × Year FE	NO	YES	YES	YES	YES
Region × Year FE	NO	NO	YES	YES	YES

Notes: Dependent variables: inverse hyperbolic sine transformation of investment in machinery and equipment. Controls: firm fixed effects, year dummies, 2-digit industry-year dummies, NUTS2 region-year dummies, and the log of employment, capital intensity and output. Capital intensity stands for the ratio of fixed tangible assets per worker. Standard errors in parentheses are two-way clustered by firm and 2-digit industry-year pairs. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

the stock of fixed tangible assets.[19]

The panel analysis upholds the observed relationship between labor market power and automation. Table 4.4 demonstrates that lagged markdowns are significantly associated with future investments in machinery and equipment, used again as a proxy for automation. To integrate both the extensive and intensive margins of machinery investments, I employ the inverse hyperbolic sine transformation. The baseline estimate in specification (3) shows that a 10 percent increase in markdowns is associated with 9 percent more investment in machinery and equipment in the subsequent year. Even after adjusting for firm characteristics, including lagged employment, capital intensity, and lagged output, Specification (5) confirms the positive relationship,

[19] Given that the non-parametric production function is approximated by a second order polynomial, computing firm-year-specific output elasticities requires the use of contemporaneous input levels, including capital. The output elasticities are then used for the computation of markdowns, given in Equation 4.2. See Appendix Table D.2 for the decreasing correlation between markdowns and machinery investment as the lag length for markdowns increases.

Table 4.5: Markdowns and Investment in Machinery at the Extensive and Intensive Margins: Panel Regressions, 2005-2020 (OLS)

	Investment in machinery$_t$		
	(1) log	(2) dummy	(3) asinh
log(markdown$_{t-1}$)	0.088***	0.018***	0.164***
	(0.023)	(0.004)	(0.040)
log(output$_{t-1}$)	0.583***	0.109***	1.252***
	(0.024)	(0.004)	(0.041)
log(employment$_{t-1}$)	-0.200***	0.012**	0.004
	(0.023)	(0.005)	(0.044)
log(capital intensity$_{t-1}$)	-0.113***	0.003	-0.036**
	(0.010)	(0.002)	(0.016)
Observations	169,956	334,875	334,875
R-squared	0.67	0.49	0.59
Firm FE	YES	YES	YES
Industry × Year FE	YES	YES	YES
Region × Year FE	YES	YES	YES

Notes: Dependent variables: various transformations of investment in machinery and equipment. Specification (1) uses the logarithmic transformation, Specification (2) employs a binary indicator denoting positive investment, and Specification (3) applies the inverse hyperbolic sine transformation. Controls: firm fixed effects, 2-digit industry-year dummies, NUTS2 region-year dummies, and the log of output, employment and capital intensity. Capital intensity stands for the ratio of fixed tangible assets per worker. Standard errors in parentheses are two-way clustered by firm and 2-digit industry-year pairs. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

albeit with a reduced magnitude and higher precision of estimates, showing that a 10 percent rise in markdowns is associated with a 1.6 percent increase in machinery investments in the following year. This finding is also evident when looking at the intensive and extensive margins of machinery investments in Table 4.5. Specification (1) reveals a 9 percent increase in investment in machinery following a 100 percent rise in lagged markdowns at the intensive margin, while Specification (2) documents a significantly higher likelihood of such investment with increased markdowns at the extensive margin. These combined findings confirm a robust, positive association between markdowns and automation at the firm-level.

In sum, this section provides evidence on a positive relationship between a firm's labor market power and its level of automation. I find that higher labor market power in terms of markdowns is associated with larger machinery stocks per worker as well as a higher propensity to adopt industrial robots. Panel regressions further confirm this relationship, showing that within-firm increases in labor market power are linked to higher subsequent machinery investment. The panel regression framework, which accounts for time-invariant firm-level unobservables and firm characteristics, marks a significant improvement. Yet, achieving more robust causal identification requires leveraging plausibly exogenous sources of variation in markdowns. The final Section 4.5 aims to address this challenge.

4.5 Robustness

This section investigates the unexpected introduction of tolls on a subset of Portuguese highways in 2010 as a source of plausibly exogenous variation in firms' labor market power, aiming to further test the robustness of the positive relationship between labor market power and automation. Section 4.5.1 offers the institutional and historical context of the event that notably increased commuting costs for workers, likely impacting the market power of local employers due to the reduced mobility and outside options of workers. Section 4.5.2 details the empirical strategy, which combines an event study approach with an instrumental variables estimation. Section 4.5.3 presents estimation results indicating no significant long-term effect of the toll introduction on markdowns, suggesting limited suitability of the event for establishing further causality.

4.5.1 Background on SCUT Highway Toll Introduction

Since joining the European Communities in 1986, Portugal has made substantial investments in its road transport infrastructure. These investments resulted in a remarkable growth of the highway network, expanding from 196 km in 1986 to 3065 km by 2013, making Portugal the country with the 5th highest highway density in the European Union (Leitão et al., 2014). Co-funded by the European Union, these highway investments aimed to enhance safety and efficiency, address disparities between coastal and inland regions, and improve access to the broader European transport network.[20] Consequently, travel time between Lisbon and the Spanish border decreased by over 40 percent, resulting in lower transport costs for firms (Branco et al., 2023). At the same time, the new infrastructure reduced commuting time for workers, leading to a significant increase in inter-municipal commuting (Rocha et al., 2023).

During the 1990s the Portuguese government entered into public-private partnerships with various companies to both construct and operate the new highway infrastructure. While the majority of the newly established highways were designated to be operated as classical tollways under a pay-per-use scheme, the government also implemented a shadow toll scheme known as SCUT (Sem Custos para o Utilizador, translating to "without costs to the user") covering about 30 percent of the network. Unlike the direct toll collection on users, the SCUT scheme was financed by taxpayers and involved concessionaires receiving a direct rent based on traffic volume (Santos & Santos, 2012). The primary goal of the SCUT highway scheme was to foster economic development in disadvantaged areas by providing free access to the highway network, and to encourage private companies to build infrastructure in regions where traditional toll schemes might not have been lucrative enough. While the public-private partnerships allowed the government to quickly expand the infrastructure at low initial investment cost to leverage management capabilities of private companies, the SCUT highway scheme turned out to be a long-term financial burden on the government's budget (Sarmento, 2010).

In 2008, the government conducted an evaluation of the SCUT program, revealing that the operating costs for SCUT highways were significantly higher than initially estimated. Subsequently, the Portuguese government, prompted by this study, opted to transform three out of the seven SCUT highways into tollways on October 15, 2010, focusing on the more affluent regions with sufficient municipal purchasing power and available alternative routes. However, as the sovereign debt crisis intensified, leading to a large bailout negotiation with the International Monetary Fund, the European Commission, and the European Central Bank, the Portuguese government had to reassess its decision. Consequently, on December 8, 2011, tolls were introduced on all four remaining SCUT highways as well. By the end of 2011, the 900 km of former-SCUT highways had been converted into tollways, imposing a user fee of 9 cents per kilometer (Audretsch, Dohse, & dos Santos, 2020).

The introduction of tolls made the use of the former SCUT highways unaffordable

[20]See European Commission, "Accessibility and Transport" Operational Programme (POAT), accessed on 29 February 2024 from .

for many Portuguese commuters, leading to a significant reduction in traffic in the following years.[21] Public traffic monitoring institutes conducted research indicating a substantial decline in traffic, approximately 48% for the Algarve concession and 36% for the Beira Interior concession (Leitão et al., 2014). This reduction surpassed the impact on other highways affected by the overall economic downturn. Simultaneously, studies revealed a rising trend in the use of alternative toll-free routes. However, since most highways developed under this system lacked alternative routes to accommodate a substantial increase in traffic, the diversion resulted in a significant rise in congestion (Dias, 2015). This increase in congestion substantially elevated commuting costs in terms of both travel time and toll expenses. Given that car usage already accounted for 10 percent of average household expenses, the introduction of tolls imposed a considerable additional financial burden on workers, likely reducing the geographical range of labor supply (Ferreira, Ramos, & Cruz, 2012; Brooks et al., 2021).

4.5.2 Empirical Strategy

To identify the causal effect of labor market power on machinery investments, I leverage the unexpected introduction of tolls on SCUT highways as a source of exogenous variation in labor market power of local employers. The rationale is that the introduction of tolls reduced the mobility and outside options of workers living in close proximity to the SCUT highways, strengthening the bargaining power of local employers. The identification strategy incorporates an event study specification into an instrumental variables framework to better address the concerns of endogeneity and reverse causality. Accordingly, I estimate the following two-stages least squares model:

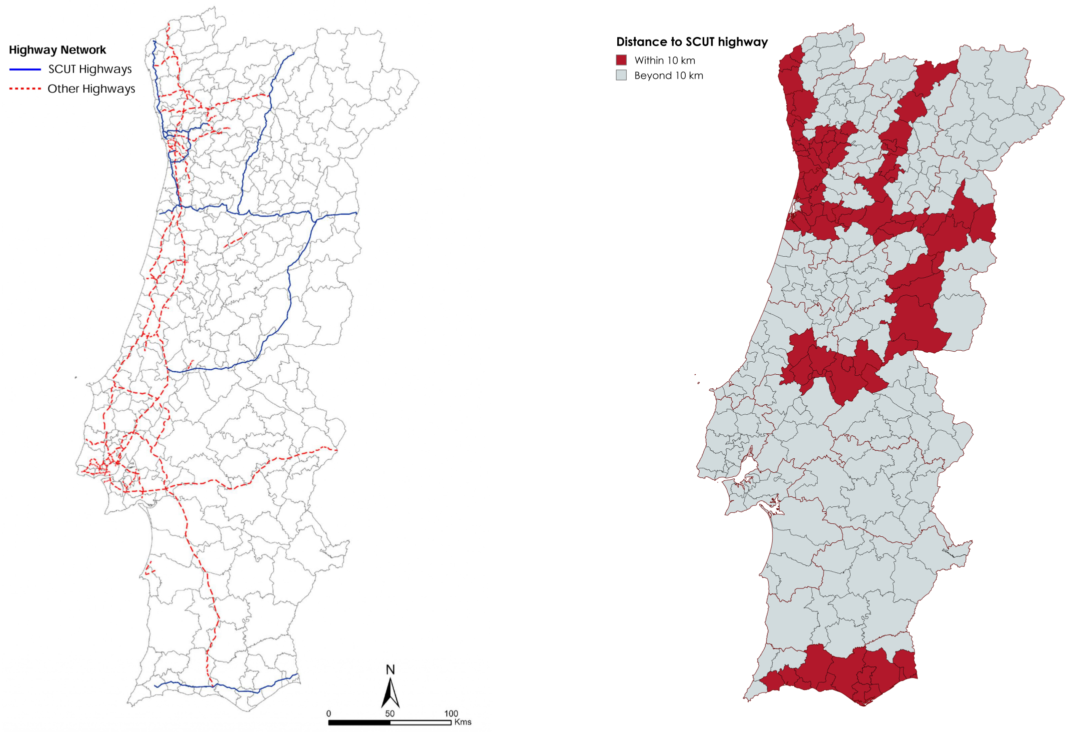
$$Y_{it} = \alpha_i + \beta\ \nu_{it} + \gamma_{jt} + \delta_{rt} + \varepsilon_{i,t} \tag{4.10}$$

$$\nu_{it} = \alpha_i + \sum_{t=2007, t\neq 2010}^{2019} \phi_t\ Treated_i \times Year_t + \gamma_{jt} + \delta_{rt} + \varepsilon_{it} \tag{4.11}$$

with equation 4.11 capturing the first-stage equation, estimating the dynamic treatment effects of the toll introduction, and equation 4.10 the second stage. Y_{it} denotes machinery investment and ν_{it} the markdown of firm i in year t. Firm fixed effects are captured by α_i, while γ_{jt} represents 2-digit industry-by-year fixed effects, and δ_{rt} denotes NUTS2 region-by-year fixed effects. $Treated_i$ is a binary indicator, set to 1 for

[21] See Financial Times, "Portugal's ghost roads", released on 20 August 2013, accessed on 29 February 2024 from https://www.ft.com/video/520499bc-eb03-34ce-846e-b7d66cfe0dc8.

Figure 4.6: Overview of the Portuguese Highway Network and Geographical Distribution of Treated Municipalities.



(a) Highway Network in 2010 **(b)** Municipalities by Treatment Status

Notes: Figure 4.6a maps the SCUT highways within the Portuguese highway network in 2010, based on Branco et al. (2023). Figure 4.6b illustrates the assignment of treatment to firms located in municipalities within a 10 km distance from the nearest SCUT highway ramp. Details on municipalities intersected by SCUT highways are sourced from Audretsch, Dohse, and dos Santos (2020), while data on road distances between population-weighted centroids of municipalities and highway access ramps are obtained from the TiTuSS database (Afonso et al., 2023).

firms located in municipalities within a 10 km road distance from the nearest SCUT highway ramp.[22] Figures 4.6a and 4.6b provide an overview of the Portuguese highway network and treated municipalities, spanning from the northern littoral around the metropolitan area of Porto to interior regions bordering Spain, and extending to the southern coast. Furthermore, I define the post-treatment period as the years after 2010, following the first SCUT highway tollway conversion, with the pre-treatment

[22]See Appendix Table D.3 for the list of SCUT highways, their conversion dates, and the 78 municipalities within a 10 km range. To assess distance, I leverage data on road distances from the population-weighted centroids of municipalities to the nearest highway entry ramps in 2011 from Afonso et al. (2023).

period set as 2007 to 2009.[23] Accordingly, I include all treatment-by-year interactions, except for the year 2010 which is taken as reference point. Thereby, all the coefficients ϕ_t are estimated in relative terms to that year, capturing the dynamic effects of the introduction of tolls on SCUT highways. To evaluate the effect over time, I restrict the panel to manufacturing firms that were observed as active in 2010, excluding those observed only before or after this year.[24]

The instrumental variables approach relies on the assumptions of instrument relevance and exogeneity. To validate the relevance of the event for local employers' labor market power, I conduct first-stage regressions analyzing the impact of treatment-year interactions on markdowns, expecting a positive and significant effect. The exogeneity assumption further requires that the toll introduction affected machinery investments only through changes in markdown, not via other channels. This is partially testable by examining the event's influence on key investment predictors like output and employment. Accordingly, to assess exogeneity, I also apply the event study equation to these outcomes.

4.5.3 Results

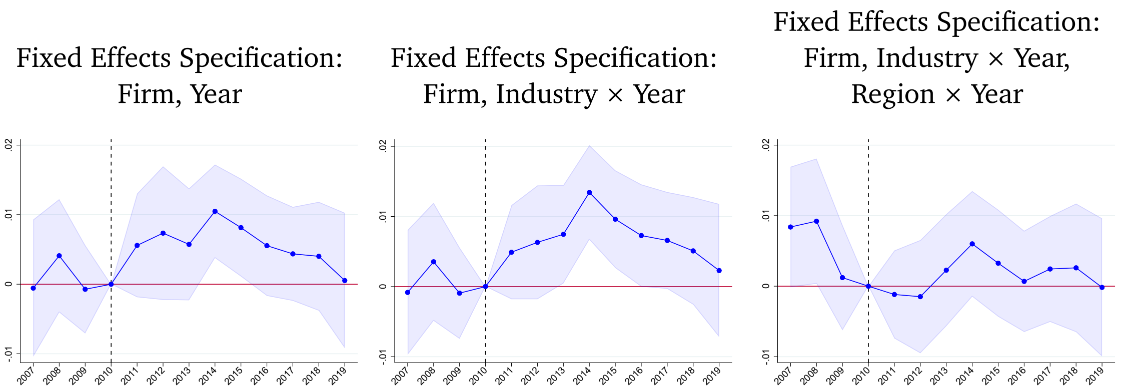
First stage regression results suggest a modest positive impact of toll introduction on firms' labor market power, as reflected in markdowns, in the initial years following the toll implementation. Figure 7a shows that the positive effects reached their peak in 2014 and then began to decline in subsequent years. This pattern is most pronounced and statistically significant in the two-way fixed effects model and especially when also controlling for industry-year fixed effects. The 2014 peak persists but loses statistical significance under the most stringent fixed effects specification, which includes controlling for NUTS2 region-year fixed effects and narrows the comparison group to other firms within the same region. The observed pattern may be explained by local labor market adjustments, such as workers changing their means of transportation, and by changes in toll scheme enforcement as of 2015, specifically modifications in

[23] To ensure consistency and avoid sample selection issues, the analysis is confined to the post-2006 period. For 2005 and 2006, markdown estimations are based on the Industrial Production Survey's energy expense data, which includes only a subset of firms representing 90% of manufacturing output. This results in a smaller sample size and less precise estimates in the event study for these years.

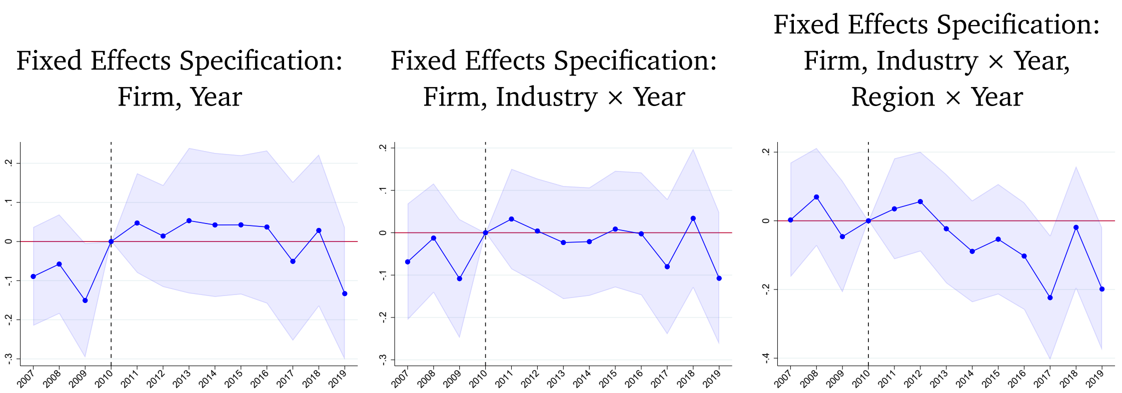
[24] Summary statistics and balance tests are detailed in Appendix Tables D.4 and D.5.

Figure 4.7: Dynamic Effects of Toll Introduction on Markdowns and Machinery Investments (2007-2019)

(a) Dependent variable: log(markdown)



(b) Dependent variable: asinh(machinery investment)



Notes: The figures present estimates for coefficients ϕ_t from equation 4.11, including 90% confidence intervals. The dependent variables are the logarithm of markdowns in Figure 4.7a and the inverse hyperbolic sine transformation of machinery investment in Figure 4.7b, with standard errors clustered at the municipality level.

the rules for fines on unpaid tolls and the reduction in tolls enacted in 2016.[25][26] Overall, the first stage results suggest that toll's introduction had a limited positive impact on local employers' labor market power during the initial post-introduction years.

Further analysis in the second stage partially validates the hypothesis that higher labor

[25] In 2015, Portuguese Tax Authority offered a tax amnesty for unpaid SCUT tolls until April 30, with reduced penalties and process costs, and no late payment interest. See, for instance, https://rr.sapo.pt/noticia/pais/2015/08/03/amnistia-fiscal-para-multas-nas-scut-oportunidade-termina-a-29-de-setembro/17689/

[26] In 2016, the newly elected socialist government decided to cut back the tolls on SCUT highways by 15% from 1 August 2016 onwards. See, for instnace, https://www.theportugalnews.com/news/dismay-at-trivial-toll-reduction/38908.

Table 4.6: Markdowns and Investment in Machinery: Panel Regressions, 2007-2019 (IV)

	asinh(investment in machinery)		
	(1)	(2)	(3)
log(markdown)	18.41**	6.470	5.314
	(8.072)	(6.280)	(6.813)
Kleibergen-Paap F-Stat	0.825	1.156	0.679
Observations	280,251	280,242	280,242
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Industry × Year FE	NO	YES	YES
Region × Year FE	NO	NO	YES

Notes: Dependent variables: inverse hyperbolic sine transformation of investment in machinery and equipment. Specification (1) controls for firm and year fixed effects. Specification (2) adds 2-digit industry-year dummies. Specification (2) adds NUTS2 region-year dummies. Standard errors in parentheses are two-way clustered by firm and 2-digit industry-year pairs. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

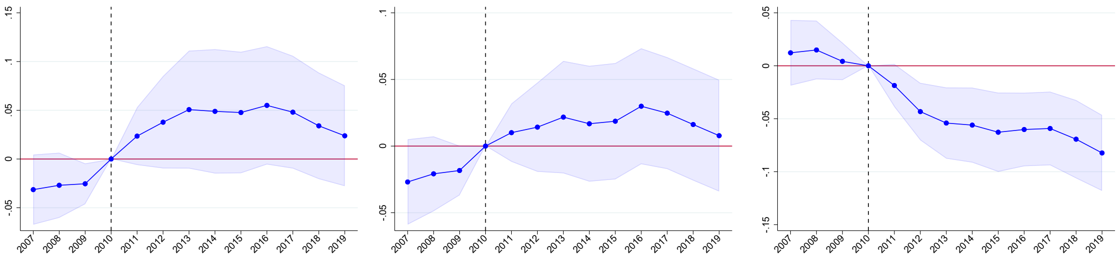
market power predicts increased automation, as evidenced by machinery investments, but lacks the robustness necessary for definitive conclusions. Table 4.6 presents estimation results, demonstrating a positive and significant effect in the two-way fixed effects model in specification (1). Yet, with a Kleibergen-Paap F-Statistic below 10 indicating instrument weakness, it seems that the impact of the toll introduction on the labor market power of firms may not have been sufficiently strong. The positive effect loses its statistical significance in the more stringent specifications (2) and (3), which also confirm the instrument weakness. Although the IV regression results yield positive estimates, supporting the hypothesis of a positive link between labor marker power and automation, they indicate that the instruments are too weak to robustly confirm a causal relationship within the 2SLS framework.

