Economic Outcomes and Driving Forces of Innovation – Evidence on Digitization and Migration

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Chapter 1

Global Megatrends Through the Lens of Innovation Economics

1.1 Big Challenges in Today's Industrialized Economies

The key terms differ, but leading political institutions, economists and consultancies agree: Globalization, climate change, demographic change and digitization are the main challenges for our economies – currently and in the future. These megatrends impact the way we produce, work, collaborate and trade and thereby also our societies' consumption, communication and cohesion. Economic policy needs to deal with these four challenges in order to ensure sustainable growth.

Globalization is overarching the other megatrends: The world economy is increasingly integrated and is shifting towards Asia. Trade in goods may slow down, whereas service and investment flows are growing (ESPAS, 2015). On the one hand, the integration of global trade and rising economic activity of emerging nations will increase carbon dioxide emissions and further amplify global climate change. Globalization can also lead to more migration due to the enhanced economic interrelations and increasing inequality. Digitization, on the other hand, is an enabler and a key driver of economic integration and trade flows around the globe. The information and communication technologies (ICT) create new types of products, facilitate trade in services and allow for real-time communication and data exchange with partners and customers around the globe.

Climate change is mainly caused by greenhouse gas emissions – generated by human activity. The famous Stern Review (Stern, 2007) estimated that each year at least 5 percent of global GDP would be lost if emissions were not reduced. Macroeconomists still heavily debate these results, but there is a broad consensus that emissions reduction is an important goal for policy makers (Nordhaus, 2007). Policies can relate to the promotion of renewable energy and the design of functioning energy markets, the development and deployment of green innovation, and the adaptation of agriculture and water usage.

The third megatrend in this list, demographic change, is triggered by increasing life expectancy and declining birth rates, leading to an ageing population in most industrialized countries. The economic consequences are a reduced workforce which, again, affects production and the funding of the social protection systems (ESPAS, 2015). The impact of an ageing workforce can be slowed down by immigration but migration is not only a (potential) solution to demographic change in the industrialized economies. Due to rising global inequality, conflicts and climate change, migration is at an all-time high (Braconier et al., 2014). The challenge for policy makers is to balance different obligations: The developed economies need qualified workers whereas less developed countries fear to lose their qualified workforce. Furthermore, countries' humanitarian commitments might contrast with the economic interests of selecting migrants by their skills or skill-level.

Technological change shapes our economies. Important mile stones over the last centuries were the steam engine, electric power and, mass production. Digitization started with the arrival of personal computers and the internet, both technologies making comparatively cheap use and therefore rapid diffusion possible. Embedding machines such as computers and manufacturing equipment into large, intelligent networks is now the latest mile stone, called the *Internet of things* or the *Industry 4.0.* Digitization allows for efficiency gains in production and communication and for developing completely new products and services. Consequently, the impact on firms, value chains and trade is tremendous. Economists agree that digitization fosters skill-biased technological change by complementing skilled labor and increasing its relative productivity to the detriment of unskilled labor. In short, digitization has a great and very complex impact on economies and societies, which makes it particularly challenging for all market participants, citizens and policy makers.

Globalization, climate change, demographic change and digitization: The economic literature quantifies the megatrends with respect to their economic relevance, identifies drivers and outcomes and contributes to develop and evaluate policy advice. This dissertation contributes to two aspects of these megatrends: Digitization in firms and migration as a consequence of globalization and a potential solution to demographic change. The analyses employ a varied set of empirical methods from statistical tools to causal identification and exploit variation at the firm and at the regional level. Conceptually, the chapters draw on the ideas of the economics of innovation.

1.2 Innovation as a Response to the Megatrends

The study of innovation – comprising the invention and development as well as the adoption of new technologies and processes – provides valuable answers for policy advice in the context of the megatrends.