Further analysis indicates that the introduction of tolls affected other variables that predict machinery investment, notably output and employment, thereby challenging the assumption of instrument exogeneity. Figures 4.8a and 4.8b report persistent negative effects on employment and output, at 6% and 7% respectively by the end of the period, in the most stringent fixed effects specification. This suggests that the toll introduction had a negative effect on firm growth, most likely due to increased trans-

Figure 4.8: Dynamic Effects of Toll Introduction on Output and Employment (2007-2019)

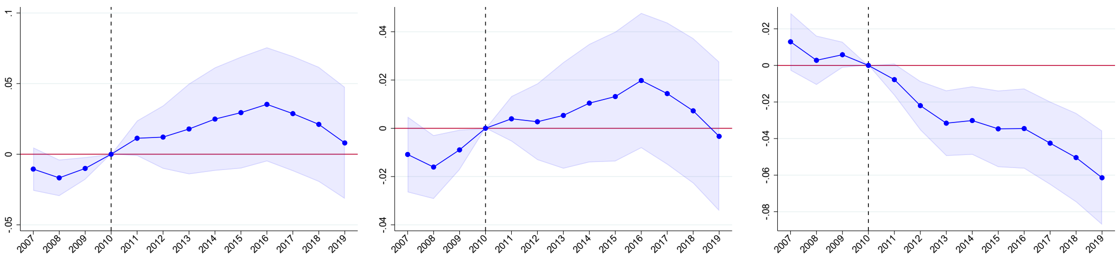
(a) Dependent variable: log(output)

Fixed Effects Specification: Firm, Year | Fixed Effects Specification: Firm, Industry × Year | Fixed Effects Specification: Firm, Industry × Year, Region × Year



(b) Dependent variable: log(employment)

Fixed Effects Specification: Firm, Year | Fixed Effects Specification: Firm, Industry × Year | Fixed Effects Specification: Firm, Industry × Year, Region × Year



Notes: The figures present estimates for coefficients ϕ_t from equation 4.11, including 90% confidence intervals. The dependent variables are the logarithm of output in Figure 4.8a and the logarithm of employment in Figure 4.8b, with standard errors clustered at the municipality level.

portation cost. However, if the output decline also affected investment in machinery, then it follows that the toll introduction does not fulfill the exogeneity assumption of IV estimation, which requires the instrument to affect the dependent variable only through the endogenous variable. This violation likely biases the IV estimates towards zero. Indeed, when looking at the reduced form regressions of machinery investments on treatment-year interactions shown in Figure 4.7b, one can find no significant effect in the aftermath of the toll introduction, suggesting that the output effect of the toll introduction might have outweighed the labor market power effect. These findings further highlight the difficulty of exploiting the 2010 toll introduction as a valid instrument for robust causal inference.

This case study aims to improve causal identification, moving beyond the correlational evidence presented so far. Combining a dynamic treatment effects within an instrumental variable framework, the study partially corroborates the positive link between markdowns and machinery investments. Although this relationship loses statistical significance in more demanding specifications, the insufficient instrument strength and exogeneity preclude definitive conclusions. The findings show the challenge of exploiting transportation cost shocks as valid instruments for the labor market power of local employers. Future research could thus expand on this work by exploring alternative sources of quasi-experimental variation in firms' labor market power, such as changes in labor market institutions or sectoral bargaining, and by examining specific industry and technology settings.

4.6 Conclusion

In this chapter, I provide empirical evidence on the relationship between labor market power and the degree of automation in manufacturing firms. Using detailed administrative microdata on the universe of Portuguese manufacturing firms over the period 2004 to 2020, I quantify labor market power by estimating firm-specific markdowns. I uncover significant variation in labor market power within Portuguese manufacturing firms, suggesting that labor markets in Portuguese manufacturing are characterized by imperfect competition for labor. On average, the marginal revenue product of labor in these firms is 18 percent above the wage, implying that workers receive about 85 percent of the value they generate.

Cross-sectional data show a strong correlation between markdowns and automation, as measured by both the machine-to-worker ratio and, more specifically, imports of industrial robots. Further panel regressions with fixed effects specifications show that a 10 percent increase in markdowns is associated with a 1.6 percent increase in machinery investment in the following year. To address endogeneity and reverse causality concerns, I use the unexpected introduction of tolls on previously toll-free highways as a proxy for the labor market power of local employers. I find results that partially confirm the positive relationship, but the instruments lack the strength and exogeneity to draw robust and definitive conclusions in this setting. Taken together, these results suggest a robust positive association between labor market power and automation investment in Portuguese manufacturing, while pointing to the need for further exploration of quasi-experimental settings to improve robust inference.

This study presents a new perspective on the influence of imperfect competition in labor markets on technology adoption in manufacturing, corroborating the positive association between monopsony power and automation as theorized by Azar et al. (2023). The findings shed light on the cross-country variations in automation adoption, highlighting a potential connection to the strength of collective bargaining institutions that modulate labor market power. Furthermore, the findings imply that the observed decline in workers' bargaining power, likely caused by falling unionization rates in most high-income countries, may have amplified the trend towards more automation in manufacturing. These insights directly relate to policy discussions aimed at enhancing labor market competitiveness, as discussed in recent reports of the Biden administration or the OECD.[27][28] My results highlight the potential impact of mitigating anti-competitive practices, such as non-compete agreements, on firms' technology adoption decisions. They suggest that one way for policymakers to protect workers from the effects of excessive automation is to ensure that labor markets remain competitive, for example through policies that limit firms' wage-setting power or increase worker mobility.

While this study provides novel insights, it also has limitations that highlight areas for further research. First, future efforts should focus on improving causal identification, for example by exploiting other events that induced variation in labor market power, such as institutional changes in collective bargaining. Second, future research can further investigate the heterogeneity in markdowns across skill groups and the differences in rent sharing that result from unionization, closely following the literature on skill-biased technological change. A third promising avenue for future research is to examine the generalizability of the present results to other industries and automation technologies, with a particular focus on the role of artificial intelligence in automating cognitive tasks in high-skill labor markets.

[27] See U.S. Department of the Treasury, "The State of Labor Market Competition", released on March 7, 2022, accessed from https://home.treasury.gov/news/press-releases/jy0634.

[28] See also OECD Directorate for Financial and Enterprise Affairs, "Competition Issues in Labour Markets – Note by Portugal", released on 5 June 2019, accessed from https://one.oecd.org/document/DAF/COMP/WD(2019)47/en/pdf.

A

Appendix to Chapter 1

Structural Shocks and Political Participation in the US

A.1 Tables

A.1.1 Local Labor Market Analysis

Table A.1: Descriptive Statistics for Commuting Zone Analysis: 1990-2015

	(1)	(2)	(3)	(4)	(5)	(6)
		Exposure to robots	Exposure to China	Relative exposure to robots vs. China		
Quartiles	All	Q4	Q4	Q1	Q4	Q4-Q1
Observations	722	180	180	181	180	361
Changes in outcomes, 1990-2015:						
Log manufacturing employment	-16.3	-27.3	-29.5	-22.9	-18.3	4.5
Log non-manufacturing employ.	21.9	19.8	21.6	23.3	17.6	-5.7***
Annual household income/adult	2,973.5	1,639.0	1,816.3	2,607.2	2,156.9	-450.2*
from wages and salaries	3,039.1	1,736.8	1,808.6	2,562.7	2,358.5	-204.2
from business investment	-475.8	-582.7	-506.6	-428.6	-615.8	-187.2***
from social security & welfare	410.3	484.9	514.4	473.1	414.3	-58.8**
Log number of adults in poverty	27.8	35.5	35.2	32.2	30.0	-2.1
Share of population, 1990 (in %):						
Above 65 years old	13.4	13.7	13.5	13.4	13.8	0.4
Female	51.1	51.5	51.4	51.1	51.3	0.2***
Less than college	71.4	73.7	74.2	71.8	72.7	0.9
Some college or more	25.4	23.2	22.9	25.1	24.3	-0.8
White	87.0	90.4	87.4	86.1	90.6	4.5***
Black	7.8	8.0	10.5	9.8	6.2	-3.6***
Asian	0.1	0.1	0.1	0.1	0.1	-0.1**
Hispanic	5.8	1.4	1.9	4.2	3.8	-0.4
Share of employment, 1990 (in %):						
Agriculture	6.6	4.6	4.9	6.1	6.0	-0.1
Mining	1.8	0.7	0.8	1.0	1.7	0.7***
Construction	6.4	6.1	6.3	6.5	6.2	-0.3*
Manufacturing	16.9	24.5	25.4	19.9	19.7	-0.2
Routine employment	35.7	38.4	39.8	37.0	36.9	-0.1
Index, 1990:						
Offshorability Index	-0.1	-0.0	-0.0	-0.0	-0.1	-0.0*

Notes: Column's (1) to (5) display unweighted means of changes in outcomes between 1990 and 2015 as well as unweighted means of commuting zone characteristics in 1990. Changes in logged outcomes are scaled by 100. For each commuting zone, we compute the average exposure to robots and China over the periods 1990 to 2000, 2000 to 2007 and 2007 to 2015. Columns (2) and (3) display unweighted means for commuting zones in the highest quartiles of the average exposure to robots and China, respectively. We compute a measure of relative exposure to robots vs. China by standardizing both exposure measures to have a mean of zero and a standard deviation of 1 and take the difference between the standardized measures of exposure to robots and China. Column (6) displays the difference in the mean commuting zone characteristics between the forth and the first quartile of relative exposure and reports statistical significance of the underlying ttest. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table A.2: First Stage Regressions for Commuting Zone Analysis: Stacked Differences, 1990-2015 (OLS)

	US Exposure to robots	US exposure to Chinese imports
	(1)	(2)
Exposure to Robots	0.80***	-0.02*
	(0.11)	(0.01)
Exposure to Chinese Imports	0.00	0.53***
	(0.04)	(0.06)
Observations	2166	2166
R^2	0.65	0.42
Region × time	✓	✓
Demographics	✓	✓
Industry shares	✓	✓
Routine Jobs & Offshorability	✓	✓

Notes: N=2,166 (3×722 Commuting Zones) The dependent variable in columns (1) and (2) is the US exposure to robots and the US exposure to Chinese imports, respectively. Explanatory and dependent variables are all standardized to have a mean of zero and a standard deviation of 1. All regressions include: census division dummies interacted with time period dummies as covariates; 1990 demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Asian, Black, Hispanic, and White population, and the share of women in the labor force); shares of employment in broad industries in 1990 (i.e., agriculture, mining, construction, manufacturing); and the share of routine jobs and the average offshorability index in 1990, following D. Autor and Dorn (2013). Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (48 states). Regressions are weighted by a CZ's 1990 share in the national population. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table A.3: Impact of Robots and Chinese Imports on Commuting-Zone Employment: Stacked Differences, 1990-2015 (2SLS)

	Δ log(employment)		
	Total (1)	Manufacturing (2)	Non-manufacturing (3)
US Exposure to Robots	-1.21***	-1.12***	-1.20***
	(0.22)	(0.34)	(0.24)
US Exposure to Chinese Imports	-0.89	-5.69***	0.80
	(1.25)	(1.72)	(1.08)
Kleibergen-Paap F-Stat	32.77	32.13	32.79
Observations	2166	2166	2166
R^2	0.33	0.16	0.30
Region × Period	✓	✓	✓
Demographics	✓	✓	✓
Industry shares	✓	✓	✓
Routine Jobs & Offshorability	✓	✓	✓
Pre-trends	✓	✓	✓

Notes: N=2,166 (3×722 Commuting Zones). The dependent variables in columns (1), (2) and (3) is the change in the log of total, manufacturing and non-manufacturing employment respectively, multiplied by 100 (i.e., $[ln(y_{t+1})-ln(y_t)]\times 100$). Explanatory variables all standardized to have a mean of zero and a standard deviation of 1. All regressions include: census division dummies interacted with time period dummies as covariates; 1990 demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Asian, Black, Hispanic and White population, and the share of women in the labor force); shares of employment in broad industries in 1990 (i.e., agriculture, mining, construction, manufacturing); and the share of routine jobs and the average offshorability index in 1990, following Autor and Dorn (2013). Specifications (1) to (3) control for the change of the respective outcome variable between 1970 and 1990. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (48 states). Regressions are weighted by a CZ's 1990 share in the national population. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table A.4: Impact of Robots and Chinese Imports on Commuting-Zone Household Income: Stacked Differences, 1990-2015 (2SLS)

	Δ Average HHI/adult			
	Total (1)	Wage- salary (2)	Business- invest (3)	SocSec + Welfare (4)
US Exposure to Robots	-571.19***	-572.12***	-25.88*	26.80***
	(86.23)	(79.12)	(10.42)	(2.61)
US Exposure to Chinese Imports	-765.18**	-764.31***	-13.13	12.26
	(236.76)	(217.77)	(37.05)	(12.32)
Kleibergen-Paap F-Stat	32.32	32.32	32.32	32.32
Observations	2166	2166	2166	2166
R^2	0.14	0.17	0.03	0.22
Region × Period	✓	✓	✓	✓
Demographics	✓	✓	✓	✓
Industry shares	✓	✓	✓	✓
Routine Jobs & Offshorability	✓	✓	✓	✓

Notes: N=2,166 (3×722 Commuting Zones) The dependent variable in column (1) is the ten-year equivalent real dollar change in the commuting-zone average household income per adult which is defined as the sum of individual incomes of all working-age household members (age 16–64), divided by the number of household members of that age group. Following D. Autor, Dorn, and Hanson (2013), total income is split up into wage and salary income in column (2); self-employment, business, and investment income in column (3); social security and welfare income in column (4). Explanatory variables all standardized to have a mean of zero and a standard deviation of 1. All regressions include: census division dummies interacted with time period dummies as covariates; 1990 demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force); shares of employment in broad industries in 1990 (i.e., agriculture, mining, construction, manufacturing); and the share of routine jobs and the average offshorability index in 1990, following Autor and Dorn (2013). Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (48 states). Regressions are weighted by a CZ's 1990 share in the national population. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

A.1.2 County-Level Analysis

Table A.5: Descriptive Statistics for County-Level Analysis: 2000-2016

	(1)	(2)	(3)	(4)	(5)	(6)
		Exposure to robots	Exposure to China	Relative exposure to robots vs. China		
Quartiles	All	Q4	Q4	Q1	Q4	Q4-Q1
Observations	3066	761	765	771	759	1543
Changes in county-level outcomes, 2000-2016:						
Log voters at presidential elections	15.9	13.9	15.1	16.7	13.4	-3.2***
Log voters at house elections	16.5	14.5	15.9	18.4	13.3	-5.1***
Voter turnout at presidential elections	4.7	4.5	5.2	5.0	4.3	-0.7***
Voter turnout at house elections	4.7	4.5	5.2	5.4	4.0	-1.4***
Share of commuting-zone population, 2000 (in %):						
Above 65 years old	13.0	13.3	13.3	13.0	13.1	0.1
Female	50.8	51.1	51.0	50.7	50.9	0.2***
Less than college	65.7	67.6	68.0	66.2	66.5	0.2
Some college or more	30.0	28.2	28.1	29.6	29.3	-0.2
White	82.7	88.5	85.1	81.5	86.4	4.9***
Black	9.9	7.7	10.5	11.5	8.4	-3.1***
Asian	0.2	0.2	0.2	0.2	0.2	-0.0***
Hispanic	7.0	2.6	3.4	5.9	4.6	-1.3***
Share of commuting-zone employment, 2000 (in %):						
Agriculture	5.4	3.9	4.7	5.2	4.4	-0.7***
Mining	1.5	0.6	0.7	1.2	1.3	0.1
Construction	6.4	6.0	6.2	6.5	5.9	-0.5***
Manufacturing	17.9	25.0	25.0	19.7	21.3	1.5***
Routine employment	31.6	34.3	35.4	32.9	32.7	-0.2
Commuting-zone index, 2000:						
Offshorability Index	-0.1	-0.1	-0.1	-0.1	-0.1	0.0***

Notes: Columns (1) to (5) display unweighted means of changes in county-level outcomes between 2000 and 2016 and of counties' commuting-zone characteristics in 2000. Changes in logged outcomes are scaled by 100. For each county, we compute the average exposure to robots and China if its commuting-zone over the periods 2000 to 2008 and 2008 to 2016. Columns (2) and (3) display unweighted means of counties in the highest quartiles of the average commuting zone exposure to robots and China, respectively. We compute a measure of relative exposure to robots vs. China by standardizing both exposure measures to have a mean of zero and a standard deviation of 1 and take the difference between the standardized measures of exposure to robots and China. Column (6) displays the difference in means between the forth and the first quartile of relative exposure and reports statistical significance of the underlying ttest. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table A.6: First Stage Regressions for County-Level Analysis: Stacked Differences, 2000-2016 (OLS)

	US Exposure to robots	US exposure to Chinese imports
	(1)	(2)
Exposure to Robots	0.45***	-0.04***
	(0.02)	(0.01)
Exposure to Chinese Imports	-0.09	0.49***
	(0.09)	(0.06)
Observations	6136	6136
R^2	0.61	0.49
Region × Period	✓	✓
Lagged mfg. share × Period	✓	✓
Demographics	✓	✓
Routine Jobs & Offshorability	✓	✓

Notes: The dependent variables in columns (1) and (2) is the US exposure to robots and the US exposure to Chinese imports, respectively. Exposure measures are computed for 8-year election periods, from 2000 to 2008 and from 2008 to 2016. Explanatory and dependent variables are all standardized to have a mean of zero and a standard deviation of 1. All specifications control for census division dummies interacted with period dummies as covariates, the 10-year lagged share of manufacturing in commuting zone employment interacted with period dummies, commuting zone demographic characteristics in 2000 (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Asian, Black, Hispanic and White population, and the share of women in the labor force) as well as the commuting zone share of routine jobs and the average offshorability index in 2000, following D. Autor and Dorn (2013). Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the commuting zone level. Regressions are weighted by a county's citizen voting age population in 2000. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table A.7: Impact of Robot Exposure and Chinese Imports on Voting on U.S. Presidential Elections: County-Level Stacked Differences, 2000-2016 (2SLS)

	Δlog(votes) × 100				
	(1)	(2)	(3)	(4)	(5)
US Exposure to Robots	-1.841***	-0.722***	-0.859***	-1.013***	-1.006***
	(0.384)	(0.240)	(0.250)	(0.262)	(0.265)
US Exposure to Chinese Imports	0.470	0.538	0.569	0.535	0.561
	(0.848)	(0.592)	(0.591)	(0.581)	(0.581)
Δlog(CVAP)		0.940***	0.753***	0.750***	0.721***
		(0.0249)	(0.0422)	(0.0413)	(0.0440)
Net in-migration rate			23.25***	23.18***	20.34***
			(4.247)	(4.202)	(4.327)
Δshare of college educated			-23.87*	-26.72**	-27.60**
			(12.87)	(13.35)	(13.45)
Perennial swing state				1.452***	1.266***
				(0.484)	(0.488)
TV campaign ads, USD per HH				0.114***	0.110***
				(0.0232)	(0.0232)
Kleibergen-Paap F-Stat	31.99	32.18	32.38	32.97	33.01
R^2	0.65	0.83	0.83	0.84	0.84
Observations	6172	6172	6168	6136	6136
Wald Test [R=C] p-Value	0.008	0.039	0.022	0.012	0.010
Region × Period	✓	✓	✓	✓	✓
Lagged mfg. share × Period	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓
Routine jobs & Offshorability	✓	✓	✓	✓	✓
Pre-trend					✓

Notes: The dependent variable is the change in the log count of votes at US presidential elections multiplied by 100 (i.e., $[ln(y_{t+1}) - ln(y_t)] \times 100$). Differences are computed over 8-year election periods, from 2000 to 2008 and from 2008 to 2016. All specifications control for census division dummies interacted with period dummies as covariates, the 10-year lagged share of manufacturing in commuting zone employment interacted with period dummies, commuting zone demographic characteristics in 2000 (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Asian, Black, Hispanic and White population, and the share of women in the labor force) as well as the commuting zone share of routine jobs and the average offshorability index in 2000, following D. Autor and Dorn (2013). Regressions in column (2) to (5) control for the contemporaneous change in the log count of the citizen voting age population (CVAP) multiplied by 100. Specifications (4) and (5) control whether counties are situated in a "perennial" swing state (Colorado, Florida, Iowa, Michigan, Minnesota, Ohio, Nevada, New Hampshire, North Carolina, Pennsylvania , Virginia, Wisconsin). Specification (5) accounts for pre-trends controlling for the log change in votes between 1992 and 2000. Explanatory variables are all standardized to have a mean of zero and a standard deviation of 1. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the commuting zone level. Regressions are weighted by a county's citizen voting age population in 2000. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table A.8: Impact of Robot Exposure and Chinese Imports on Voting in U.S. House of Representatives Elections: County-Level Stacked Differences, 2000-2016 (2SLS)

	Δlog(votes) × 100				
	(1)	(2)	(3)	(4)	(5)
US Exposure to Robots	-2.130***	-1.218*	-1.378*	-1.634**	-1.308**
	(0.669)	(0.721)	(0.720)	(0.732)	(0.584)
US Exposure to Chinese Imports	2.232*	2.114**	2.048*	2.188**	1.846*
	(1.218)	(1.059)	(1.062)	(1.093)	(0.999)
Δlog(CVAP)		0.784***	0.530***	0.527***	0.690***
		(0.128)	(0.155)	(0.155)	(0.0911)
Net in-migration rate			31.00***	31.08***	40.10***
			(7.245)	(7.434)	(9.422)
Δ share of college educated			3.098	0.118	4.411
			(24.66)	(25.38)	(25.68)
Perennial swing state				2.176***	2.978***
				(0.721)	(0.836)
TV campaign ads, USD per HH				0.163	0.164*
				(0.101)	(0.0984)
Kleibergen-Paap F-Stat	28.32	28.47	28.68	29.39	29.49
R^2	0.44	0.53	0.54	0.54	0.57
Observations	5483	5483	5479	5448	5432
Wald Test [R=C] p-Value	0.002	0.011	0.010	0.005	0.005
Region × Period	✓	✓	✓	✓	✓
Lagged manufct. share × Period	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓
Routine Jobs & Offshorability	✓	✓	✓	✓	✓
Pre-trend					✓

Notes: The dependent variable is the change in the log count of votes at elections of the US House of Representatives multiplied by 100 (i.e., $[ln(y_{t+1})-ln(y_t)]\times 100$). Differences are computed over 8-year election periods, from 2000 to 2008 and from 2008 to 2016. All specifications control for census division dummies interacted with period dummies as covariates, the 10-year lagged share of manufacturing in commuting zone employment interacted with period dummies, commuting zone demographic characteristics in 2000 (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force) as well as the commuting zone share of routine jobs and the average offshorability index in 2000, following D. Autor and Dorn (2013). Counties in congressional districts with uncontested races are excluded from the sample. Regressions in column (2) to (5) control for the contemporaneous change in the log count of the citizen voting age population (CVAP) multiplied by 100. Specifications (4) and (5) control whether counties are situated in a "perennial" swing state (Colorado, Florida, Iowa, Michigan, Minnesota, Ohio, Nevada, New Hampshire, North Carolina, Pennsylvania , Virginia, Wisconsin). Specification (5) accounts for pre-trends controlling for the log change in votes between 1992 and 2000. Explanatory variables are all standardized to have a mean of zero and a standard deviation of 1. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the commuting zone level. Regressions are weighted by a county's citizen voting age population in 2000. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table A.9: Seperate Impacts of Robot Exposure and Chinese Imports on Voting: County-Level Stacked Differences, 2000-2016 (2SLS)

	Δ log(votes) $\times$ 100		
Panel A: Presidential Elections	(1)	(2)	(3)
US Exposure to Robots	-1.066***		-1.006***
	(0.271)		(0.265)
US Exposure to Chinese Imports		0.791	0.561
		(0.549)	(0.581)
Kleibergen-Paap F-Stat	878.03	58.08	33.01
R^2	0.84	0.84	0.84
Observations	6136	6136	6136
Panel B: House of Representatives Elections	(4)	(5)	(6)
US Exposure to Robots	-1.507**		-1.308**
	(0.598)		(0.584)
US Exposure to Chinese Imports		2.163**	1.846*
		(0.982)	(0.999)
Kleibergen-Paap F-Stat	922.77	53.34	29.49
R^2	0.57	0.57	0.57
Observations	5432	5432	5432
Region × Period	✓	✓	✓
Lagged mfg. share × Period	✓	✓	✓
Demographics	✓	✓	✓
Routine Jobs & Offshorability	✓	✓	✓
Controls	✓	✓	✓
Pre-trend	✓	✓	✓

Notes: The dependent variable is the change in the log count of votes multiplied by 100 (i.e., $[ln(y_{t+1}) - ln(y_t)] \times 100$). Differences are computed over 8-year election periods, from 2000 to 2008 and from 2008 to 2016. All specifications control for census division dummies interacted with period dummies as covariates, the 10-year lagged share of manufacturing in commuting zone employment interacted with period dummies, commuting zone demographic characteristics in 2000 (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Asian, Black, Hispanic, and White population, and the share of women in the labor force) as well as the commuting zone share of routine jobs and the average offshorability index in 2000, following D. Autor and Dorn (2013). All regressions control for the net-in migration rates, the change in the share of college educated residents, the swing state status, TV campaign spending per household and account for pre-trends by controlling for the log change in votes between 1992 and 2000. Explanatory variables are all standardized to have a mean of zero and a standard deviation of 1. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the commuting zone level. Regressions are weighted by a county's citizen voting age population in 2000. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table A.10: Period-Specific Effects of Exposure to Robots and Chinese Imports on Voting: County-Level Stacked Differences, 2000-2016 (Reduced Form)

	Δ log(votes) × 100			
	US President		US House of Representatives	
	(1)	(2)	(3)	(4)
Exposure to Robots	-0.845***		-1.046***	
	(0.162)		(0.314)	
Exposure to Chinese Imports	0.394		1.262**	
	(0.366)		(0.567)	
Exposure to Robots		-0.450		-1.321**
× 2000-2008		(0.319)		(0.563)
Exposure to Robots		-1.041***		-0.912***
× 2008-2016		(0.172)		(0.298)
Exposure to Chinese Imports		0.522		1.208**
× 2000-2008		(0.409)		(0.615)
Exposure to Chinese Imports		-0.193		1.368
× 2008-2016		(0.746)		(1.184)
R^2	0.67	0.67	0.46	0.46
Observations	6172	6172	5483	5483
Region × Period	✓	✓	✓	✓
Lagged mfg. share × Period	✓	✓	✓	✓
Demographics	✓	✓	✓	✓
Routine Jobs & Offshorability	✓	✓	✓	✓

Notes: The dependent variable is the change in the log count of votes multiplied by 100 (i.e.,$[ln(y_{t+1})-ln(y_t)]\times 100$). Differences are computed over 8-year election periods, from 2000 to 2008 and from 2008 to 2016. All specifications control for census division dummies interacted with period dummies as covariates, the 10-year lagged share of manufacturing in commuting zone employment interacted with period dummies, commuting zone demographic characteristics in 2000 (i.e. log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Asian, Black, Hispanic, and White population, and the share of women in the labor force) as well as the commuting zone share of routine jobs and the average offshorability index in 2000, following D. Autor and Dorn (2013). Specifications (2) and (4) interact exposure measures with dummies for each period. Explanatory variables are all standardized to have a mean of zero and a standard deviation of 1. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the commuting zone level. Regressions are weighted by a county's citizen voting age population in 2000. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table A.11: Robustness of Effect on Voting in U.S. Federal Elections to Different Measures of Voting Population: County-Level Stacked Differences, 2000-2016 (2SLS)

	Δ log(votes) × 100					
	US President			US House of Representatives		
	(1)	(2)	(3)	(4)	(5)	(6)
US Exposure to Robots	-1.013***	-0.992***	-1.643***	-1.634**	-1.636**	-2.302***
	(0.262)	(0.278)	(0.251)	(0.732)	(0.754)	(0.663)
US Exposure to Chinese	0.535	0.763	0.761	2.188**	2.505**	2.401*
Imports	(0.581)	(0.597)	(0.701)	(1.093)	(1.117)	(1.267)
Net in-migration rate	23.18***	17.96***	45.63***	31.08***	26.31***	40.56***
	(4.202)	(4.338)	(5.153)	(7.434)	(7.335)	(9.416)
Δ Share of College	-26.72**	-16.13	-32.94**	0.118	8.926	-13.01
Educated	(13.35)	(13.25)	(14.96)	(25.38)	(25.43)	(27.11)
Perennial swing state	1.452***	1.424***	2.453***	2.176***	2.182***	2.915***
	(0.484)	(0.473)	(0.465)	(0.721)	(0.729)	(0.682)
TV campaign ads,	0.114***	0.115***	0.0818***	0.163	0.151	0.0961
USD per HH	(0.0232)	(0.0239)	(0.0310)	(0.101)	(0.102)	(0.0907)
Δ CVAP	0.750***			0.527***		
	(0.0413)			(0.155)		
Δ VAP		0.773***			0.562***	
		(0.0395)			(0.155)	
Δ Reg			0.422***			0.374***
			(0.0340)			(0.0464)
Kleibergen-Paap F-Stat	32.97	31.94	33.47	29.39	28.82	30.26
Observations	6136	5939	5660	5448	5284	4973
Wald Test [R=C] p-Value	0.012	0.006	0.001	0.00461	0.003	0.002
Region × Period	✓	✓	✓	✓	✓	✓
Lagged mfg. share × Period	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓
Routine Jobs & Offshor.	✓	✓	✓	✓	✓	✓

Notes: The dependent variable is the log change in the number of voters at elections of the US President and the US House of Representatives, respectively, multiplied by 100 (i.e., $[ln(y_{t+1}) - ln(y_t)] \times 100$). Differences are computed over 8-year election periods, from 2000 to 2008 and from 2008 to 2016. Counties with uncontested races are excluded from the sample in specifications (4), (5) and (6). Specifications (1) and (4) control for the same set of controls specification (5) of both A.7 and A.8 and weight by the initial citizen voting-age population of each county in the year 2000. Specifications (2) and (5) control for log changes in the voting-age population multiplied by 100 and weight by the initial voting-age population of each county in the year 2000. Specifications (3) and (6) control for log changes in the number of registered voters multiplied by 100 and weight by the initial number of registered voters of each county in the year 2000. Explanatory variables are all standardized to have a mean of zero and a standard deviation of 1. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the commuting zone level. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table A.12: Effect on Voter Turnout in U.S. Federal Elections: County-Level Stacked Differences, 2000-2016 (2SLS)

	Δ Voter Turnout × 100	
	US President (1)	US House of Representatives (2)
US Exposure to Robots	-0.515***	-0.533*
	(0.168)	(0.297)
US Exposure to Chinese Imports	0.168	0.358
	(0.324)	(0.648)
Net in-migration rate	3.788***	6.425***
	(1.125)	(2.047)
Δ Share of College Educated	-19.26**	0.898
	(7.500)	(15.55)
Perennial swing state	1.142***	1.320***
	(0.291)	(0.362)
TV campaign ads, USD per HH	0.0693***	0.0446
	(0.0144)	(0.0634)
Kleibergen-Paap F-Stat	32.78	30.75
Observations	6136	5556
Region × Period	✓	✓
Lagged mfg. share × Period	✓	✓
Demographics	✓	✓
Routine Jobs & Offshorability	✓	✓
Further controls	✓	✓

Notes: Table reports 2SLS estimates from a stacked difference regression over two 8-year election periods, from 2000, 2008, to 2016. The dependent variable is the change in voter turnout (votes per citizen voting-age population) multiplied by 100. Regressions also control for net migration, swing state status and political campaigning intensity. Explanatory variables are all standardized to have a mean of zero and a standard deviation of 1. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the commuting zone level. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table A.13: Impact of Robots and Chinese Imports on Political Advertising at US House of Representatives Elections in 2008 and 2016: County-Level Analysis (2SLS)

	Spending on Political Ads / HH			
	Total	Jobs w/ China and Trade	Jobs w/o China or Trade	Social Security
Panel A:	(1)	(2)	(3)	(4)
US Exposure to Robots	-0.395	0.0108	-0.00707	-0.130**
	(0.301)	(0.00719)	(0.0446)	(0.0544)
US Exposure to Chinese Imports	-0.350	-0.0305	-0.0741	-0.0501
	(0.284)	(0.0203)	(0.0680)	(0.0406)
Kleibergen-Paap F-Stat	30.06	30.06	30.06	30.06
Observations	5560	5560	5560	5560
Wald Test [R=C] p-Value	0.909	0.0893	0.387	0.252
	Number of Political Ads			
	Total	Jobs w/ China and Trade	Jobs w/o China or Trade	Social Security
Panel B:	(5)	(6)	(7)	(8)
US Exposure to Robots	-463.6	15.12*	-21.19	-209.8**
	(516.6)	(8.969)	(74.66)	(98.20)
US Exposure to Chinese Imports	-245.0	-38.92	-84.61	-32.00
	(465.3)	(23.81)	(102.0)	(63.78)
Kleibergen-Paap F-Stat	30.06	30.06	30.06	30.06
Observations	5560	5560	5560	5560
Wald Test [R=C] p-Value	0.735	0.0506	0.587	0.147
Region × time	✓	✓	✓	✓
Demographics	✓	✓	✓	✓
Lagged mfg. share × time	✓	✓	✓	✓
Routine Jobs & Offshorability	✓	✓	✓	✓
Swing State	✓	✓	✓	✓

Note: The dependent variables are the estimated dollar value of spending on political ads per household (Panel A) and the total number of political ads in the designated market area a county belongs in the election year 2008 and 2016. All specifications include census division dummies interacted with a time period dummy as covariates, control for 2000 demographic characteristics of the commuting zone (i.e., log population, share of women, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Asian, Black, Hispanic, and White population), the 10-year lagged share of manufacturing employment interacted with a time period dummy as well as the share of routine jobs and the average offshorability index in 2000, following Autor and Dorn (2013). All specifications also control whether counties are situated in a "perennial" swing state (Colorado, Florida, Iowa, Michigan, Minnsota, Ohio, Nevada, New Hampshire, North Carolina, Pennsylvania , Virgina, Wisconsin). Explanatory variables are all standardized to have a mean of zero and a standard deviation of 1. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the commuting zone level. Regressions are weighted by a county's share in the national number of households in 2000. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table A.14: Effect of Robot Exposure and Chinese Imports on County-Level Employment: Stacked Differences, 2000-2016 (2SLS)

	Δ log(employment)× 100		
	Total (1)	Manufacturing (2)	Non-manufacturing (3)
US Exposure to Robots	-1.267***	0.965	-1.667***
	(0.449)	(0.679)	(0.452)
US Exposure to Chinese Imports	-1.254	-7.452***	0.846
	(1.247)	(2.393)	(1.262)
Kleibergen-Paap F-Stat	36.57	36.31	36.67
R^2	0.28	0.10	0.25
Observations	6170	6170	6170
Region × time	✓	✓	✓
Demographics	✓	✓	✓
Industry shares	✓	✓	✓
Routine Jobs & Offshorability	✓	✓	✓
Pre-trends	✓	✓	✓

Note: Table reports 2SLS estimates from a stacked difference regression over two 8-year election periods, from 2000, 2008, to 2016. The dependent variables in columns (1), (2) and (3) is the change in the log count of employment in total, manufacturing and non-manufacturing employment respectively, multiplied by 100 (i.e., [ln(yt+1)-ln(yt)] x 100). Explanatory variables all standardized to have a mean of zero and a standard deviation of 1. All regressions include: census division dummies interacted with time period dummies as covariates; 2000 demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Asian, Black, Hispanic, and White population, and the share of women in the labor force); shares of employment in broad industries in 2000 (i.e., agriculture, mining, construction, manufacturing); and the share of routine jobs and the average offshorability index in 2000, following D. Autor and Dorn (2013). Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the commuting zone level. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

A.1.3 Results of T-tests

In the following tables, additionally to p values we account for multiple hypothesis testing and report sharpened q values by Benjamini, Krieger, and Yekutieli (2006) as implemented by Anderson (2008).

Table A.15: T-test Results: Manipulation Check

I can relate to the story described in the article.						
	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	4.107	1.642	t(556) = -1.312	t(556) = -1.550	t(552) = -0.212
Control	277	4.289	1.636	p = 0.190	p = 0.122	p = 0.832
Trade	277	4.318	1.572	q = 0.457	q = 0.359	q = 0.983

Table A.16: T-test Results: Consequences for Workers and Search Strategies

I believe the employees who are about to lose their jobs will find another job easily.						
	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	2.911	1.166	t(556) = -0.708	t(556) = -1.313	t(552) = -0.579
Control	277	2.982	1.199	p = 0.479	p = 0.190	p = 0.563
Trade	277	3.040	1.149	q = 0.713	q = 0.457	q = 0.779

I believe the employees who are about to lose their jobs will be able to find a position in the same occupation.						
	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	3.288	1.349	t(556) = -2.563	t(556) = -2.923	t(552) = -0.347
Control	277	3.581	1.351	p = 0.011	p = 0.004	p = 0.728
Trade	277	3.621	1.339	q = 0.053	q = 0.024	q = 0.906

Table A.17: T-test Results: Consequences for Workers and Search Strategies (Continued)

If one is in the position of the workers to be laid off due to introduction of new technologies/ increased competition with China/ the company reorganization, there is nothing one can do.

	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	4.562	1.480	t(556) = -1.060	t(556) = 1.457	t(552) = 2.415
Control	277	4.700	1.595	p = 0.289	p = 0.146	p = 0.016
Trade	277	4.372	1.607	q = 0.530	q = 0.388	q = 0.065

I believe automation/ increased trade competition/ the introduction of new organisational practices has long lasting consequences.

	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	5.630	1.388	t(556) = -1.264	t(556) = -0.156	t(552) = 1.279
Control	277	5.765	1.129	p = 0.207	p = 0.876	p = 0.201
Trade	277	5.646	1.062	q = 0.467	q = 1.000	q = 0.464

I believe the best that the laidoff employees can do is: (*with answer*: to retrain into a new occupation)

	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	0.285	0.452	t(556) = 3.152	t(556) = 2.066	t(552) = -1.079
Control	277	0.173	0.379	p = 0.002	p = 0.039	p = 0.281
Trade	277	0.209	0.408	q = 0.015	q = 0.156	q = 0.530

I believe the best that the laidoff employees can do is: (*with answer*: to get additional qualifications that would be beneficial for the worker's current occupation)

	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	0.181	0.386	t(556) = 2.463	t(556) = 1.679	t(552) = -0.786
Control	277	0.108	0.311	p = 0.014	p = 0.094	p = 0.432
Trade	277	0.130	0.337	q = 0.061	q = 0.320	q = 0.642

Table A.18: T-test Results: Consequences for Workers and Search Strategies (Continued)

I believe the best that the laidoff employees can do is: (*with answer*: to start looking for another position right away)						
				t- and p-value for treatment comparisons		
Treatment	Obs	Mean	Std. Deviation	Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	0.420	0.494	t(556) = -4.210	t(556) = -2.717	t(552) = 1.457
Control	277	0.596	0.492	p = 0.000	p = 0.007	p = 0.146
Trade	277	0.534	0.500	q = 0.001	q = 0.039	q = 0.388

Table A.19: T-test Results: Preventability of Structural Shocks and Government Action

Do you think the layoffs described in the article could be prevented? If so, by whom? (*with answer*: No, the layoffs are inevitable)						
				t- and p-value for treatment comparisons		
Treatment	Obs	Mean	Std. Deviation	Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	0.495	0.501	t(556) = 3.034	t(556) = 4.698	t(552) = 1.620
Control	277	0.368	0.483	p = 0.003	p = 0.000	p = 0.106
Trade	277	0.303	0.460	q = 0.020	q = 0.001	q = 0.325

Do you think the layoffs described in the article could be prevented? If so, by whom? (*with answer*: Yes, by the state government)						
				t- and p-value for treatment comparisons		
Treatment	Obs	Mean	Std. Deviation	Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	0.021	0.145	t(556) = -0.568	t(556) = -0.025	t(552) = 0.541
Control	277	0.029	0.168	p = 0.570	p = 0.980	p = 0.589
Trade	277	0.022	0.146	q = 0.779	q = 1.000	q = 0.779

Do you think the layoffs described in the article could be prevented? If so, by whom? (*with answer*: Yes, by the federal government)						
				t- and p-value for treatment comparisons		
Treatment	Obs	Mean	Std. Deviation	Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	0.060	0.239	t(556) = 1.570	t(556) = -5.273	t(552) = -6.622
Control	277	0.032	0.178	p = 0.117	p = 0.000	p = 0.000
Trade	277	0.209	0.408	q = 0.354	q = 0.001	q = 0.001

Table A.20: T-test Results: Preventability of Structural Shocks and Government Action (Continued)

Do you think the layoffs described in the article could be prevented? If so, by whom? (*with answer*: Yes, by the company management)

Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons: Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	0.302	0.460	t(556) = -3.052	t(556) = -1.734	t(552) = 1.301
Control	277	0.426	0.495	p = 0.002	p = 0.083	p = 0.194
Trade	277	0.372	0.484	q = 0.015	q = 0.300	q = 0.457

What, if anything, do you think should be the response of the government? (*with answer*: Government should do nothing)

Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons: Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	0.093	0.290	t(556) = -0.755	t(556) = 1.925	t(552) = 2.656
Control	277	0.112	0.316	p = 0.451	p = 0.055	p = 0.008
Trade	277	0.051	0.219	q = 0.663	q = 0.217	q = 0.042

What, if anything, do you think should be the response of the government? (*with answer*: Government should provide some financial assistance to workers who lose their jobs (e.g., unemployment compensation or training assistance))

Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons: Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	0.751	0.433	t(556) = -0.600	t(556) = 1.151	t(552) = 1.745
Control	277	0.773	0.420	p = 0.549	p = 0.250	p = 0.081
Trade	277	0.708	0.456	q = 0.779	q = 0.523	q = 0.300

What, if anything, do you think should be the response of the government? (*with answer*: Government should restrict imports from overseas, by placing import tariffs on such imports for example)

Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons: Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	0.043	0.203	t(556) = -1.499	t(556) = -6.533	t(552) = -5.134
Control	277	0.072	0.259	p = 0.135	p = 0.000	p = 0.000
Trade	277	0.224	0.418	q = 0.378	q = 0.001	q = 0.001

Table A.21: T-test Results: Preventability of Structural Shocks and Government Action (Continued)

What, if anything, do you think should be the response of the government? (*with answer*: Government should impose higher taxes on laboursaving technology and regulate automation more strictly)

Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons: Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	0.114	0.318	t(556) = 3.113	t(556) = 4.627	t(552) = 1.726
Control	277	0.043	0.204	p = 0.002	p = 0.000	p = 0.085
Trade	277	0.018	0.133	q = 0.015	q = 0.001	q = 0.300

Table A.22: T-test Results: Voting and Political Attention

I believe it is important to always vote in elections.

Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons: Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	6.327	1.121	t(556) = 1.729	t(556) = 0.103	t(552) = -1.633
Control	277	6.148	1.323	p = 0.084	p = 0.918	p = 0.103
Trade	277	6.318	1.113	q = 0.300	q = 1.000	q = 0.325

I believe it is important to draw the attention of the public and of politicians to the fact that people lose jobs due to automation/ due to increased trade competition with China/ due to modern organisational practices.

Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons: Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	5.480	1.389	t(556) = 0.938	t(556) = 0.977	t(552) = -0.032
Control	277	5.368	1.435	p = 0.348	p = 0.329	p = 0.975
Trade	277	5.372	1.232	q = 0.580	q = 0.568	q = 1.000

I believe politicians do not pay enough attention to the unemployment due to automation/ due to increased trade competition with China/ due to the introduction of new organisational practices.

Treatment	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons: Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	5.356	1.430	t(556) = 1.209	t(556) = 2.457	t(552) = 1.113
Control	277	5.202	1.570	p = 0.227	p = 0.014	p = 0.266
Trade	277	5.061	1.401	q = 0.475	q = 0.061	q = 0.530

Table A.23: T-test Results: Emotional Responses

If I were laid off due to automation/ due to increased competition with China/ as a part of the reorganisation, as described in the article, I would be very angry.						
	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	5.463	1.386	t(556) = -0.782	t(556) = -1.058	t(552) = -0.263
Control	277	5.552	1.322	p = 0.434	p = 0.291	p = 0.792
Trade	277	5.581	1.259	q = 0.642	q = 0.530	q = 0.983

If I were laid off due to automation/ due to increased competition with China/ as a part of the reorganisation, as described in the article, I would be very frustrated.						
	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	5.964	1.127	t(556) = -0.806	t(556) = -0.907	t(552) = -0.081
Control	277	6.040	1.078	p = 0.420	p = 0.365	p = 0.935
Trade	277	6.047	1.019	q = 0.642	q = 0.593	q = 1.000

If I were laid off due to automation, as described in the article/ due to increased competition with China/ as a part of the reorganisation, I would be very worried about my future.						
	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	6.053	1.171	t(556) = -0.193	t(556) = 0.219	t(552) = 0.421
Control	277	6.072	1.137	p = 0.847	p = 0.827	p = 0.674
Trade	277	6.032	1.081	q = 0.983	q = 0.983	q = 0.815

Table A.24: T-test Results: Risk, Trust, Time, Altruism, Locus of Control

In general, how willing or unwilling you are to take risks.						
	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	5.324	2.305	t(556) = -0.415	t(556) = -1.006	t(552) = -0.551
Control	277	5.408	2.475	p = 0.678	p = 0.315	p = 0.582
Trade	277	5.520	2.299	q = 0.815	q = 0.563	q = 0.779

Table A.25: T-test Results: Risk, Trust, Time, Altruism, Locus of Control (Continued)

How well does the following statement describe you as a person? As long as I am not convinced otherwise, I assume that people have only the best intentions.