Innovation contributes, for instance, to maintaining international competitiveness: Trade integration is the centerpiece of globalization and subject to a growing strand of literature measuring the effects of rising Chinese import competition on the labor markets in the United States and Europe (e.g., Autor et al., 2013, 2016; Acemoglu et al., 2016; Dauth et al., 2014) but also on technical change. Bloom et al. (2016) find that Chinese import competition accelerated technical change in Europe by pushing innovation (in the form of patenting) and the adoption of new technologies (in the form of information technologies) and contributed to productivity growth via this channel.

A way to reduce greenhouse gas emissions and slow down climate change is to increase the global share of green innovation. Aghion et al. (2016) study the incentives for firms in the automotive industry to choose green over dirty innovation and find that tax-inclusive fuel prices drive clean innovation as well as a firm's and its partners' own earlier experience with this kind of inventions. The work of Acemoglu et al. (2012, 2016) confirms that carbon taxes and also research subsidies are crucial policy measures for the generation of green innovation. Other research mostly focuses on regional markets and local policy measures and deals with incentives to adopt green technologies such as smart grids, solar panels or fuel-efficient passenger cars (e.g., Beise and Rennings, 2005; Bauner and Crago, 2015; Costa et al., 2017).

In consequence of the megatrend of population ageing in industrialized countries, the workforce might decrease significantly, which is a threat for the economies' production and growth. Developing and adopting new technologies is an important way to tackle this problem. Another solution is to increase the work participation of the elderly and parents – and to hire migrants. Immigration has been shown to be a major force of stabilizing population numbers in the European Union (Lodovici and Patrizio, 2013). According to the seminal model by Borjas (1994), the push and pull effects of migration are based on the wage distribution and unemployment rates in the home and the destination country and determine the (skill) composition of immigrants. Also the empirical economic research on migration has mostly been focusing on wages and employment in (local) labor markets (e.g., Card, 1990; Dustmann et al., 2005; Peri et al., 2015). Lewis (2011) is one of the first to relate the topic of immigration to the adoption of automation technologies in production. He finds that in areas with high supply of low-skilled (migrant) workforce plants get equipped with significantly less production automation machinery. A direct link between migrants and innovation is the subject of a growing strand of literature which our work on Polish immigration to Germany and local innovativeness (**Chapter 4**) contributes to. Related studies show that migration has positive effects on migrant patenting and/or on the total number of patents (e.g., Hunt and Gauthier-Loiselle, 2010; Kerr and Lincoln, 2010; Bosetti et al., 2015). These results speak towards a positive growth contribution of migration and suggest that migration can alleviate some of the economic problems of the ageing population.

Digitization is a sequence of innovations in the information and communication technologies (ICT) that are emerging at an accelerating pace. Existing knowledge about innovation and its markets therefore needs to be constantly adjusted. **Chapters 2 and 3** investigate how two innovative digital technologies benefit firms and help to understand firm incentives and complementarities in the context of adoption. Hence, digitization is the megatrend with the highest weight in this dissertation.

In the next section, I will outline the key ideas of the economics of innovation and growth and will describe this dissertation's contributions to the field as I go along.

1.3 Innovation Economics – Studying an Important Driver of Economic Growth

The field of innovation economics postulates the need of innovation to spur higher productivity and economic growth. In neoclassical macroeconomics, growth is generated by accumulating productive factors such as capital and labor. The work of Solow (1957) then was the first approach to model rising output with constant labor and capital driven by an exogenously given and unexplained rate of technical progress, the Solow residual. Next, Arrow (1962) and Romer (1986) started to seek an explanation for the source of technical change and added technological progress as an endogenous variable to the model. Endogenous growth theory explains technological progress with the accumulation of knowledge through education, scientific research, learning by doing, or innovation (Aghion and Howitt, 1992).

Joseph Schumpeter (1942) shaped economic thinking on innovation at the micro level. According to his concept of creative destruction, an innovation is the development and introduction of a new product or process. Technological change is therefore discontinuous and the result of a competitive process where entrepreneurs constantly seek new ideas that challenge existing technologies and business models.