Treatment	Obs	Mean	Std. Deviation	Automation v. Control	Automation v. Trade	Control v. Trade
				t- and p-value for treatment comparisons		
Automation	281	5.217	2.430	t(556) = 0.867	t(556) = 0.215	t(552) = -0.662
Control	277	5.036	2.500	p = 0.386	p = 0.830	p = 0.509
Trade	277	5.173	2.379	q = 0.613	q = 0.983	q = 0.756

In comparison to others, are you a person who is generally willing to give up something today in order to benefit from it in the future or are you not willing to do so?

Treatment	Obs	Mean	Std. Deviation	Automation v. Control	Automation v. Trade	Control v. Trade
				t- and p-value for treatment comparisons		
Automation	281	7.060	1.865	t(556) = -0.781	t(556) = 0.629	t(552) = 1.355
Control	277	7.188	1.982	p = 0.435	p = 0.529	p = 0.176
Trade	277	6.957	2.030	q = 0.642	q = 0.776	q = 0.446

How willing are you to give to good causes without expecting anything in return?

Treatment	Obs	Mean	Std. Deviation	Automation v. Control	Automation v. Trade	Control v. Trade
				t- and p-value for treatment comparisons		
Automation	281	7.053	2.181	t(556) = 0.593	t(556) = 0.782	t(552) = 0.188
Control	277	6.942	2.243	p = 0.553	p = 0.434	p = 0.851
Trade	277	6.906	2.265	q = 0.779	q = 0.642	q = 0.983

When you think about the course of your life, to what extent do you think you have control over the direction it is taking?

Treatment	Obs	Mean	Std. Deviation	Automation v. Control	Automation v. Trade	Control v. Trade
				t- and p-value for treatment comparisons		
Automation	281	6.530	2.007	t(556) = 1.618	t(556) = 0.104	t(552) = -1.514
Control	277	6.249	2.097	p = 0.106	p = 0.917	p = 0.130
Trade	277	6.513	1.997	q = 0.325	q = 1.000	q = 0.374

Table A.26: T-test Results: Perception of Consequences for Society

There will be more opportunities for the next generation.						
	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	4.214	1.562	t(556) = -0.188	t(556) = 0.865	t(552) = 1.056
Control	277	4.238	1.549	p = 0.851	p = 0.387	p = 0.291
Trade	277	4.101	1.507	q = 0.983	q = 0.613	q = 0.530

In the future, people will be sharply separated into haves and havenots						
	Obs	Mean	Std. Deviation	t- and p-value for treatment comparisons		
Treatment				Automation v. Control	Automation v. Trade	Control v. Trade
Automation	281	4.826	1.469	t(556) = 0.080	t(556) = -0.039	t(552) = -0.121
Control	277	4.816	1.419	p = 0.937	p = 0.969	p = 0.904
Trade	277	4.830	1.384	q = 1.000	q = 1.000	q = 1.000

Table A.27: T-test Results: Differences to Control Condition

Statement	**Obs**	**Mean**	**Std. Dev.**	**Test Result**
I do not believe there is anything society can do to prevent job losses due to technological progress.	835	3.68	0.059	p=0.000
I do not think there is something that society can do to prevent job losses due to intensified trade with other countries.	835	3.32	0.052	q=0.001

Table A.28: Survey Regression on Heterogeneity along Respondents' Political Ideology

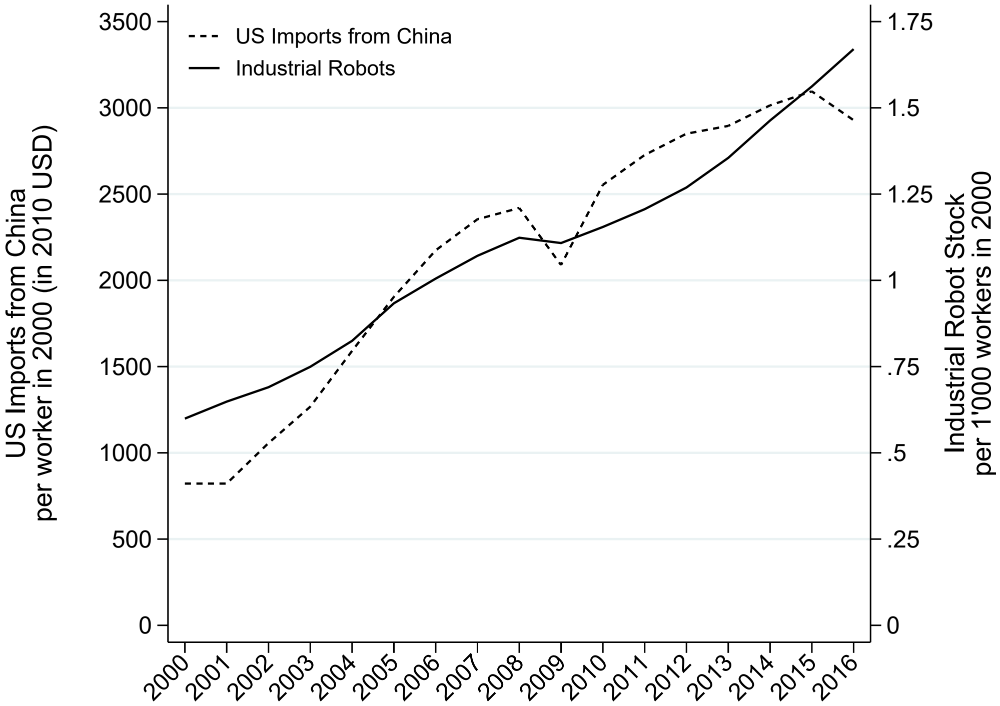
	Not Enough Political Attention (1)	Important to Draw Attention (2)
Control	-0.271	-0.0911
	(0.261)	(0.238)
Trade	-1.363***	-1.207***
	(0.243)	(0.233)
Age	0.00715	0.00798*
	(0.00507)	(0.00439)
Edu	-0.141***	-0.0863*
	(0.0540)	(0.0462)
DV: Male	0.161	0.0499
	(0.104)	(0.0953)
DV: White	-0.0863	0.0256
	(0.150)	(0.134)
DV: Affected industry	-0.0729	-0.0224
	(0.117)	(0.104)
More Conservative	-0.205***	-0.239***
	(0.0524)	(0.0540)
Control#More Conservative	0.0111	-0.0205
	(0.0809)	(0.0762)
Trade#More Conservative	0.349***	0.357***
	(0.0706)	(0.0680)
Constant	6.276***	6.222***
	(0.312)	(0.291)
Observations	812	812
R-squared	0.060	0.077

Notes: Attitudes towards the statement: (1) ”I believe politicians do not pay enough attention to the unemployment due to [the introduction of new organizational practices/increased trade competition with China/automation].”. (2) "I believe it is important to draw the attention of the public and of politicians to the fact that people lose jobs [due to modern organizational practices / due to automation / due to increased trade competition with China]". The variable "More Conservative" is continuous with higher values corresponding to a more conservative political position. Robust standard errors given in parentheses. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

A.2 Figures

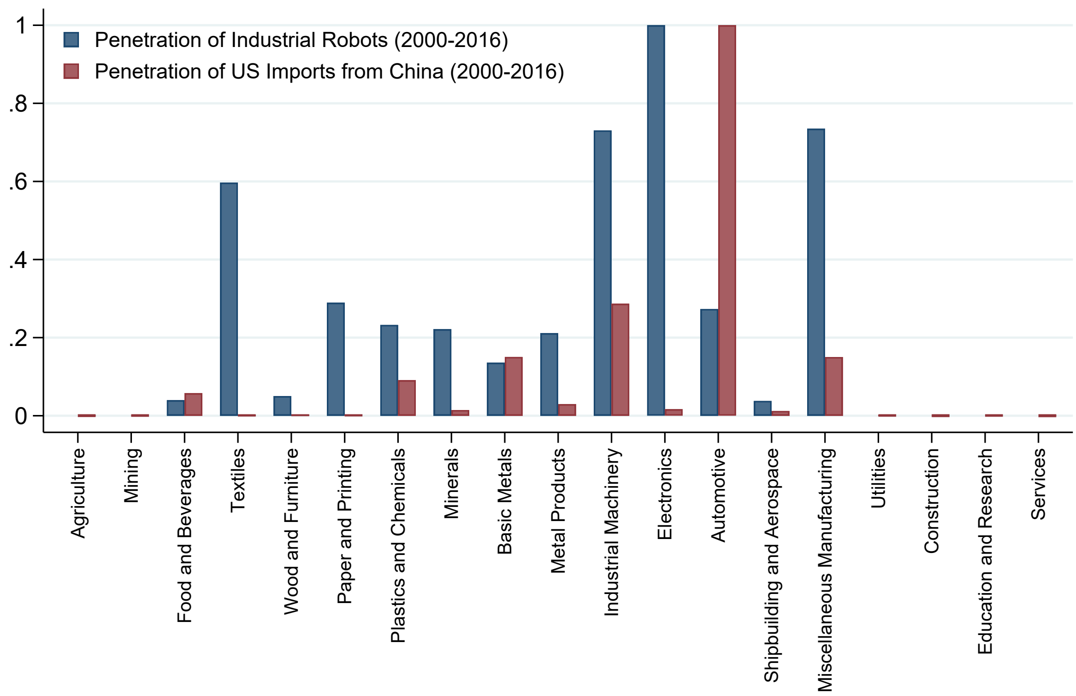
A.2.1 Local-level Analysis

Figure A.1: Temporal Variation of US Imports from China and US Industrial Robot Stocks



Notes: The solid line shows the annual number of operational industrial robots in the US between 2000 and 2016 per 1,000 workers in 2000. The dotted line plots total annual imports from China to the US between 2000 and 2016 scaled by the total number of workers in 2000 (in 2010 USD). Source: Authors' calculations based on UNCOMTRADE, IFR, County Business Patterns.

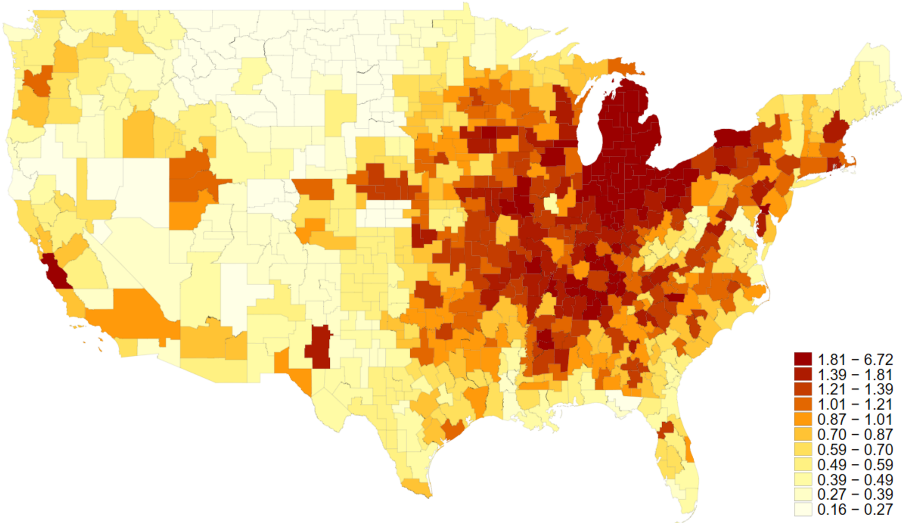
Figure A.2: Industry Variation of US Imports from China and US Industrial Robot Stocks



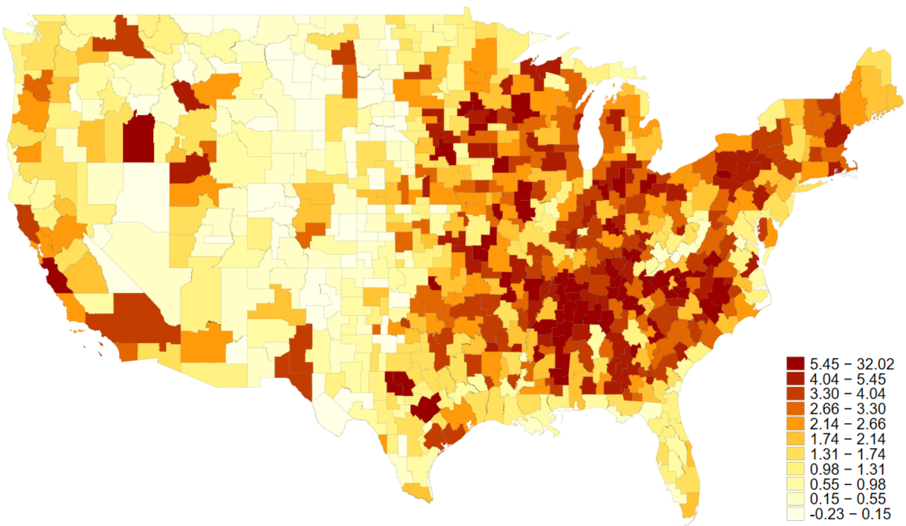
Notes: Import penetration is computed by industry as the increase in US imports from China from 2000 to 2016 scaled by the number of US workers in 2000. Industrial robot penetration is computed by industry as the increase in the US operational stock of industrial robots from 2000 to 2016 per US worker in 2000. Both measures of penetration are normalized such that the industry with the highest penetration has a value of 1. Source: Authors' calculations based on UNCOMTRADE, IFR, County Business Patterns.

Figure A.3: Geographical Variation in Commuting-Zone Exposure to Robots and Chinese Imports (2000-2015)

(a) US exposure to robots

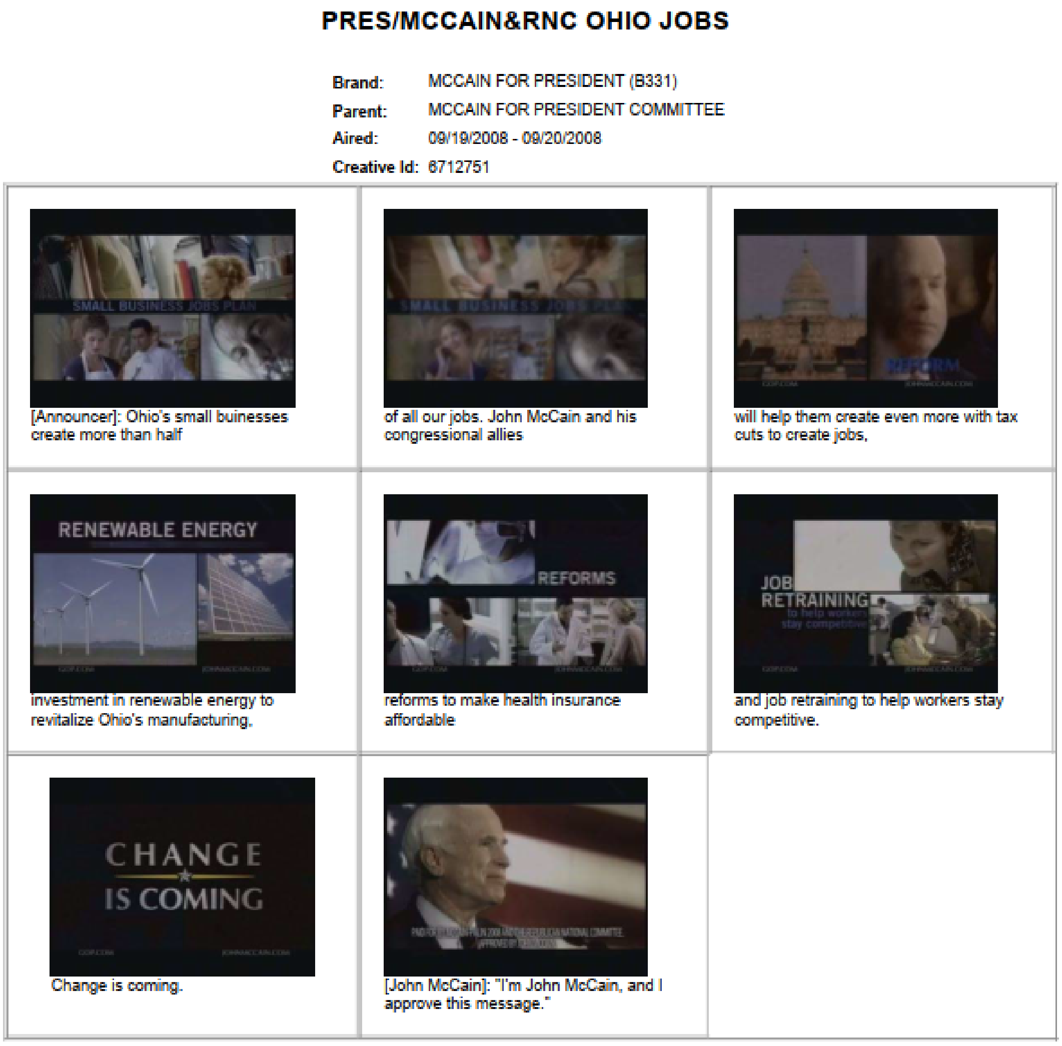


(b) US exposure to Chinese imports



Notes: Figures display variation in exposure to robots and Chinese imports across 11 bins, each containing an equal number of commuting zones. Source: Author's calculations based on UNCOMTRADE, IFR, IPUMS, EUKLEMS.

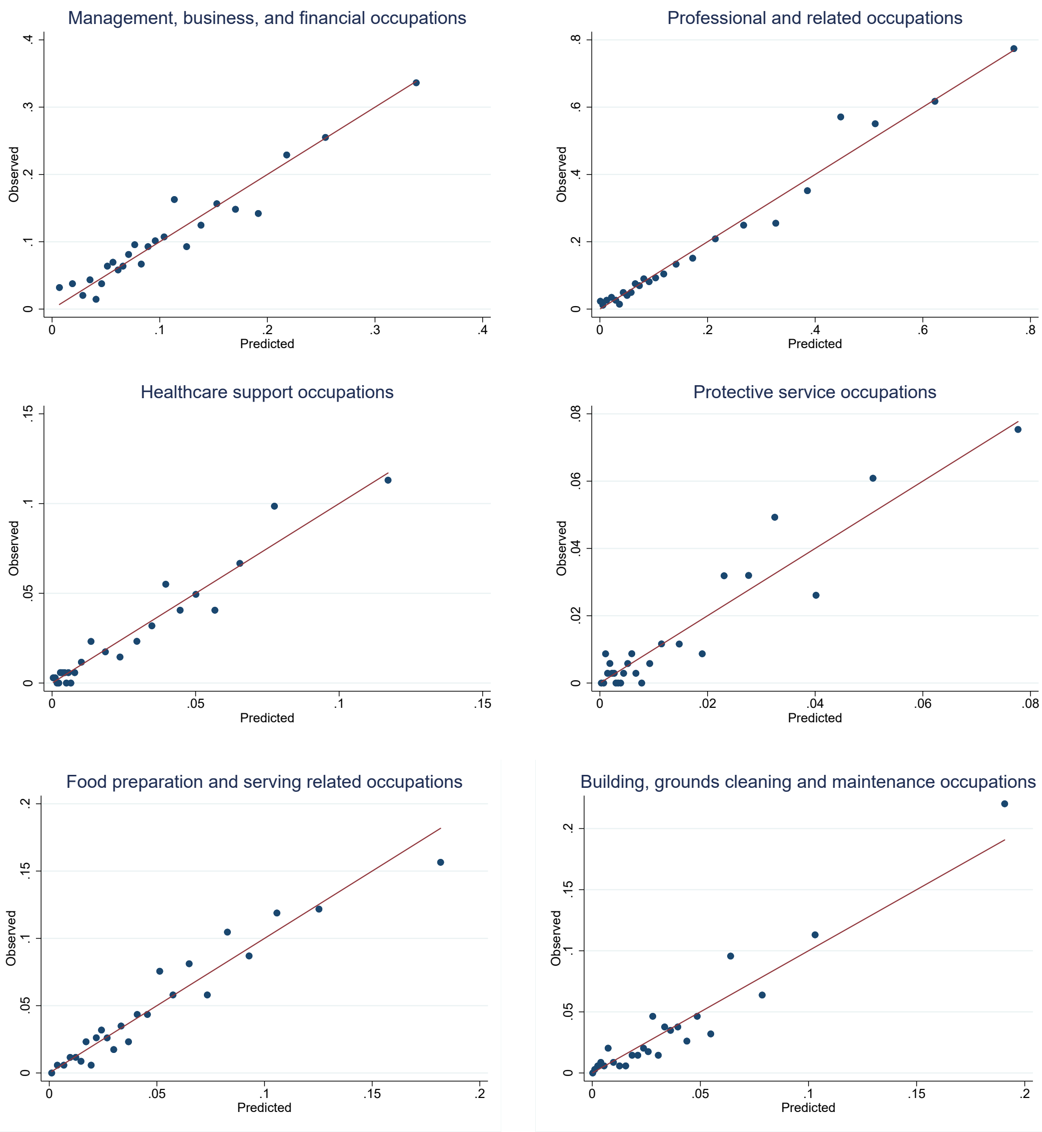
Figure A.4: Example of Campaign Ad Storyboard from Wisconsin Data Project



Source: Goldstein et al. (2011).

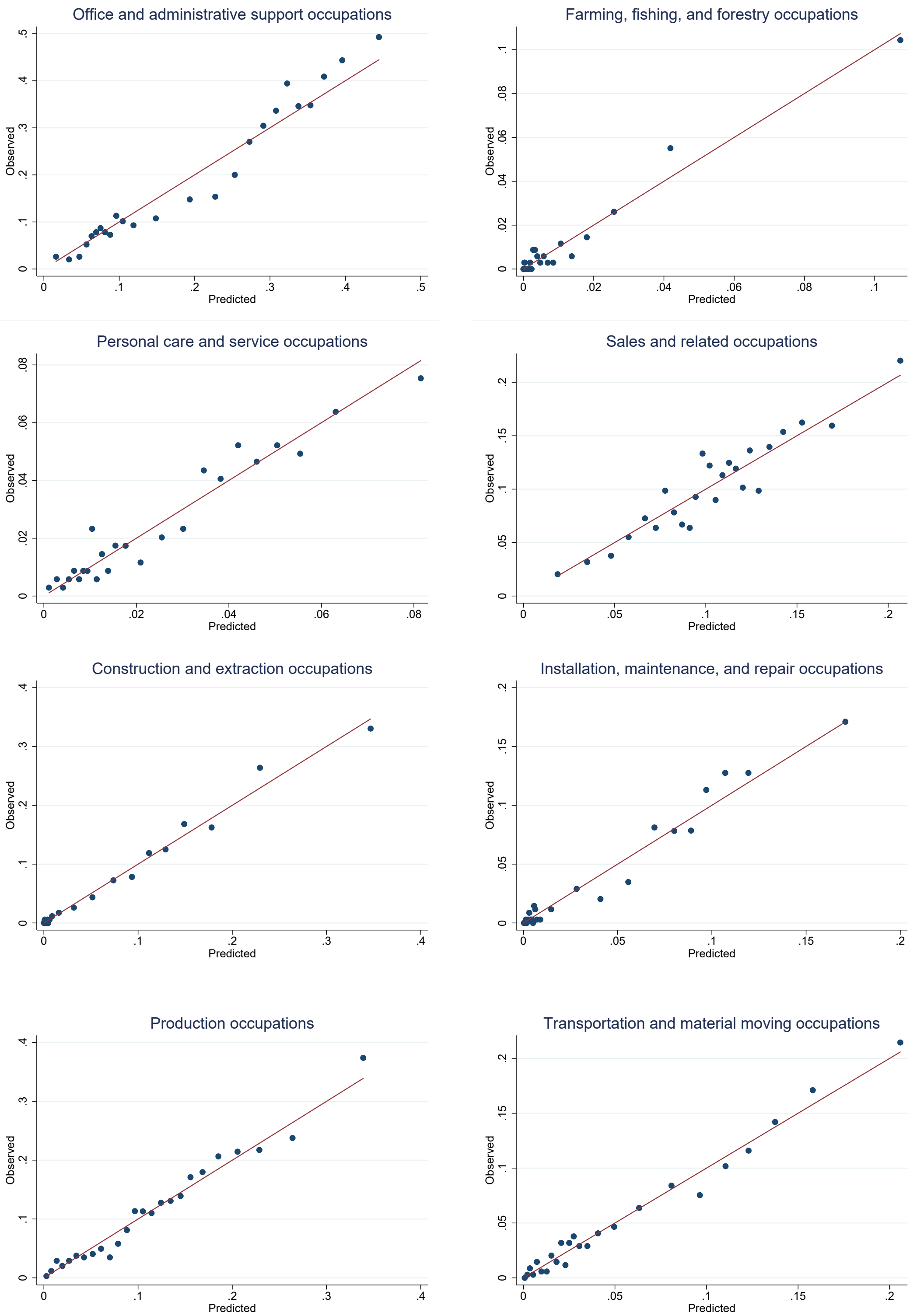
A.2.2 Individual-level Analysis

Figure A.5: Prediction Accuracy across Occupational Groups



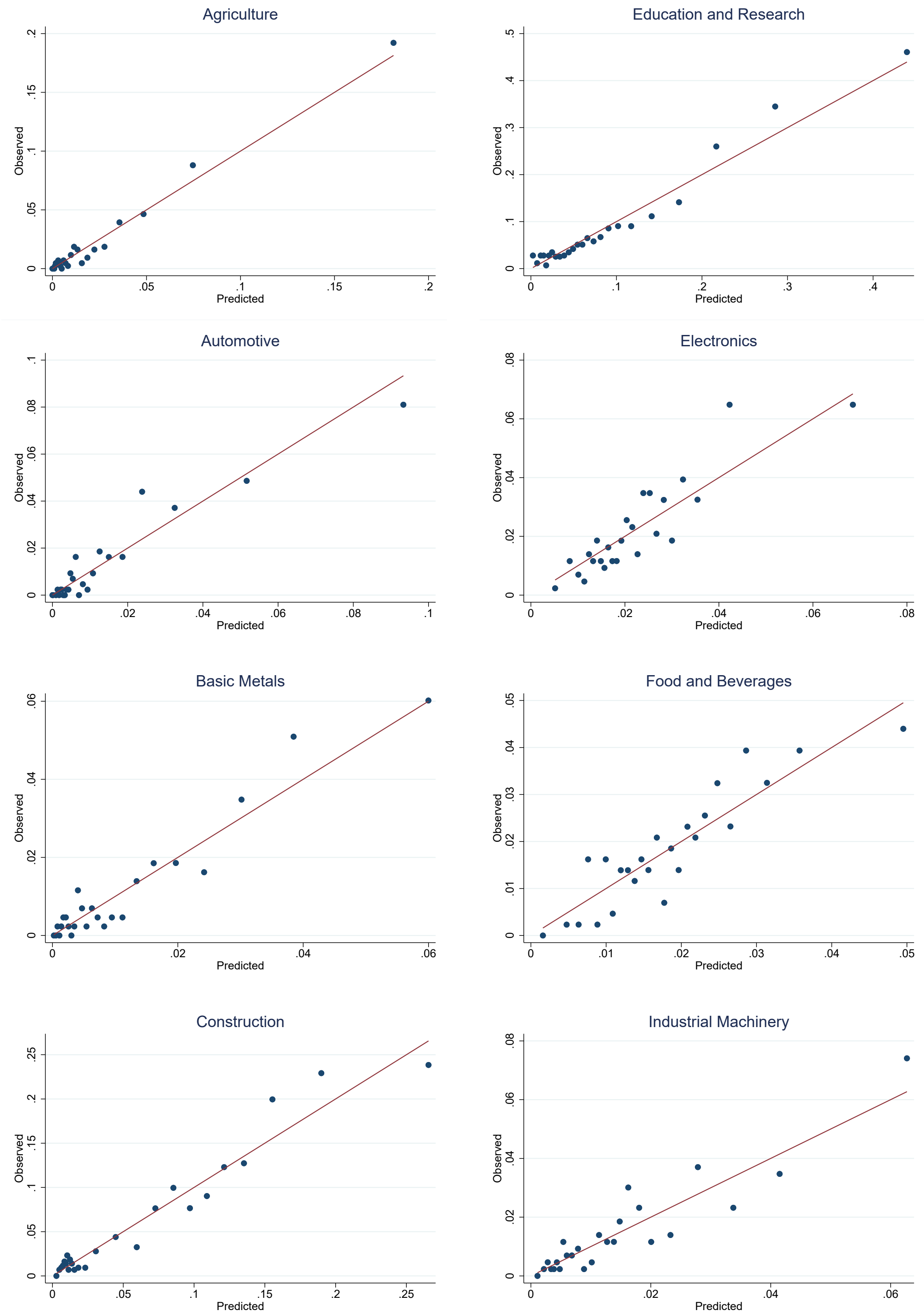
Notes: This figures shows predicted and observed shares of individuals working in an occupational group. To obtain these plots, we rank individuals by their predicted probability to work in a given occupation and cut the sample in 25 equally sized bins. Then we compute the mean of the predicted probability in each bin and compare it to the share of individuals in that bin that were actually observed to work in that occupation. Source: Authors' calculations based on General Social Survey.

Figure A.6: Prediction Accuracy across Occupational Groups (Continued)



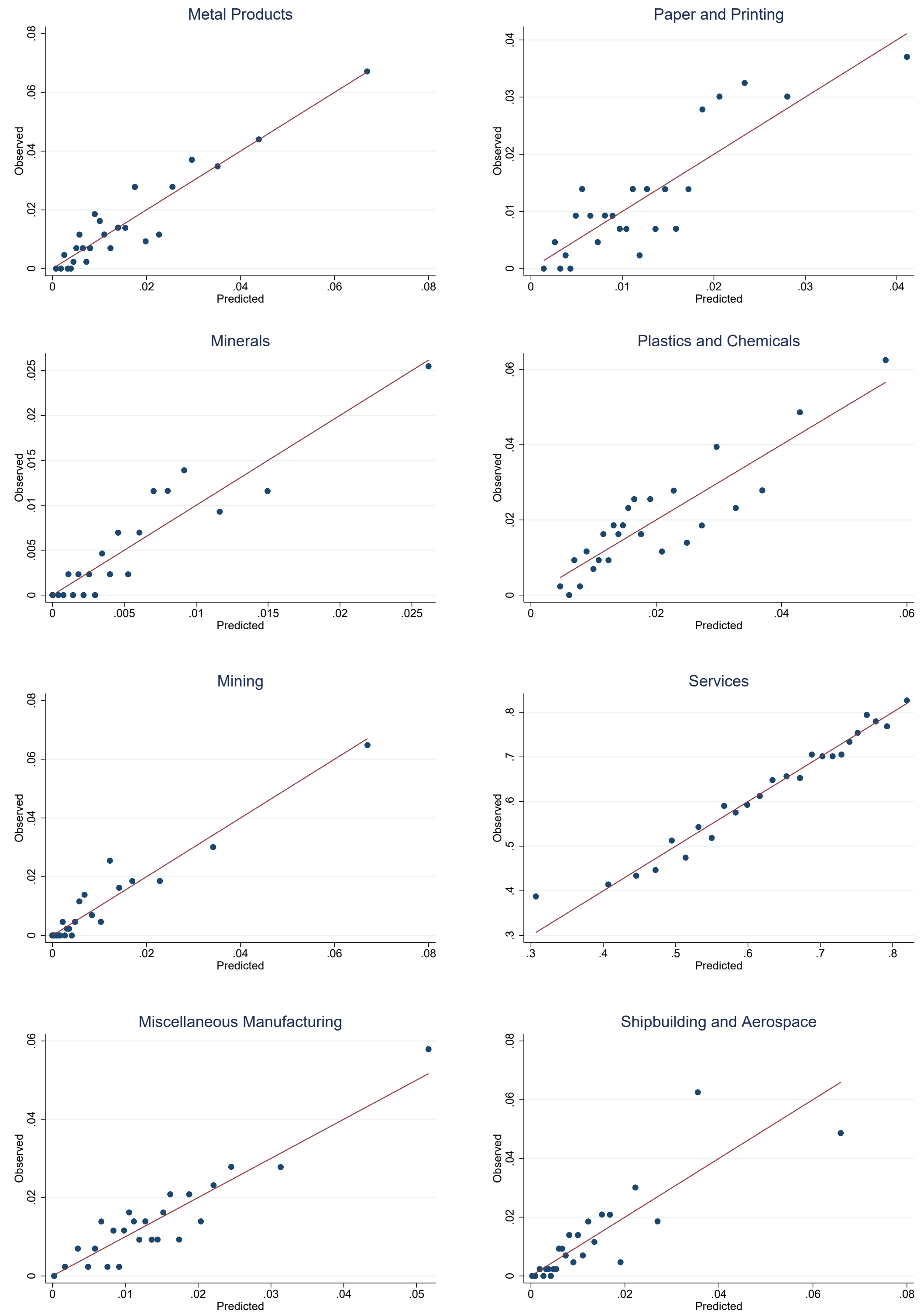
Notes: This figures shows predicted and observed shares of individuals working in an occupational group. To obtain these plots, we rank individuals by their predicted probability to work in a given occupation and cut the sample in 25 equally sized bins. Then we compute the mean of the predicted probability in each bin and compare it to the share of individuals in that bin that were actually observed to work in that occupation. Source: Authors' calculations based on General Social Survey.

Figure A.7: Prediction Accuracy across Industry Groups



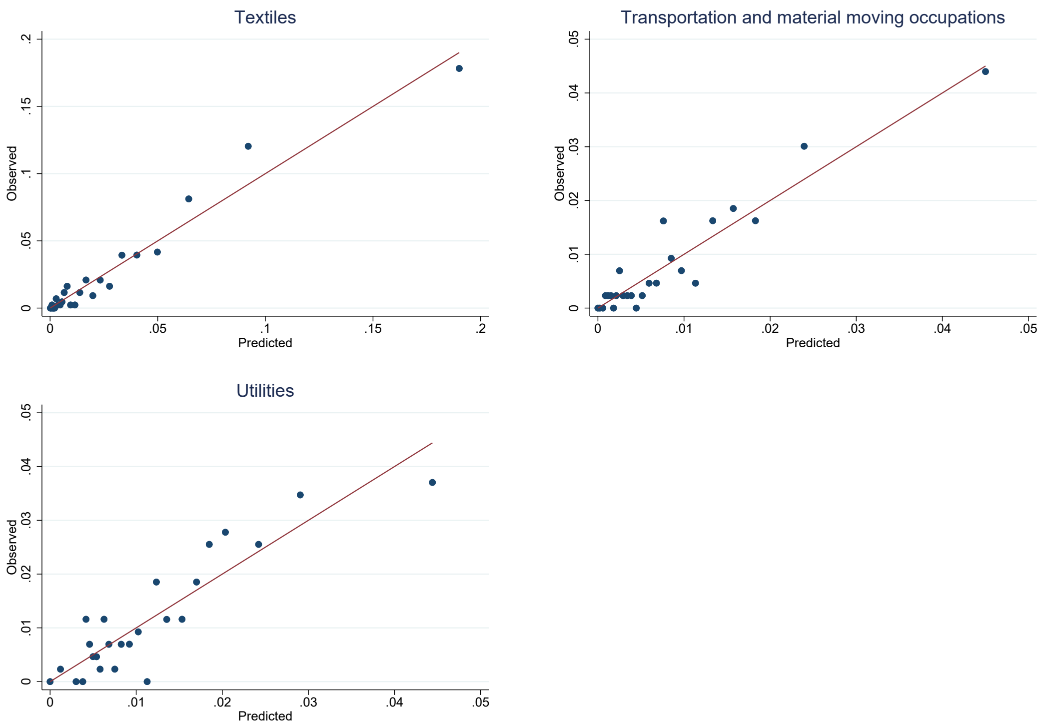
Notes: This figure shows predicted vs. observed shares of individuals working in an industry group. To obtain these plots, we rank individuals by their predicted probability to work in a given industry and cut the sample in 25 equally sized bins. Then we compute the mean of the predicted probability in each bin and compare it to the share of individuals in that bin that were actually observed to work in that industry. Source: Authors' calculations based on General Social Survey.

Figure A.8: Prediction Accuracy across Industry Groups (Continued)



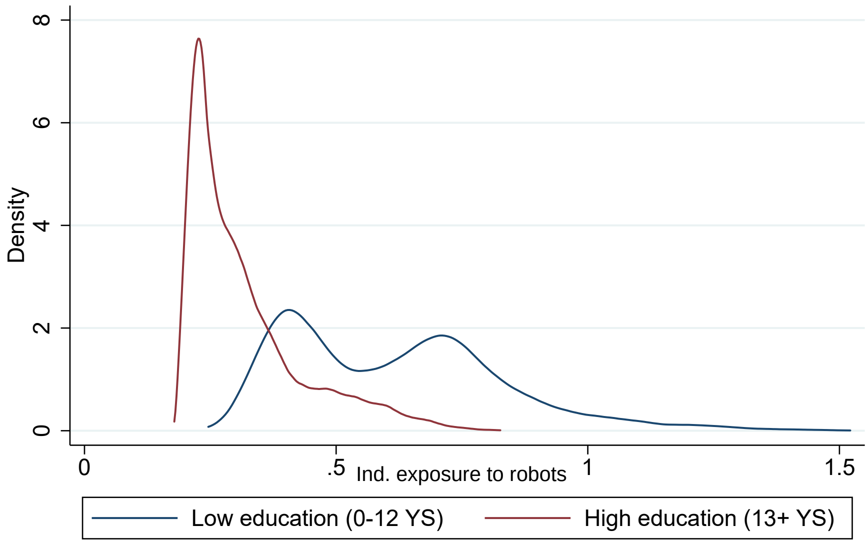
Notes: This figure shows predicted vs. observed shares of individuals working in an industry group. To obtain these plots, we rank individuals by their predicted probability to work in a given industry and cut the sample in 25 equally sized bins. Then we compute the mean of the predicted probability in each bin and compare it to the share of individuals in that bin that were actually observed to work in that industry. Source: Authors' calculations based on General Social Survey.

Figure A.9: Prediction Accuracy across Industry Groups (Continued)



Notes: This figure shows predicted vs. observed shares of individuals working in an industry group. To obtain these plots, we rank individuals by their predicted probability to work in a given industry and cut the sample in 25 equally sized bins. Then we compute the mean of the predicted probability in each bin and compare it to the share of individuals in that bin that were actually observed to work in that industry. Source: Authors' calculations based on General Social Survey.

Figure A.10: Distribution of Individual Exposure to Robots by Years of Schooling



Notes: The figure shows kernel density lots of individual exposure scores by levels of schooling. Source: Authors' calculations based on Webb (2019), GSS.

A.2.3 Survey Materials

Figure A.11: Other Vignettes used in Online Survey Experiment

BUSINESS NEWS September 18, 2019

US Manufacturing Faces Headwinds

A view of the shop floor at the VBMC factory.

In the past month, many companies presented their new business strategies. One of the companies is VBMC, a large manufacturing company, which announced plans to phase out parts of their operations. They plan to discontinue the production of goods that face strong competition from producers abroad, in particular from China. A VBMC spokesman said: "To remain competitive, we have to offer competitive prices and discontinuing the production of items where we can't compete with manufacturers from China and focusing on our most competitive products is the way forward. As a result of shutting down some of the production lines that used to produce those goods, we will become more efficient. However, in the course of these changes, about 900 good workers will lose their jobs. It is very regretful, but necessary to stay in business these days".

Many industries have been affected in recent years by greater ease of trading with other nations. An employee of VBMC, who has been employed there for eighteen years, said the change would have devastating consequences for the workers. "Many will become unemployed and the rest might have to accept lower wages," he added.

(a) Trade condition

BUSINESS NEWS September 18, 2019

US Manufacturing Faces Headwinds

A view of the shop floor at the VBMC factory.

In the past month, many companies presented their new business strategies. One of the companies is VBMC, a large manufacturing company, which announced plans to phase out parts of their operations. They plan to restructure the company and optimize the organization of the production lines. A VBMC spokesman said: "To remain competitive, we have to offer competitive prices and restructuring and optimizing our production processes is the way forward. As a result of shutting down some of the production lines that are not needed in the new streamlined production flow, we will become more efficient. However, in the course of these changes, about 900 good workers will lose their jobs. It is very regretful, but necessary to stay in business these days".

Many industries have been affected in recent years by developments in new organizational practices. An employee of VBMC, who has been employed there for eighteen years, said the change would have devastating consequences for the workers. "Many will become unemployed and the rest might have to accept lower wages," he added.

(b) Control condition

Notes: This figure shows the mock newspaper article presented to survey participants in the 'trade' and 'control' conditions. Highlighted parts are added and varied depending on the treatment. Source: Authors' original writing based on Di Tella and Rodrik (2020).

A.3 Data

A.3.1 Exposure to Robots

We follow Acemoglu and Restrepo (2020a) and construct a measure of commuting zone exposure using the following data sources:

Industrial robots: We use data on operational stock of industrial robots from the International Federation of Robotics (IFR) for the United States and six European countries (Denmark, Finland, France, Italy, Sweden, Germany) from 1993 to 2016.[1] We classify the IFR data into 13 manufacturing industries, and 6 broad industries outside manufacturing.[2] To obtain the 19 IFR industries as in Acemoglu and Restrepo (2020a), we perform the following adjustments to the original data: First, we keep the industry "all other manufacturing branches" and label it as "Miscellaneous manufacturing". Second, "All other non-manufacturing branches" are considered as "Services". Third, the residual category "Metal (unspecified)" is allocated proportionally to all industries in the "Metal industries" (Basic Metals, Metal Products, Electronics, Industrial Machinery) and 4.) the residual "Unspecified", which is allocated proportionally over all 19 IFR industries. The IFR data comes with two drawbacks: first, it groups the US together with Canada as Northern America before 2011 and second, it doesn't provide a split-up by industries for the Northern America before 2004. Given that the US accounts for about 90 percent of the North American robot stock, we accept the first limitation. To deal with the second limitation, we apply an algorithm that attributes the total stock in each year before 2004 according to an industry's share in the total stock in 2004, the first year with disaggregated information on the industry level. We apply this solution also to Denmark, which similarly lacks data by industry before 1996.

Industry employment and output: Furthermore, we use data on employment and output from the 2007 and 2019 EU KLEMS releases (Timmer, O Mahony, Van Ark,

[1] These selected European countries exhibit levels and an evolution of the number of robots per 1000 workers that mirror the US over the sample period from 1993 to 2015 and will be used to construct an instrumental variable.

[2] Manufacturing industries include Food and Beverages, Textiles, Wood and Furniture, Paper and Printing, Plastics and Chemicals, Minerals, Basic Metals, Metal Products, Electronics, Industrial Machinery, Automotive, Shipbuilding and Aerospace, Miscellaneous Manufacturing; Non-Manufacturing industries include Agriculture, Mining, Utilities, Construction, Education and Research, Services.

et al., 2007; Stehrer et al., 2019).[3] As in Acemoglu and Restrepo (2020a), we translate the numbers of persons employed in each European country-industry in 1990 into "US equivalent workers" by dividing the total number of hours worked in a European industry by the hours per worker in the corresponding US industry. This is to account for the fact that European workers work on average less hours and to make employment numbers comparable. To adjust for the growth in robot stock due to output growth, we compute an output growth rate and use the output deflators provided by EU KLEMS to correct for inflation.

Commuting zone employment: Finally, we compute industry employment shares in each commuting zone using data from the US Decennial Census for the years 1970, 1990 and 2000 as well as from the American Community Survey in 2006, 2007, 2008 and 2009 and 2014, 2015, 2016 and 2017 provided by the *Integrated Public Use Microdata Series* (IPUMS). We use the crosswalks by D. Autor and Dorn (2013) to map geographies provided in the IPUMS data to 722 continental commuting zones. To compute the industry employment in each commuting zone in a given year, we sum over working individuals between 15 and 64 by industry using person weights from IPUMS multiplied with probability weights from the geographical crosswalks. We calculate the total commuting zone employment simply as the sum of employment across all industries.[4].

A.3.2 Exposure to Chinese Imports

To construct a measure of commuting zone exposure to Chinese imports as in D. Autor, Dorn, and Hanson (2013), we use the following data:

International trade: We obtain data on merchandise imports from China to the US as well as to Australia, Denmark, Germany, Finland, Japan, New Zealand, Spain and Switzerland from 1990 to 2016 at the HS 1996 6-digit product level from *Uncomtrade*. We map this data to SIC 1987 4-digit codes using a crosswalk provided by D. Autor, Dorn, and Hanson (2013) and adjusted trade values to 2007 US$ prices using the personal consumption expenditure deflator provided by the Federal Reserve Bank of St. Louis.

[3]We use both releases as the 2019 release in NACE 2 only covers the period 2000 to 2018, while the 2007 NACE1 release only provides data from 1970 to 2005. To obtain industry employment and output data for multiple countries from 1990 to 2016 we do therefore need to combine both the 2007 NACE 1 and the 2019 NACE 2 releases. The mapping of NACE 1/2 to IFR industries is available upon request.

[4]The mapping of 1990 Census Bureau industry classes to corresponding IFR industries is also available upon request.