1.3.1 The Innovation Process

Technological progress starts with an invention, that is often the result of fundamental research, and the development of the invention into a product for the market. Important success factors in this phase are, apart from the necessary funds, the education and knowledge of researchers, creativity and promising ideas. The incentives for an individual or a firm to innovate are the expected economic rents from the innovation consisting of profits above the opportunity cost of capital (Coyle et al., 2017). Collecting the innovation rents is, however, challenging because, first, knowledge is a non-rival good. Second, generating knowledge is initially costly, but once produced this knowledge can be distributed and used at relatively low cost. An innovation can therefore be of value for a great number of individuals or firms and create a social benefit which is above the innovating firm's private benefit. The difficulty for firms to appropriate the returns to the investment in research and development (R&D) then leads to the underprovision of R&D in the economy (Hall and Lerner, 2010). As innovation drives productivity and economic growth, there is reason for policy makers to intervene if market incentives to innovate are not sufficient.

A policy can consist in funding research in various ways (such as direct government R&D funding programs or R&D tax incentives), implementing innovation systems and partnerships (e.g., cluster programs), designing education and labor market institutions accordingly, and providing the relevant infrastructure or regulatory framework. In addition, intellectual property protection is a crucial instrument to incentivize innovation: A patent grants a fixed-term monopoly right for exploitation of an invention in exchange for disclosure. By this means, it allows the patentee to collect the rents of her R&D investments.

In economic research, patents and the patent system are, on the one hand, an explicit subject of study (like, for example, in Williams and Sampat, 2018 or Galasso and Schankerman, 2015). On the other hand, patent data are often used to measure innovation. Moser and Voena (2012), for instance, study the impact of a historical regulatory change on innovation measured by the number of patents, whereas Forman et al. (2016) use patent data to localize innovative activity across the United States. Patent data are also critically discussed: When counting patents, only granted patents are taken into account and (potentially) less valuable inventions in rejected patent applications are not considered. This is a problem when measuring innovative activity.[1] In **Chapter 4**, my coauthors and I therefore use data from patent applications and exploit information on the nationality of the inventors to distinguish the innovativeness of immigrants from the innovativeness of locals. The study contributes to the understanding of driving forces of innovation and, by extension, to growth.

An innovation on the market, protected or not, is then commercialized leading to adoption by firms or individuals and to a diffusion process across the market. Adoption decisions in firms are taken by the management based on their strategy, the firm's requirements and prices. **Chapter 2** explores the characteristics of firms that adopted ICT structures similar to cloud computing and shows that firms' adoption decisions differ by industry, the place in the value chain and the related main tasks of the firm's business activities.

The sum of all individual adoption decisions in the market, that is, diffusion, was first empirically studied by Griliches (1957) using the example of hybrid corn in the United States. The S-curve (or logistic curve) he found to be the pattern of diffusion in his setting was confirmed to be universally applicable to the diffusion of innovations. Catalini and Tucker (2016), for

[1] Depending on the research question, information on the value of a patent can be required. Whether a patent has been granted is already a signal. Still, also inventions in granted patents differ in their technical merit and economic potential. An approach to further grasp the value or novelty of a patent is, therefore, to count or analyze references to scientific research or citations of prior art in patents. Patent citations are also used to measure knowledge spillovers (Jaffe et al., 1993).

example, build on this finding and the characteristics of adopters (initially introduced by Rogers, 1962) to analyze the role of early adopters in the diffusion process of a very recent innovation. They find that small obstacles in the initial availability of the digital currency Bitcoin to the most interested adopters can have lasting effects on the diffusion across the market. This work on Bitcoin is also an example of the major field of study around adoption and diffusion in economics, that is, the information and communication technologies.