Industry employment: We obtain employment counts by SIC 1987 industry for each commuting zone in 1980, 1990 and 2000 using an algorithm by David Dorn that assigns employment counts to employment brackets reported in the establishment data of the US Census Bureau's *County Business Patterns*. For years after 2007, we make use of industry employment imputations by Eckert et al. (2021) also based on the *County Business Patterns* dataset.[5] This data allows us to compute a measure of exposure to Chinese imports for each commuting zone as the sum of changes in Chinese imports per worker in each industry at the national level weighted by an industry's share in total commuting zone employment.

[5] Industry crosswalks from NAICS 2007 to SIC 1987 necessary to use the data from Eckert et al. (2021) for our purpose are available upon request.

B

Appendix to Chapter 2

Robotizing to Compete

B.1 Tables

Table B.1: Summary Statistics for Manufacturing Exporters in 1992

	Mean	SD	p25	p75	p99	Sum
Number of employees	94.01	188.76	22.00	90.00	800.00	497,602
Sales, in Million EUR	4.56	40.41	0.41	2.92	49.63	24,116
Total exports, in Million EUR	1.43	7.06	0.02	0.97	17.10	7,583
Number of establishments	1.29	1.46	1.00	1.00	6.00	6,848
Foreign ownership	0.04	0.20	0.00	0.00	1.00	211
Firm age	17.17	16.79	6.00	22.00	73.00	
Export intensity	0.41	0.40	0.03	0.88	1.00	
Sales/employee, in Million EUR	0.05	1.09	0.01	0.04	0.30	
Sum of product shares	0.34	0.38	0.01	0.70	1.00	
Exporting to CEECs	0.06	0.23	0.00	0.00	1.00	292
Export entry to CEECs	0.06	0.23	0.00	0.00	1.00	304
Observations	5293					

Notes: This table provides summary statistics of firm-level characteristics in 1992 for the sample of manufacturing exporters with at least 10 employees. Source: Author's calculations based on Comercio Internacional, Quadros de Pessoal.

Table B.2: Comparative Summary Statistics for Manufacturing Exporters in 1992: Automation Adopters vs. Non-Adopters

	Non-Adopters			Adopters		
	Mean	SD	Sum	Mean	SD	Sum
Number of employees	89.54	174.18	450,118	181.96	361.97	47,310
Sales, in Million EUR	4.43	41.30	22,247	7.13	15.69	1,854
Total exports, in Million EUR	1.31	6.77	6,592	3.80	11.04	989
Number of establishments	1.29	1.47	6,498	1.31	1.41	340
Foreign ownership	0.04	0.19	184	0.10	0.31	27
Firm age	17.09	16.84		18.13	15.21	
Export intensity	0.40	0.40		0.43	0.37	
Sales/employee, in Million EUR	0.05	1.12		0.04	0.05	
Sum of product shares	0.34	0.38		0.35	0.34	
Exporting to CEECs	0.05	0.23	271	0.08	0.27	21
Export entry to CEECs	0.05	0.22	262	0.16	0.37	42
Observations	5027			260		

Notes: This table provides summary statistics of firm-level characteristics in 1992 for the sample of manufacturing exporters with at least 10 employees. Statistics are reported for separately for adopters and non-adopters. Adopters are defined as firms that exhibit positive automation imports over the period from 1992 to 1998. Source: Author's calculations based on Comercio Internacional, Quadros de Pessoal.

Table B.3: Automation Adoption Rates among Manufacturing Exporters by Industry and Employment Size: 1988-1998

		By Number of Employees					
	Total	1-9	10-49	50-249	250-499	500-999	≥ 1000
Food and beverages	0.01	0.00	0.01	0.00	0.10	0.00	0.33
Tobacco products	0.33	.	.	0.00	.	.	1.00
Textiles	0.01	0.00	0.01	0.01	0.02	0.00	0.13
Wearing apparel	0.01	0.00	0.00	0.01	0.02	0.08	0.00
Leather products	0.01	0.00	0.00	0.01	0.05	0.14	1.00
Wood and wood products	0.04	0.01	0.02	0.13	0.13	0.75	.
Paper and paper products	0.01	0.00	0.00	0.00	0.00	0.20	.
Printing and publishing	0.01	0.00	0.00	0.02	0.43	0.00	.
Coke and petroleum prod.	0.00	.	0.00	.	.	.	0.00
Chemical products	0.01	0.00	0.02	0.02	0.00	0.00	0.00
Rubber and plastics	0.10	0.03	0.09	0.15	0.00	0.00	.
Mineral products	0.02	0.00	0.01	0.05	0.10	0.27	0.00
Basic metals	0.36	0.00	0.35	0.48	0.17	0.33	1.00
Fabricated metal products	0.19	0.04	0.15	0.34	0.57	0.00	.
Machinery and equipment	0.42	0.09	0.40	0.58	0.50	0.80	.
Office equipment	0.20	.	0.00	0.33	.	.	.
Electrical machinery	0.17	0.04	0.07	0.29	0.14	0.75	0.60
Electronics	0.27	0.10	0.17	0.15	0.75	1.00	1.00
Precision instruments	0.14	0.00	0.13	0.25	0.00	1.00	.
Motor vehicles	0.35	0.00	0.20	0.53	0.50	0.75	.
Other transport equipment	0.17	0.00	0.00	0.38	0.33	.	1.00
Furniture	0.07	0.01	0.03	0.26	0.50	1.00	.
Total	0.07	0.01	0.06	0.11	0.13	0.20	0.47

Notes: This table shows the shares of automating manufacturing exporter from 1988 to 1998, broken down by 2-digit ISIC industry and employment size class. The denominator in each cell is the total number of manufacturing exporters active during the period. Automation adopters are defined as firms with positive imports of industrial robots or numerically controlled machinery over the 1988-1998 period. Source: Author's calculations based on Comercio Internacional, Quadros de Pessoal.

Table B.4: Effects of Exposure to Tariff Reductions on Sales by Destination: Long Differences with Controls, 1992-1998 (OLS)

	Δ log(Y) $\times$ 100 from 1992 to 1998				
	Total Sales	Domestic Sales	Total Exports	Intra-EU Exports	Extra-EU Exports
Δ FC	-21.57***	-12.71	-12.67**	-12.84*	-6.55
	(7.02)	(28.68)	(5.38)	(7.22)	(10.52)
Sales, in Million EUR	-1.43***	-2.81**	-0.02	-0.38	0.27
	(0.25)	(1.11)	(0.29)	(0.30)	(0.31)
Firm age	-0.53***	-1.16*	-1.06***	-1.45***	-0.36
	(0.15)	(0.64)	(0.25)	(0.33)	(0.27)
Foreign ownership	7.13	-55.88	18.44	21.42	47.29**
	(7.07)	(58.88)	(12.93)	(13.48)	(20.13)
Exporting to CEECs	0.62	12.97	-11.47	-19.46*	0.17
	(5.23)	(47.97)	(10.86)	(10.83)	(13.67)
Export entry to CEECs	33.85***	-75.90**	63.08***	48.31***	94.13***
	(7.10)	(33.92)	(11.87)	(12.33)	(11.75)
Δ FC^{China}	-3.93	-14.12	-3.52	-2.71	-2.08
	(2.49)	(11.71)	(2.62)	(2.14)	(3.31)
Observations	4,150	4,150	3,307	2,580	1,945
R-squared	0.12	0.15	0.09	0.20	0.07
Region FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Industry x Size FE	YES	YES	YES	YES	YES

Notes: The dependent variable is the change in the log of a given sales variable between 1992 and 1998 multiplied by 100.Explanatory variable is normalized to have a mean of 0 and a standard deviation of 1. All regressions include dummies for 2-digit industry by employment size cells and NUTS2 regions. Standard errors are robust to heteroskedasticity and allow for clustering at the 3-digit industry-level (99 industries). Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table B.5: Effects of Exposure to Tariff Reductions on Employment and Wages: Long Differences with Controls, 1992-1998 (OLS)

	Δ log(x) $\times$ 100 from 1992 to 1998				
	Total employment	Total wage bill	Total workhours	Monthly wage	Hourly wage
Δ FC	-6.52**	-9.04***	-8.58***	-2.37***	-0.46
	(2.66)	(3.06)	(2.77)	(0.81)	(0.75)
Sales, in Million EUR	0.23**	0.34***	0.31***	0.11*	0.03
	(0.09)	(0.13)	(0.11)	(0.06)	(0.03)
Firm age	-0.45***	-0.51***	-0.42***	-0.07**	-0.09***
	(0.07)	(0.07)	(0.07)	(0.03)	(0.02)
Foreign ownership	6.77	7.39	9.89*	0.46	-2.50
	(5.26)	(6.33)	(5.90)	(2.07)	(2.12)
Exporting to CEECs	6.63	5.31	5.82	-1.55	-0.51
	(4.35)	(4.87)	(4.34)	(1.68)	(1.54)
Export entry to CEECs	20.64***	20.48***	19.70***	1.21	0.78
	(3.66)	(4.49)	(3.81)	(1.52)	(1.30)
Δ FC^{CH-EU}	-1.66*	-2.30**	-1.81*	-0.50	-0.49*
	(0.91)	(1.13)	(1.01)	(0.34)	(0.29)
Sum of product shares	36.62***	43.81***	42.43***	6.51***	1.38
	(7.86)	(8.43)	(7.70)	(2.17)	(2.25)
Observations	4,028	4,028	4,028	4,028	4,028
R-squared	0.13	0.12	0.11	0.06	0.04
Industry x Size FE	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES

Notes: The dependent variables is the change in the log of a given employment or wage variable between 1992 and 1998 multiplied by 100. Explanatory variable is normalized to have a mean of 0 and a standard deviation of 1. All regressions include dummies for 2-digit industry by employment size cells and NUTS2 regions. Standard errors are robust to heteroskedasticity and allow for clustering at the 3-digit industry-level (99 industries). Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table B.6: Effects of Exposure to Tariff Reductions on Automation Investment per Worker in Levels: 1992-1998 (OLS)

	Automation per worker from 1992 to 1998				
	(1)	(2)	(3)	(4)	(5)
Δ FC	-564.86***	-549.18***	-557.73**	-168.98	-195.55
	(192.98)	(189.82)	(215.01)	(128.66)	(126.11)
Sales		2.61	1.64	1.09	2.85
		(3.79)	(3.63)	(3.27)	(5.03)
Firm age		-9.58*	-10.54**	-9.21**	-8.08**
		(4.91)	(5.17)	(4.18)	(4.04)
Foreign ownership		664.41	623.69	0.09	-460.33
		(567.59)	(546.37)	(447.50)	(368.28)
Exporting to CEECs			198.07	232.21	120.46
			(211.75)	(220.84)	(303.41)
Export entry to CEECs			698.38	322.49	33.50
			(468.39)	(444.03)	(446.62)
Δ FC^{China}			-40.23	-39.22	-42.47
			(74.11)	(45.81)	(42.47)
Observations	3,991	3,964	3,964	3,964	3,953
R-squared	0.00	0.01	0.01	0.05	0.09
Region FE	NO	NO	NO	YES	YES
Industry FE	NO	NO	NO	YES	YES
Industry x Size FE	NO	NO	NO	NO	YES

*Notes:*The dependent variable is the sum of firm-level imports of industrial robots and numerically controlled machinery from 1992 to 1998, deflated to 1990 prices, and divided by the number of production workers in 1992. Explanatory variable is normalized to have a mean of 0 and a standard deviation of 1. Specification (4) include dummies for NUTS2 regions and 2-digit ISIC industries. Specification (5) includes a dummy variable for each 2-digit industry by employment size category (10-49,50-249,250-499, 500-999,≥1000). Standard errors are robust to heteroskedasticity and allow for clustering at the 3-digit industry-level (99 industries). Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table B.7: Heterogeneous Effects of Exposure to Tariff Reductions on Automation Investment in Levels by Sectoral Exposure: 1992-1998 (OLS)

	Automation per worker from 1992 to 1998			
	(1)	(2)	(3)	(4)
△ FC	-607.31***	-237.05*		
	(204.02)	(126.25)		
Labor productivity	67.83	-695.35		
	(540.06)	(932.48)		
△ FC × labor prod.	997.78*	863.89*		
	(524.83)	(460.84)		
△ FC × Low			-379.08**	-194.56
			(175.75)	(128.08)
△ FC × High			-2,391.24***	-1,068.91**
			(774.82)	(424.91)
Labor productivity × Low			-584.00	-329.33
			(567.86)	(714.33)
Labor productivity × High			38,709.63***	19,157.21*
			(11,310.41)	(10,490.42)
△ FC × Labor prod. × Low			255.59	410.72*
			(183.05)	(214.39)
△ FC × Labor prod. × High			77,377.88***	47,267.07**
			(24,255.46)	(22,880.90)
Observations	3,991	3,953	3,991	3,953
R-squared	0.00	0.09	0.03	0.09
Firm characteristics	NO	YES	NO	YES
Contemporaneous controls	NO	YES	NO	YES
Region FE	NO	YES	NO	YES
Industry FE	NO	YES	NO	YES
Industry x Size FE	NO	YES	NO	YES

Notes: Explanatory variable is normalized to have a mean of 0 and a standard deviation of 1. Specifications (2) and (4) incorporate all control variables included in the fully specified model detailed in column (5) of Table 2.4. Standard errors are robust to heteroskedasticity and allow for clustering at the 3-digit industry-level (99 industries). Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table B.8: Effects of Exposure to Tariff Reductions on Employment and Wages by Skill Type: Long Differences, 1992-1998 (OLS)

	Δ log(x) × 100 from 1992 to 1998			
	Total employment	Total wage bill	Total workhours	Average hourly wage
Panel A. Low-skilled workers	(1)	(2)	(3)	(4)
Δ FC	-6.95**	-10.73***	-9.75***	-0.98
	(2.86)	(3.38)	(3.15)	(0.79)
Observations	4,009	3,921	3,921	3,921
R-squared	0.06	0.06	0.05	0.04
Panel B. High-skilled workers	(5)	(6)	(7)	(8)
Δ FC	-4.76	-0.84	-9.07	8.24***
	(6.11)	(6.09)	(6.36)	(2.28)
Observations	1,888	1,506	1,506	1,506
R-squared	0.04	0.04	0.04	0.03
Firm characteristics	YES	YES	YES	YES
Contemp. controls	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Region FE	YES	YES	YES	YES

Notes: The dependent variables are defined as the change in the log of employment, wage bill, workhours or the average hourly wage between 1992 and 1998 multiplied by 100, respectively. Highly skilled workers are defined as workers with more than 12 years of formal education. The explanatory variable is normalized to have a mean of 0 and a standard deviation of 1. All regressions control for the following firm characteristics in 1992: sales, firm age, foreign ownership, CEEC exporter status as well as the sum of product shares. All regressions account for the following contemporaneous changes: a dummy for entry into the CEEC market and exposure to Chinese imports. Regressions also include dummies for 2-digit ISIC industries and NUTS2 regions. Standard errors are robust to heteroskedasticity and allow for clustering at the 3-digit industry-level (99 industries). Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table B.9: Balance Checks: Exposure to Tariff Reductions and Firm-level Controls

	Sales	Firm age	Foreign ownership	Export to CEECs in 1992	Export entry to CEECs by 1998	Chinese imports
	(1)	(2)	(3)	(4)	(5)	(6)
Δ FC	-1.22	1.44	-0.02*	-0.01	0.01	-0.02***
	(0.99)	(0.95)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	5,277	5,277	5,277	5,277	5,277	5,277
R-squared	0.05	0.27	0.11	0.08	0.13	0.29
Ind. x Size FE	YES	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES	YES

Notes: Explanatory variable is normalized to have a mean of 0 and a standard deviation of 1. Regressions control for the sum of shares of product exports to EU in total sales in 1992, region and industry by employment size bracket dummies. Standard errors are robust to heteroskedasticity and allow for clustering at the 3-digit industry-level (99 industries). Regressions are unweighted. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

C

Appendix to Chapter 3

Monopsony and Automation

C.1 Proofs and Propositions

C.1.1 Proof of Proposition 3.2.1:

Proof. Conditional on a level of automation, equation (3.16) always has a solution, since the left-hand side is decreasing in L, and the right-hand side is increasing in L and its range is $[0, \infty)$. We can calculate the equilibrium level of employment for every possible level of automation, calculate the ratio of the marginal product of labor and the marginal product of capital, and find $\tilde{I}$ as the level where the ratio of MPL to MPK is equal to the ratio of γ to η. The ratio of MPL to MPK goes to infinity in the limit when zero tasks are automated, and to zero in the limit when all tasks are automated, which ensures an intersection with the ratio of γ to η curve. The intersection of these two curves determines the unrestricted equilibrium level of automation $\tilde{I}$. If the resulting $\tilde{I}$ is higher than the threshold of automatable tasks I, then the threshold is binding and the equilibrium I^* is equal to the theshold I.
To see that an increase in labor market power increases the equlibrium level of automation when the automation threshold is not binding, we need to show that the MPL/MPK schedule shifts to the right. To see why this is the case, note that the derivative of (log) MPL/MPK with respect to $\log(1+1/\theta)$ taking the level of automation as given is

$$\frac{d\log(F_L/F_K)}{d\log(1+1/\theta)} = \frac{\frac{\varphi}{\sigma}}{1+\frac{\varphi}{\sigma}(1-s_L(1+1/\theta))} > 0. \tag{C.1}$$

□

C.1.2 Further Propositions

Proposition C.1.1 (Displacement Effect)**.** *The derivative of the log labor share with respect to I when the automating threshold is binding is always negative.*

Proof. We start by obtaining an expression for the labor share. Combining the first-order condition for labor and the production function in equation 3.13, yields the following expression:

$$s_{l_j} = \frac{1}{1+\left(\frac{A_K k_j}{A_L l_j}\right)^{\frac{\sigma-1}{\sigma}}} \cdot \frac{1}{1+\frac{1}{\theta}}. \tag{C.2}$$

Since all firms are symmetric, in equilibrium the labor share is the firm-level labor share evaluated at the aggregate labor supply and the capital endowment:

$$s_L = \frac{1}{1+\left(\frac{A_K K}{A_L L}\right)^{\frac{\sigma-1}{\sigma}}} \cdot \frac{1}{1+\frac{1}{\theta}}. \tag{C.3}$$

We rewrite the equation for equilibrium employment as

$$\log(L) = \log(\overline{\varphi}) + \varphi \log(A_L) - \frac{\varphi}{\sigma-1}\log(s_L) - \frac{\sigma\varphi}{\sigma-1}\log\left(1+\frac{1}{\theta}\right). \tag{C.4}$$

This equation does not have a closed-form solution. However, using the implicit function theorem we can take derivative with respect to I:

$$\frac{d\log(L)}{dI} = \varphi\frac{d\log(A_L)}{dI} + \frac{\varphi}{1-\sigma}\frac{d\log(s_L)}{dI}. \tag{C.5}$$

The expression for this derivative is

$$\begin{aligned}
\frac{d\log(s_L)}{dI} &= -s_K\frac{\sigma-1}{\sigma}\left[\frac{d\log A_K}{dI} - \frac{d\log A_L}{dI} - \frac{d\log L}{dI}\right] \\
&= -\frac{s_K}{\sigma}\left[\frac{\eta(I)^{\sigma-1}}{A_K^{\sigma-1}} + (1+\varphi)\frac{\gamma(I)^{\sigma-1}}{A_L^{\sigma-1}}\right] - \frac{s_K\varphi}{\sigma}\frac{d\log(s_L)}{dI} \\
&= -\frac{\frac{s_K\varphi}{\sigma}}{1+\frac{s_K\varphi}{\sigma}}\left[\frac{1}{\varphi}\frac{\eta(I)^{\sigma-1}}{A_K^{\sigma-1}} + \frac{1+\varphi}{\varphi}\frac{\gamma(I)^{\sigma-1}}{A_L^{\sigma-1}}\right],
\end{aligned}$$

which is always negative. □

Proposition C.1.2 (Productivity Effect)**.** *The derivative of the log labor productivity with respect to I when the automation threshold is binding is always positive.*

Proof. Labor productivity is

$$\begin{aligned}
\frac{Y}{L} &= A_L\left[1+\left(\frac{A_K K}{A_L L}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \\
&= A_L\left[s_L\left(1+\frac{1}{\theta}\right)\right]^{\frac{\sigma}{1-\sigma}}
\end{aligned}$$

The expression for the derivative with respect to the automation threshold, when it is binding, is

$$
\begin{aligned}
\frac{d\log(Y/L)}{dI} &= \frac{d\log(A_L)}{dI} + \frac{\sigma}{1-\sigma}\frac{d\log(s_L)}{dI} \\
&= \frac{1}{1-\sigma}\left[\frac{\gamma(I)^{\sigma-1}}{A_L^{\sigma-1}} + \sigma\frac{d\log(s_L)}{dI}\right] \\
&= \frac{1}{1-\sigma}\left[\frac{\gamma(I)^{\sigma-1}}{A_L^{\sigma-1}} - \frac{s_K}{1+\frac{s_K\varphi}{\sigma}}\left(\frac{\eta(I)^{\sigma-1}}{A_K^{\sigma-1}} + (1+\varphi)\frac{\gamma(I)^{\sigma-1}}{A_L^{\sigma-1}}\right)\right] \\
&= \frac{1}{1-\sigma}\frac{1}{1+\frac{s_K\varphi}{\sigma}}\left[(1-s_K+s_K\varphi\frac{(1-\sigma)}{\sigma})\frac{\gamma(I)^{\sigma-1}}{A_L^{\sigma-1}} - s_K\frac{\eta(I)^{\sigma-1}}{A_K^{\sigma-1}}\right] \\
&= \frac{1}{1-\sigma}\frac{1}{1+\frac{s_K\varphi}{\sigma}}\left[(1-s_K)\frac{\gamma(I)^{\sigma-1}}{A_L^{\sigma-1}} - s_K\frac{\eta(I)^{\sigma-1}}{A_K^{\sigma-1}}\right] + \frac{\frac{s_K\varphi}{\sigma}}{1+\frac{s_K\varphi}{\sigma}}\frac{\gamma(I)^{\sigma-1}}{A_L^{\sigma-1}},
\end{aligned}
$$

which is always positive. □

Proposition C.1.3. *The derivative of the equilibrium log wage with respect to I when the automation threshold is binding is the sum of the productivity effect and the displacement effects, with the sign of the overall effect being ambiguous.*

Proof. The expression for the derivative is:

$$
\begin{aligned}
\frac{d\log(W)}{dI} &= \frac{d\log(Y/L)}{dI} + \frac{d\log(s_L)}{dI} \\
&= -\frac{1}{\varphi}\frac{\frac{s_K\varphi}{\sigma}}{1+\frac{s_K\varphi}{\sigma}}\left[\frac{1}{1-\sigma}\frac{\eta(I)^{\sigma-1}}{A_K^{\sigma-1}} + \left(1-\frac{\sigma}{1-\sigma}\frac{1-s_K}{s_K}\right)\frac{\gamma(I)^{\sigma-1}}{A_L^{\sigma-1}}\right].
\end{aligned}
$$

□

Proposition C.1.4. *The derivative of equilibrium log employment with respect to I when the automation theshold is binding is simply the elasticity of labor supply times the derivative of the log wage, and therefore it has the same sign as the latter.*

Proof. The expression for this derivative is

$$
\begin{aligned}
\frac{d\log(L)}{dI} &= \varphi\frac{d\log(W)}{dI} \\
&= -\frac{\frac{s_K\varphi}{\sigma}}{1+\frac{s_K\varphi}{\sigma}}\left[\frac{1}{1-\sigma}\frac{\eta(I)^{\sigma-1}}{A_K^{\sigma-1}} + \left(1-\frac{\sigma}{1-\sigma}\frac{1-s_K}{s_K}\right)\frac{\gamma(I)^{\sigma-1}}{A_L^{\sigma-1}}\right].
\end{aligned}
$$

□

C.2 Data Sources

C.2.1 Local Labor Market Exposure to Robots

We follow Acemoglu and Restrepo (2020a) and construct a measure of commuting zone exposure using the following data sources:

Industrial robots: We use data on the operational stock of industrial robots from the International Federation of Robotics (IFR) for the United States and six European countries (Denmark, Finland, France, Italy, Sweden, Germany) from 1993 to 2016.[1] We classify the IFR data into 13 manufacturing industries, and 6 broad industries outside manufacturing.[2] To obtain the 19 IFR industries as in Acemoglu and Restrepo (2020a), we perform the following adjustments to the original data: First, we keep the industry "all other manufacturing branches" and label it as "Miscellaneous manufacturing". Second, "All other non-manufacturing branches" are considered as "Services". Third, the residual category "Metal (unspecified)" is allocated proportionally to all industries in the "Metal industries" (Basic Metals, Metal Products, Electronics, Industrial Machinery) and 4.) the residual "Unspecified", which is allocated proportionally over all 19 IFR industries. The IFR data comes with two drawbacks: first, it groups the US together with Canada as Northern America before 2011 and second, it doesn't provide a split-up by industries for the Northern America before 2004. Given that the US accounts for about 90 percent of the North American robot stock, we accept the first limitation. To deal with the second limitation, we apply an algorithm that attributes the total stock in each year before 2004 according to an industry's share in the total stock in 2004, the first year with disaggregated information on the industry level. We apply this solution also to Denmark, which similarly lacks data by industry before 1996.

Industry employment and output: Furthermore, we use data on employment and output from the 2007 and 2019 EU KLEMS releases (Timmer, O Mahony, Van Ark,

[1] These selected European countries exhibit levels and an evolution of the number of robots per 1000 workers that mirror the US over the sample period from 1993 to 2015 and will be used to construct an instrumental variable.

[2] Manufacturing industries include Food and Beverages, Textiles, Wood and Furniture, Paper and Printing, Plastics and Chemicals, Minerals, Basic Metals, Metal Products, Electronics, Industrial Machinery, Automotive, Shipbuilding and Aerospace, Miscellaneous Manufacturing; Non-Manufacturing industries include Agriculture, Mining, Utilities, Construction, Education and Research, Services.

et al., 2007; Stehrer et al., 2019).[3] As in Acemoglu and Restrepo (2020a), we translate the numbers of persons employed in each European country-industry in 1990 into "US equivalent workers" by dividing the total number of hours worked in a European industry by the hours per worker in the corresponding US industry. This is to account for the fact that European workers work on average less hours and to make employment numbers comparable. To adjust for the growth in robot stock due to output growth, we compute an output growth rate and use the output deflators provided by EU KLEMS to correct for inflation.

Commuting zone employment: Finally, we compute industry employment shares in each commuting zone in 1970 and 1990 as well as changes in labor market outcomes using microdata from the US Decennial Census for the years 1970, 1990 and 2000 as well as from the American Community Survey in 2006, 2007 and 2008 and 2014, 2015 and 2016 provided by the *Integrated Public Use Microdata Series* (IPUMS). We use the crosswalks by D. Autor and Dorn (2013) to map geographies provided in the IPUMS data to 722 continental commuting zones.

To compute the industry employment in each commuting zone in a given year, we sum over working individuals aged 16 or older by industry using person weights from IPUMS multiplied with probability weights from the geographical crosswalks. We calculate the total commuting zone employment simply as the sum of employment across all industries.[4]

C.2.2 Local Labor Market Outcomes

Employment, unemployment and non-participation: Following Acemoglu and Restrepo (2020a), we calculate averages for demographic groups within commuting zones using microdata from the US Decennial Census for 1970, 1990, and 2000, the American Community Survey for 2006, 2007, and 2008, and for 2014, 2015, and 2016 provided by the *Integrated Public Use Microdata Series* (IPUMS). We focus on individuals aged 16 to 65 employed in the private sector, specifically in manufacturing or blue-collar occupations. Unemployment rates are computed relative to the commuting zone's total labor force, and non-participation rates are relative to the total

[3]We use both releases as the 2019 release in NACE 2 only covers the period 2000 to 2018, while the 2007 NACE1 release only provides data from 1970 to 2005. To obtain industry employment and output data for multiple countries from 1990 to 2016 we do therefore need to combine both the 2007 NACE 1 and the 2019 NACE 2 releases. The mapping of NACE 1/2 to IFR industries is available upon request.

[4]The mapping of 1990 Census Bureau industry classes to corresponding IFR industries is also available upon request.

working-age population.

Average wages: To calculate average wages across demographic groups within commuting zones, we use microdata on annual wage income, number of weeks worked, and hours worked per week from the 1990, and 2000 U.S. decennial censuses, as well as data from the 2006, 2007, and 2008 American Community Survey. As the American Community Survey data lack information on the number of weeks worked per year for the years 2014, 2015, and 2016, we cannot compute differences for the period 2007 to 2015 and have to limit the wage regression analysis to the years 1990 to 2007. Our analysis focuses on individuals aged 16 to 65 employed.

To handle top-coded wage incomes, we cap them at 1.5 times the respective annual top-coded wage for each year and deflate wages using the 1999 consumer price index. Average weekly income is computed by dividing total annual wage income by weeks worked, while hourly wages are derived by dividing the average weekly wage by the usual number of hours worked per week, as indicated in the microdata. We winsorize hourly wages at $2 USD, in line with Acemoglu and Restrepo (2020a).

Individuals are categorized into one of 250 demographic cells within each commuting zone, defined by age groups (16-25, 26-35, 36-45, 46-55, 56-65), educational attainment (less than high school, high school degree, some college, college/professional degree, and masters/doctoral degree), sex (male/female), and race (Hispanic, Black, White, Asian, Other). We calculate average yearly, weekly, and hourly wages for each demographic group within each commuting zone cell.

C.3 Tables

Table C.1: Details on Employment Size Brackets in County Business Patterns Data

Size bracket	Mid-Point
1-4	3
5-9	7
10-19	15
20-49	35
50-99	75
100-249	175
250-499	375
500-999	750
1000-1499	1250
1500-2499	2000
2500-4999	3750
5000-more	imputed

Notes: This table displays the size brackets used to categorize establishment statistics in the County Business Patterns Dataset. It shows mid-points used by the authors to compute employer concentration as defined in Equation 3.20. Source: Authors' calculations based on County Business Patterns.

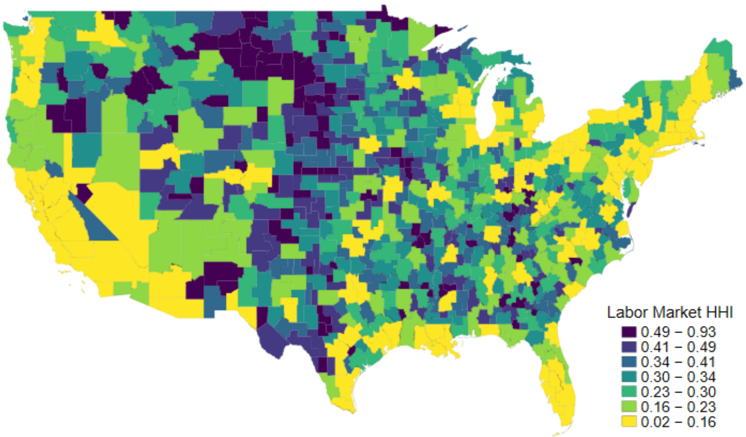
Table C.2: Summary Statistics of the Commuting Zone Data: 1990-2015

		Means by quartiles of exposure to robots		
	All	Q1	Q4	Q4-Q1
	(1)	(2)	(3)	(4)
Changes in outcomes, 1990-2015:				
Log private sector employment	21.72	28.23	14.23	-14.00***
Log manufacturing employment	-13.87	4.25	-28.48	-32.73***
Log blue-collar employment	1.80	16.42	-11.37	-27.79***
Employment to population ratio	2.00	4.23	0.22	-4.01***
Unemployment rate	-0.45	-0.85	-0.31	0.55***
Non-participation rate	1.84	0.40	3.14	2.74***
Changes in outcomes, 1990-2007:				
Log average yearly wage	10.69	15.66	6.31	-9.35***
Log average weekly wage	5.00	9.94	1.00	-8.93***
Log average hourly wage	2.80	8.41	-0.98	-9.39***
Share of population, 1990:				
Female	0.51	0.51	0.51	0.01***
Less than college	0.71	0.69	0.74	0.05***
Some college or more	0.25	0.28	0.23	-0.05***
White	0.87	0.87	0.89	0.03**
Black	0.08	0.03	0.09	0.05***
Asian	0.00	0.00	0.00	-0.00
Hispanic	0.06	0.10	0.02	-0.09***
Above 65 years old	0.13	0.14	0.13	-0.00
Share of employment, 1990:				
Manufacturing	0.17	0.08	0.24	0.16***
Light manufacturing (in manufacturing)	0.22	0.21	0.22	0.01
Female employment (in manufacturing)	0.33	0.32	0.32	0.00
Routine employment	0.36	0.33	0.38	0.05***
Labor market concentration, 1990:				
Employment $\overline{\text{HHI}}$	0.33	0.38	0.29	-0.10***
Observations	722	181	180	361

Note: Columns (1) to (3) display unweighted means of changes in outcomes *multiplied by 100* as well as unweighted means of commuting zone characteristics in 1990. For each commuting zone we compute the average exposure to robots the periods 1990 to 2000, 2000 to 2007 and 2007 to 2015. Columns (2) and (3) display unweighted means within commuting zones in the first and last quartile of the exposure distribution, respectively. Column (4) displays the difference in the mean commuting zone characteristics between means forth and the first quartile of robot exposure and reports statistical significance of the underlying ttest. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

C.4 Figures

Figure C.1: Local Labor Market Concentration across US Commuting Zones in 1990



Notes: This figure shows the geographic variation in local labor market concentrations, as defined in Equation 3.20, across 722 continental US commuting zones in 1990. Source: Author's own calculations based on County Business Patterns.

D

Appendix to Chapter 4

Labor Market Power and Automation

D.1 Theoretical Framework

This appendix summarizes the theoretical framework by Yeh, Macaluso, and Hershbein (2022), providing a formal derivation of the markdown expression in Equation 4.2. Section D.1.1 presents the derivation of a firm's markup in the output market as the wedge between a flexible input's output elasticity and its revenue share under the assumption that the flexible input is unaffected by monopsony power or adjustment frictions. Building on the markup derivation, Section D.1.2 shows how to further derive an expression of a firm's markdown in terms of output elasticities and revenue shares. It demonstrates that recovering output elasticities and revenue shares is sufficient to estimate markdowns.

D.1.1 Derivation of Markups

To derive markdowns, Yeh, Macaluso, and Hershbein (2022) start with the insight by Hall, Blanchard, and Hubbard (1986) that the wedge between the output elasticity of a flexible input and its revenue share reflects a firm's output market power in terms of its markup, defined as its output price over marginal cost of production.
To see this, consider a firms' cost minimization problem, as follows

$$\min \sum_{k=1}^{K} V_{it}^{k}\left(X_{it}^{k}\right) X_{it}^{k} + \Phi_{t}^{k}\left(X_{it}^{k}, X_{it-1}^{k}\right) \quad \text{s.t.} \quad F\left(\mathbf{X}_{it}; \omega_{it}\right) \geq Q_{it}, \tag{D.1}$$

where $\mathbf{X} = \left(X^1, \ldots, X^K\right)'$ is a firm's vector of $K > 1$ production inputs with prices V^k. Furthermore, $F\left(\mathbf{X}; \omega_{it}\right)$ denotes the firm's firms production technology, whereas ω_{it} denotes the productivity level of firm i at time t. Adjustment costs for inputs are captured in the term $\Phi_{t}^{k}\left(X_{it}^{k}, X_{it-1}^{k}\right)$
Under the assumptions stated in Yeh, Macaluso, and Hershbein (2022), there exists at least one flexible input. That is, an input that is neither characterized by market power nor adjustment costs. The first order condition for any flexible input k' is given by

$$V_{it}^{k'} = \lambda_{it} \frac{\partial F\left(\mathbf{X}_{it}; \omega_{it}\right)}{\partial X_{it}^{k'}}, \tag{D.2}$$

where λ_{it} is the Lagrangian multiplier of the cost minimization problem. The term λ_{it} reflects the shadow value of total variable costs and is also known as firm i's marginal production cost.

After multiplying both sides with $\frac{X_{it}^{k'}}{P_{it}Q_{it}}$, where P_{it} is firm's price per unit of output Q_{it}, one obtains

$$\frac{V_{it}^{k'}X_{it}^{k'}}{P_{it}Q_{it}} = \frac{\lambda_{it}}{P_{it}}\frac{\partial F\left(\mathbf{X}_{it};\omega_{it}\right)}{\partial X_{it}^{k'}}\frac{X_{it}^{k'}}{Q_{it}}. \tag{D.3}$$

Using the definition of a firm's markup as the ratio of its output price and its marginal cost of production, $\mu_{it} = \frac{P_{it}}{\lambda_{it}}$, it is possible to derive an expression of the markup of firm i at time t as:

$$\mu_{it} = \frac{\theta_{it}^{k'}}{\alpha_{it}^{k'}}, \tag{D.4}$$

where $\theta_{it}^{k'} \equiv \frac{\partial F(\mathbf{X}_{it};\omega_{it})}{\partial X_{it}^{k'}}\frac{X_{it}^{k'}}{Q_{it}}$ is the elasticity of production with respect to the flexible input k' and $\alpha_{it}^{k'} \equiv \frac{V_{it}^{k'}X_{it}^{k'}}{P_{it}Q_{it}}$ is the revenue share of the variable input k'. As such, a firm's markup is equal to the wedge between the output elasticity and the revenue share of some input k'.

D.1.2 Derivation of Markdowns

In the next step, Yeh, Macaluso, and Hershbein (2022) consider the following conditional cost-minimization problem with respect to labor:

$$\min_{l_{it}\geq 0} \; w_{it}\left(l_{it}\right)l_{it} \quad s.t. \quad F\left(l_{it},\mathbf{X}_{-l,it}^{*};\omega_{it}\right) \geq Q_{it}, \tag{D.5}$$

where $\mathbf{X}_{-l,it}^{*}$ denotes the vector of optimal inputs except of labor l_{it} and w_{it} denotes the endogenous wage.

The first-order condition with the Lagrangian multiplier λ_{it} is given by:

$$w_{it}^{\prime}l_{it} + w_{it} = \lambda_{it}\cdot\frac{\partial F\left(l_{it},\mathbf{X}_{-l,it}^{*};\omega_{it}\right)}{\partial l_{it}}, \tag{D.6}$$

which can be rearranged as:

$$\left[\frac{w_{it}^{\prime}l_{it}}{w_{it}}+1\right] = \frac{\lambda_{it}}{P_{it}}\cdot\frac{\partial F\left(l_{it},\mathbf{X}_{-l,it}^{*};\omega_{it}\right)}{\partial l_{it}}\frac{l_{it}}{Q_{it}}\cdot\frac{P_{it}Q_{it}}{w_{it}\left(l_{it}\right)l_{it}} \tag{D.7}$$

$$\equiv \mu_{it}^{-1}\cdot\frac{\theta_{it}^{l}}{\alpha_{it}^{l}}. \tag{D.8}$$

The left hand side corresponds to the markdown, while θ^l_{it} stands for the output elasticity of labor and α^l_{it} for the revenue share of labor. Given our derivation of the markup μ_{it} in equation D.4, we can rewrite the markdown as:

$$\nu_{it} = \frac{\theta^l_{it}}{\alpha^l_{it}} \cdot \left(\frac{\theta^{k'}_{it}}{\alpha^{k'}_{it}} \right)^{-1}. \tag{D.9}$$

Hence, the markdown of firm i in year t can be expressed in terms of output elasticities and revenue shares of labor and material inputs. While revenue shares are observed in the data, output elasticities need to be estimated. In sum, Equation D.9 demonstrates that recovering output elasticities and revenue shares is sufficient to estimate markdowns.

It is important to note that the summarized approach by Yeh, Macaluso, and Hershbein (2022) relies on the standard assumptions that firms are subject to a finitely elastic labor supply curve and do not have market power in material input markets. However, recent empirical evidence suggests that the assumption of perfect competition in material input markets does not always hold. For instance, Morlacco (2017) reports evidence of market power in imported intermediate inputs in a sample of French manufacturing firms. Yeh, Macaluso, and Hershbein (2022) point out that in the presence of such monopsony power in material input markets, Equation D.9 would reflect the markdown for labor *relative* to the markdown for materials. If markdowns for materials exceeded unity, then markdown estimates for labor would be biased towards zero. In other words, a violation of the flexible inputs assumption would result in an underestimation of labor market power among firms.

D.2 Markdown Estimation

This section presents an overview of the production function estimation method of Yeh, Macaluso, and Hershbein (2022). This approach allows recovering firm-specific output elasticities from estimated production function parameters, a key component in calculating markdowns as detailed in D.9. First, Section D.2.1 briefly discusses the endogeneity problem inherent in estimating production function parameters from firm-level data and describes the instrumental variable approach that Yeh, Macaluso, and Hershbein (2022) take to mitigate this problem. Next, Section D.2.2 explains the estimation procedure. Finally, Section D.2.3 outlines how to obtain output elasticities from estimated production function parameters and compute markdowns.

D.2.1 Adressing Endogeneity in Production Function Estimation

To compute markdowns as defined in Equation D.9, it is necessary to determine firm-specific output elasticities, which reflect how output changes with variations in a specific input k, while holding other factors constant. However, such elasticities are not directly observable in data. The central task, therefore, is to estimate the parameters of the production function $F(X_{it}, \omega_{it})$, defining how firms combine inputs to produce output. Once these parameters are known, the output elasticity for any input k can be determined as the partial derivative of the production function with respect to k. This section briefly discusses the challenge of endogeneity in estimating production function parameters and explains the method by Yeh, Macaluso, and Hershbein (2022) that I adopt to address this issue.

Consider the following functional relationship between a firm's inputs and outputs:

$$y_{it} = f\left(\mathbf{x}_{it}; \boldsymbol{\beta}\right) + \omega_{it} + \varepsilon_{it}, \tag{D.10}$$

where y_{it} is the log of observed output, $\mathbf{x}_{it}$ the vector of log inputs, $f\left(\mathbf{x}it; \boldsymbol{\beta}\right)$ the log-transformed production function, ω_{it} the firm-specific idiosyncratic productivity in year t, and ε_{it} the measurement error.

The goal is to estimate production function parameters $\boldsymbol{\beta}$, essential to deriving output elasticities. This estimation faces the well-known endogeneity problem of simultaneity or transmission (Marschak & Andrews, 1944; Griliches & Mairesse, 1995). The issue arises from the firm-year-specific productivity ω_{it} which simultaneously influences both a firm's choice of inputs and its output, yet remains unobservable to the econometrician. For example, a firm might implement a new technology or management practice that enhances productivity. This increase in productivity might lead to an increase in output, but it might also influence the firm's decision on how much labor or capital to use, which means that input decisions are no longer independent of output. A simple least squares regression of output on inputs, without adjusting for these unobserved factors, would therefore result in a correlation between inputs and the error term. This correlation would violate the exogeneity requirement of Ordinary Least Squares (OLS) estimation, leading to biased and inconsistent parameter estimates of the production function.

To obtain unbiased and consistent estimates of production function parameters $\boldsymbol{\beta}$, I adopt the 'proxy variable' method, as in Yeh, Macaluso, and Hershbein (2022), building on established production function estimation methodologies developed by Olley and Pakes (1996), Levinsohn and Petrin (2003), Loecker and Warzynski (2012) and

Ackerberg, Caves, and Frazer (2015). This approach addresses the endogeneity arising from simultaneity by using lagged inputs as instruments orthogonal to productivity shocks in period t and using material inputs to construct a proxy variable for unobserved productivity shocks. The theory behind the proxy variable approach can be briefly summarized as follows.

Consider the production function as defined by:

$$Q_{it} = F(\mathbf{V}_{it}, \mathbf{K}_{it}; \omega_{it}),$$

where $\mathbf{V}_{it}$ denotes flexible inputs, $\mathbf{K}_{it}$ denotes nonflexible inputs and and ω_{it} denotes a firm's year-specific productivity. Firms take $\mathbf{K}_{it}$ as given state variables when choosing flexible inputs $\mathbf{V}_{it}$. Let's further assume that measurement error enters production in a multiplicative fashion such that the log of observed output satisfies $y_{it} = ln(Q_{it}) + \varepsilon_{it}$. Firms do not observe measurement error when making their optimal input decisions. Given standard assumptions of production function methodologies detailed in Yeh, Macaluso, and Hershbein (2022), observed output can be rewritten as

$$y_{it} = f(\mathbf{v}_{it}, \mathbf{k}_{it}; \boldsymbol{\beta}) + \omega_{it} + \varepsilon_{it}$$

where $f(\mathbf{v}_{it}, \mathbf{k}_{it}, \boldsymbol{\beta})$ represents the log-transformed production function F, with $\mathbf{v}_{it}$ and $\mathbf{k}_{it}$ being the log-transformed representations of $\mathbf{V}_{it}$ and $\mathbf{K}_{it}$, respectively. Firm-level productivity is again denoted as ω_{it} which is observable by the firm but not by the econometrician.

To deal with the endogeneity stemming from the unobservable productivity, Yeh, Macaluso, and Hershbein (2022) apply the fundamental insight by Levinsohn and Petrin (2003) that under standard assumptions, material demand can be used to proxy for productivity. If firms choose flexible inputs $\mathbf{v}_{it}$ given the state variable $\mathbf{k}_{it}$, idiosyncratic productivity ω_{it} and some controls $\mathbf{c}_{it}$, the firm's input demand can be written as

$$m_{it} = m_t(\omega_{it}; \mathbf{k}_{it}, \mathbf{c}_{it}),$$

where the vector $\mathbf{c}_{it}$ denotes other observable variables that can affect a firm's optimal demand for material inputs, in particular year fixed effects. Following the insight by Levinsohn and Petrin (2003), material demand is invertible and monotonic in productivity. Under standard assumptions, a mapping $h(m_{it}; \mathbf{k}_{it}, \mathbf{c}_{it})$ can be established such that productivity is defined by

$$\omega_{it} = h(m_{it}; \mathbf{k}_{it}, \mathbf{c}_{it}).$$

Consequently, the production function can be expressed in terms of observables only:

$$\begin{aligned} y_{it} &= f(\mathbf{v}_{it}, \mathbf{k}_{it}; \boldsymbol{\beta}) + h(m_{it}; \mathbf{k}_{it}, \mathbf{c}_{it}) + \varepsilon_{it} && \text{(D.11)} \\ &= \phi_t(\mathbf{v}_{it}, \mathbf{k}_{it}, \mathbf{c}_{it}) + \varepsilon_{it} && \text{(D.12)} \\ &= \varphi_{it} + \epsilon_{it} && \text{(D.13)} \end{aligned}$$

This implies that the production function parameters $\boldsymbol{\beta}$ can be recovered from observables through estimation.

D.2.2 Production Function Estimation Procedure

As in Yeh, Macaluso, and Hershbein (2022), I specify the production function as a translog function, which is a second-order approximation of any differentiable function containing the first-, cross, and second-order terms of the input vector $\mathbf{X}_{it}$. The translog function's main advantage lies in its minimal assumptions about the functional form of production and nests a range of functional forms, including the Cobb-Douglas specification.
Using capital, labor, materials and energy as inputs, the translog specification of the production function is given by:

$$\begin{aligned} f(\mathbf{x}_{it}; \boldsymbol{\beta}) = \beta_K k_{it} &+ \beta_L l_{it} + \beta_M m_{it} + \beta_E e_{it} \\ &+ \beta_{KL} k_{it} l_{it} + \beta_{KM} k_{it} m_{it} + \beta_{KE} k_{it} e_{it} + \beta_{LM} l_{it} m_{it} + \beta_{LE} l_{it} e_{it} + \beta_{ME} m_{it} e_{it} \\ &+ \beta_{KK} k_{it}^2 + \beta_{LL} l_{it}^2 + \beta_{MM} m_{it}^2 + \beta_{EE} e_{it}^2 \end{aligned}$$

Following the methodology by Loecker and Warzynski (2012) and assuming that capital is chosen one period ahead, the instrument vector $\mathbf{z}_{it}$ is formed by lagging each input of $\mathbf{x}_{it}$, except for capital and given by

$$\begin{aligned} \mathbf{z}_{it} =& (k_{it}, l_{it-1}, m_{it-1}, e_{it-1}, k_{it} l_{it-1}, k_{it} m_{it-1}, k_{it} e_{it-1}, l_{it-1} m_{it-1}, l_{it-1} e_{it-1}, m_{it-1} e_{it-1}, \\ & k_{it}^2, l_{it-1}^2, m_{it-1}^2, e_{it-1}^2)'. \end{aligned}$$

Then, I estimate production function parameters $\boldsymbol{\beta}$ for each industry, implementing the following three-step procedure from Yeh, Macaluso, and Hershbein (2022):

Non-parametric estimation of φ_{it} and ε_{it}: First, we need to estimate φ_{it}, which is log output free of measurement error by regressing observed log output y_{it} on a second-order polynomial of the input vector $\mathbf{x}_{it}$. This allows recovering fitted values $\hat{\varphi}_{it}$ and residuals $\hat{\varepsilon}_{it}$, where the residuals represent measurement error in observed output.

Construction of innovations ξ_{it} to productivity ω_{it}: Second, we construct innovations ξ_{it} under the standard assumption that idiosyncratic productivity ω_{it} follows a Markov process. This means that expected value productivity is a function of lagged values and innovations xi_{it} are just random disturbances in this process, i.e. $\omega_{it} = g(\omega_{it-1}) + \xi_{it}$. Then productivity can be expressed as

$$\omega_{it}(\boldsymbol{\beta}) = \hat{\varphi}_{it} - f(\mathbf{x}_{it}; \boldsymbol{\beta}).$$

Following de Loecker and Warzynski (2012), productivity can be approximated with a third-order polynomial of lagged productivity:

$$\omega_{it}(\boldsymbol{\beta}) = \rho_1 \omega_{it-1}(\boldsymbol{\beta}) + \rho_2 \omega_{it-1}^2(\boldsymbol{\beta}) + \rho_3 \omega_{it-1}^3(\boldsymbol{\beta}) + \xi_{it}$$

We obtain $\hat{\boldsymbol{\rho}}$ by running a least squares regression and can finally construct innovations ξ_{it} as the residual error:

$$\xi_{it}(\boldsymbol{\beta}) = \omega_{it}(\boldsymbol{\beta}) - \hat{\rho}_1 \omega_{it-1}(\boldsymbol{\beta}) - \hat{\rho}_2 \omega_{it-1}^2(\boldsymbol{\beta}) - \hat{\rho}_3 \omega_{it-1}^3(\boldsymbol{\beta})$$

As a result of this step, we have obtained idiosyncratic productivities $\omega_{it}(\boldsymbol{\beta})$ as well as innovations $\xi_{it}(\boldsymbol{\beta})$.

GMM-IV estimation of $\hat{\beta}$: Third, Yeh, Macaluso, and Hershbein (2022) impose moment conditions on the productivity shocks that will help identify betas through GMM estimation. In particular, they impose that in expectation productivity shocks are orthogonal to the instrument vector $\mathbf{z}_{it}$:

$$\mathbb{E}(\xi_{it}(\boldsymbol{\beta}) \cdot \mathbf{z}_{it}) = \mathbf{0}_{Z\times 1}. \tag{D.14}$$

This system of equations defines a set of exogeneity conditions that the instrument vector $\mathbf{z}_{it}$ needs to satisfy. In particular, the identification strategy hinges on two key assumptions for validity. Firstly, capital is assumed to be predetermined, chosen one period ahead, thus implying orthogonality of k_{it} to the innovation ξ_{it}. Secondly, it is assumed that firms lack foresight into future productivity innovations, ensuring that past input decisions are orthogonal to current idiosyncratic productivity shocks. Beyond exogeneity, the strategy's success also depends on the relevance of the instruments, particularly for material inputs. These instruments must show a correlation with current material inputs. Yeh, Macaluso, and Hershbein (2022) propose that a sufficient condition for this relevance is the persistence of material input prices over time.

Ultimately, Yeh, Macaluso, and Hershbein (2022) implement the moment condition from Equation D.2.2 and determine the optimal production function parameters $\hat{\boldsymbol{\beta}}$ by numerically minimizing the following quadratic loss function:

$$\hat{\boldsymbol{\beta}} =_{\boldsymbol{\beta}\in\mathbb{R}^Z} \sum_{m=1}^{Z} \left(\sum_{i=1}^{N} \sum_{t=1}^{T} \xi_{it}(\boldsymbol{\beta}) z_{it}^{m} \right)^2 ,$$

with $\mathbf{z}_{it} = (z_{it}^1, ..., z_{it}^Z)$.

D.2.3 Computing Markdowns

After estimating the optimal parameters $\hat{\boldsymbol{\beta}}$, output elasticities for labor and materials can be derived. These are obtained as the partial derivatives of the translog production function with respect to labor and materials, respectively, and are expressed as follows:

$$\hat{\theta}_l^{j(i)}\left(\tilde{\mathbf{x}}_{it}; \hat{\boldsymbol{\beta}}\right) = \hat{\beta}_L^{j(i)} + \hat{\beta}_{KL}^{j(i)} k_{it} + \hat{\beta}_{LM}^{j(i)} m_{it} + \hat{\beta}_{LE}^{j(i)} e_{it} + 2\hat{\beta}_{LL}^{j(i)} l_{it}$$
$$\hat{\theta}_M^{j(i)}\left(\tilde{\mathbf{x}}_{it}; \hat{\boldsymbol{\beta}}\right) = \hat{\beta}_M^{j(i)} + \hat{\beta}_{KM}^{j(i)} k_{it} + \hat{\beta}_{LM}^{j(i)} l_{it} + \hat{\beta}_{ME}^{j(i)} e_{it} + 2\hat{\beta}_{MM}^{j(i)} m_{it}$$

It is important to note that although production function parameters are estimated seperately for each industry j and constant over time, under a translog specification, the estimated output elasticities $\hat{\theta}_l^{j(i)}$ and $\hat{\theta}_m^{j(i)}$ are permitted to vary across firms within an industry, as they are contingent on the time-varying levels of each firm's inputs.

Finally, I compute the markdown ν_{it} as derived in Equation D.9, by combining *estimated* output elasticities with *observed* revenue shares of inputs:

$$\hat{\nu}_{it} = \hat{\theta}_l^{j(i)}\left(\tilde{\mathbf{x}}_{it}; \hat{\boldsymbol{\beta}}\right) \left(\frac{l_{it}}{y_{it}}\right)^{-1} \left[\hat{\theta}_M^{j(i)}\left(\tilde{\mathbf{x}}_{it}; \hat{\boldsymbol{\beta}}\right) \left(\frac{m_{it}}{y_{it}/\exp(\hat{\varepsilon})}\right)^{-1} \right]^{-1} \tag{D.15}$$

where $\mathtt{y}_{it}$ denotes sales adjusted for inventories, $\mathtt{l}_{it}$ represents the wage bill, and $\mathtt{m}_{it}$

indicates the material consumption of firm i in year t as observed in the data.[1]

[1]Note that I observe only output values, not quantities or prices directly in the *SCIE* dataset. To derive output levels, I therefore deflate sales adjusted for inventories using EUKLEMS industry-level output price deflators, which introduces potential bias in measuring real output. To address this in markup computation, I follow Yeh, Macaluso, and Hershbein (2022) and correct the bias by scaling observed output y_{it} by the correction term $\exp(\hat{\varepsilon})$. This correction technique is consistent with the methodology established by Loecker and Warzynski (2012).

D.3 Tables

Table D.1: Descriptive Statistics of Firm-level Markdowns by Industry: 2005-2020

Industry Group	Median	Mean	IQR_{25-75}	SD	N
Food and beverages	1.073	1.145	0.449	0.394	62,260
Other non-metallic minerals	1.086	1.115	0.510	0.364	25,773
Furniture and other manufacturing	1.092	1.099	0.339	0.284	35,029
Paper, printing and reproduction	1.097	1.172	0.572	0.441	22,810
Coke and refined petroleum	1.103	1.213	0.810	0.576	1,008
Textiles and apparel	1.123	1.165	0.451	0.321	61,221
Repair and installation of machinery	1.132	1.172	0.421	0.344	15,592
Computer, electronic, optical products	1.164	1.179	0.499	0.354	1,924
Machinery and equipment n.e.c.	1.169	1.168	0.379	0.291	12,696
Wood and cork	1.171	1.164	0.410	0.334	25,695
Electrical equipment	1.189	1.205	0.417	0.347	4,872
Fabricated metal products	1.217	1.203	0.295	0.259	67,666
Leather products	1.252	1.257	0.461	0.314	20,417
Motor vehicles, trailers and semi-trailers	1.297	1.346	0.533	0.417	4,377
Basic metals	1.314	1.328	0.742	0.505	2,514
Rubber and plastics products	1.324	1.316	0.479	0.364	10,263
Other transport equipment	1.413	1.431	0.648	0.460	1,605
Chemicals and pharmaceuticals	1.446	1.472	0.644	0.476	5,745
All industries	1.154	1.178	0.430	0.348	381,467

Notes: This table provides summary statistics of estimated firm-level markdowns, organized by industry groups that broadly align with the 2-digit ISIC classification. Source: Authors' own calculations from Integrated Business Accounts data in 2004-2020.

Table D.2: Details on the Lag Structure of Markdowns and Investment in Machinery: Panel Regressions, 2005-2020 (OLS)

	asinh(investment in machinery$_t$)				
	(1)	(2)	(3)	(4)	(5)
log(markdown)	0.922***				0.883***
	(0.056)				(0.071)
log(markdown$_{t-1}$)		0.930***			0.785***
		(0.048)			(0.056)
log(markdown$_{t-2}$)			0.653***		0.439***
			(0.050)		(0.054)
log(markdown$_{t-3}$)				0.390***	0.318***
				(0.049)	(0.051)
Observations	374,871	335,053	294,662	257,322	224,273
R-squared	0.57	0.58	0.59	0.60	0.59
Industry × Year FE	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES

Notes: Dependent variables: inverse hyperbolic sine transformation of investment in machinery and equipment. Controls: 2-digit industry-year dummies and firm fixed effects. Sample size decreases with longer lags of the independent variables. Standard errors in parentheses are two-way clustered by firm and 2-digit industry-year pairs. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table D.3: Overview of SCUT Highways and Treated Municipalities

Highway	**Municipalities Within 10km**
Tolls introduced on 15 October 2010	
SCUT Grande Porto—79 km	
A4	Matosinhos, Maia, Porto
A41	Matosinhos, Valongo, Santa Maria da Feira, Espinho
A42	Valongo, Paços de Ferreira, Paredes, Lousada, Penafiel, Santo Tirso, Felgueiras
SCUT Litoral Norte—113 km	
A28	Matosinhos, Vila do Conde, Póvoa de Varzim, Esposende, Viana do Castelo, Caminha, Barcelos, Vila Nova de Cerveira
SCUT Costa da Prata—110 km	
A29	Estarreja, Ovar, Espinho, Vila Nova de Gaia, Oliveira de Azeméis, Santa Maria da Feira, São João da Madeira
Tolls introduced on 8 December 2011	
SCUT Algarve—133 km	
A22	Lagos, Monchique, Portimão, Lagoa, Silves, Albufeira, Loulé, Faro, Olhao, Tavira, Castro Marim, Vila Real de Sto. António, São Brás de Alportel
SCUT Beira interior—217 km	
A23	Torres Novas, Entroncamento, Constância, Abrantes, Sardoal, Mação, Gavião, Vila Velha de Rodao, Vila Nova da Barquinha, Castelo Branco, Fundão, Belmonte, Covilhã, Guarda, Tomar, Ourém, Alcanena, Golegã
SCUT Interior Norte—162 km	
A24	Viseu, Castro Daire, Lamego, Peso da Régua, Vila Real, Vila Pouca de Aguiar, Chaves, Tarouca, Santa Marta de Penaguião
SCUT Beiras Litoral e Alta—173 km	
A25	Ílhavo, Aveiro, Albergaria-a-Velha, Sever do Vouga, Oliveira de Frades, Vouzela, Viseu, Mangualde, Fornos de Algodres, Celorico da Beira, Guarda, Pinhel, Almeida, Penalva do Castelo, Nelas

Note: This table presents the author's classification of treated municipalities, based on information about the municipalities intersected by SCUT highways as reported in Audretsch, Dohse, and dos Santos (2020), and data on road distances between population-weighted centroids of municipalities and highway access ramps from the TiTuSS database (Afonso et al., 2023).

Table D.4: Summary Statistics of Event Study Sample

Variable	Mean	SD	Q1	Q3	Observations
Output (€)	2,592,679	46,451,051	90,548	777,021	439,517
Payroll (€)	299,659	1,486,100	25,994	183,128	439,518
Fixed Tangible Assets (€)	806,756	11,512,150	10,552	250,941	439,518
Capital Intensity (€)	25,189	146,923	1,951	22,580	439,518
Number of Employees	22	73	3	17	439,518
Annual Wage (€)	10,155	6,889	6,931	12,033	439,518
Machinery Investment (€)	80,488	1,548,704	0	9,463	439,518
Markdown	1.186	0.346	0.955	1.384	312,125

Notes: Data consists of firm-year observations from 2004 to 2020. Monetary values of production variables are adjusted to 2010 Euro prices. 'Output' denotes sales net of changes in inventory. 'Payroll' encompasses remuneration of employees and corporate bodies. 'Fixed Tangible Assets' refer to the reported net book value of fixed tangible assets at the end of each year. 'Annual Wage' is calculated as payroll divided by employment. 'Machinery Investment' refers to reported investment in machinery and equipment. 'Markdowns' are estimated as described in Appendix D.2. Source: Authors' own calculations from Integrated Business Accounts data in 2004-2020.

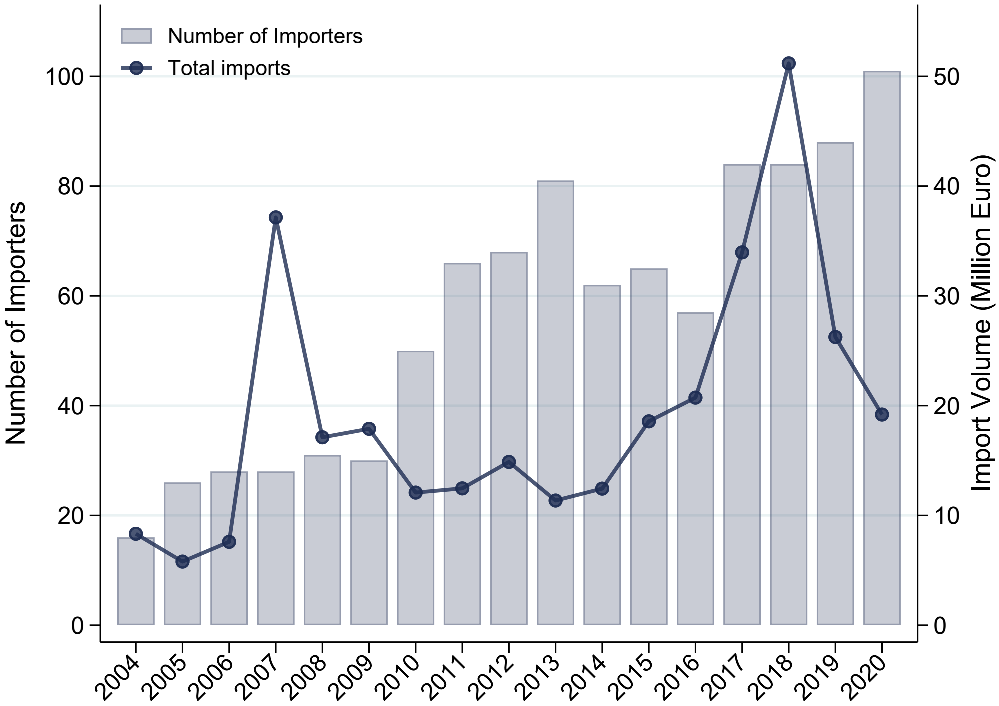
Table D.5: Balance Checks

Variable	Treatment group	Comparison group	Difference
Output (€)	1,809,544	2,532,370	-722,826***
Payroll (€)	247,197	276,737	-30,504***
Fixed Tangible Assets (€)	551,225	755,061	-211,399***
Capital Intensity (€)	18,780	24,148	-5,372***
Number of Employees	21	20	1***
Annual Wage (€)	8,688	9,539	-852***
Machinery Investment (€)	64,089	89,728	-25,975***
Markdown	1.199	1.188	0.012***

Notes: The table presents mean values of variables by treatment group and mean differences from t-tests for the pre-treatment period (2004-2009). Standard errors are not clustered. Significance levels are indicated as follows: *** for 1%, ** for 5%, and * for 10%.

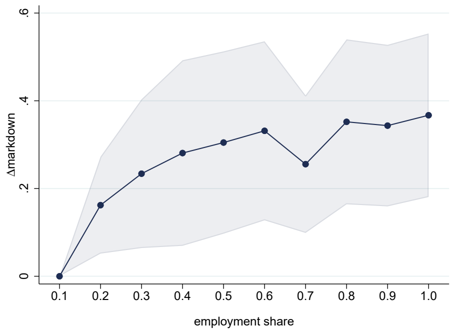
D.4 Figures

Figure D.1: Evolution of Industrial Robot Imports by Portuguese Manufacturing Firms (2004-2020)

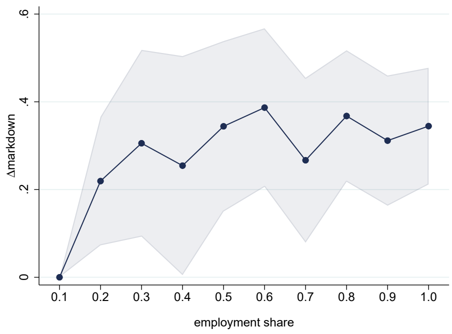


Notes: This figure illustrates the yearly number of manufacturing firms that imported industrial robots, categorized under the product class '84795000-Industrial robots n.e.s.', and the corresponding total import volume for each year over the period from 2004 to 2020. Source: Authors' own calculations from International Trade Register data.

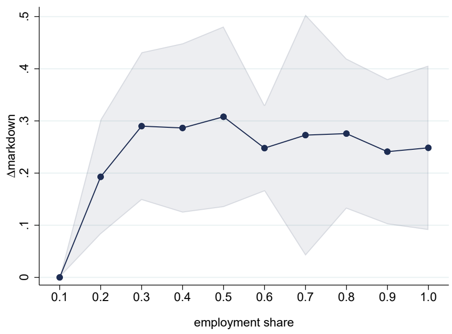
Figure D.2: Markdowns and Local Labor Market Shares by Local Labor Market Definition (2005-2020)



(a) 5-digit Industry by 3-digit Region



(b) 3-digit Industry by 3-digit Region



(c) 2-digit Industry by 3-digit Region

Notes: The figures show point estimates and 95 percent confidence intervals from an OLS regression of firm-specific markdowns on indicators for employment share deciles, as defined in Equation 4.8. Subfigures (a), (b) and (c) present estimates for different local labor market definitions, varying industry granularity within NUTS-3 regions. Regressions controll for indicators of firm age, as well as industry, region and year fixed effects. The baseline for comparison is the smallest size group. Each size indicator, such as "0.1", represents firms with employment shares in the corresponding range (e.g., s ∈ (0, 0.1]). Other indicators follow the same principle. Following Yeh, Macaluso, and Hershbein (2022), the regression applies employment weights. Standard errors are clustered by industry. Source: Authors' own calculations from Integrated Business Accounts data in 2005-2020.

Figure D.3: NUTS Regions of Portugal

Notes: The figure illustrates the administrative regions of mainland Portugal according to the NUTS 2013 classification, organizing 278 municipalities into 23 NUTS III and 5 NUTS II regions. Source: Instituto Nacional de Estatística (2015).

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