1.3.2 Information and Communication Technologies

Information and communication technologies (ICT) have been the dominating innovations since the 1990s and they are still at the heart of a profound technological change. For this reason, digitization has been identified as one of the megatrends. Economic research on ICT has considerable overlap with management studies and can be rooted in the fields of industrial organization (studying, for instance, productivity, automation, platform competition, infrastructure), labor (e.g., skill-biased technological change, online labor markets, working from home), education (e.g., IT skills, digitization in schools), macroeconomics (e.g., technological change and growth), public finance (e.g., government programs, infrastructure) and, finally, innovation economics. The boundaries between fields are, of course, blurred.

In addition to the explicit adoption and diffusion processes, economists are particularly interested in the growth impact of the emergence of new technologies on individuals, firms and the economy as a whole. The macro-level perspective of neoclassical growth accounting suggests two channels through which information technologies contribute to labor productivity increases and therefore to economic growth. First, investments in IT lead to the deepening of IT-capital: Firms increase IT use per employee or per hour worked which is closely tied to increasing labor productivity. Second, IT represents technological progress and can consequently be a determinant of increasing total factor productivity (Draca et al., 2006). Economists widely attribute the acceleration of productivity growth in the United States after 1995 to the emergence of information technologies. In the European Union, however, the opposite trend could be observed (van Ark et al., 2008), revealing the complexity of the impact channels of ICT on productivity.

Various economic studies show in more detail that the productivity effects of ICT are very heterogenous. For instance, it has been found that an important share of the measured productivity effect of ICT at the macro level, was contributed by industry sectors that either produced IT or used it intensively (e.g., Stiroh, 2002; van Ark et al., 2008; Acemoglu et al., 2014). At the micro level, Bloom et al. (2012) show that establishments owned by a U.S. multinational firm could implement IT resources in a more beneficial way than non-U.S. ones. The productivity effect of IT is significantly larger in these establishments independent of their location. The authors attribute this to the more aggressive U.S. American human resource policies that allow for substantial organizational changes complementing IT structures. Akerman et al. (2015) find that the adoption of broadband internet in firms has positive productivity effects – but only in complementarity to skilled workers.

In **Chapter 3**, I study the merge of information and communication technologies, a technical development that moved communication and collaboration in the firm away from face-to-face interaction and increasingly to the digital space. My results show that the new paradigm's effects on firm productivity and employment substantially differ with respect to firm size. In medium firms, positive labor productivity effects are the result of laying off staff, whereas large firms hire more IT workers but experience lower revenues after implementing the new technologies.

Leaving aside these heterogeneities and looking at the total productivity effect, Cardona et al. (2013) identify in their meta-study a cluster of productivity elasticities of IT capital in firms at around the value of 0.05-0.06 with several outliers in both directions. According to these results, a 10 percent increase in ICT investment in the years 1990 to 2010 translated into firm output growth of 0.5–0.6 percent. For broadband internet, Czernich et al. (2011) find that, in OECD countries, a 10 percentage point increase in broadband penetration raised annual per capita growth by 0.9–1.5 percentage points in 1996 through 2007. Brynjolfsson et al. (2018)

descriptively look at the latest major break-through in ICT, that is, artificial intelligence, but do not find any indication of an impact on economic growth. However, they also argue that this potential new general purpose technology has not yet diffused widely.

1.3.3 Empirical Methods

Methodologically, the field of innovation economics, just as many other empirical research fields, is challenged by the implementation of causal identification. Correlation, such as measured in an ordinary least squares regression, is helpful to explore associations between variables and other statistical tools can complement such a descriptive approach. In **Chapter 2**, my coauthors and I apply several methods and heterogeneity analyses to better understand the diffusion and implementation of a new technology that is still difficult to grasp. This approach helps to enter a new research topic and to learn about the important questions that need to be answered.

Evidence-based economics, however, aims at giving specific business or policy advice. It is often the next step in a research topic and requires that correlations can be interpreted as the causal effect of one variable on the other. Researchers want to learn about the impact of a certain treatment on the outcome variable – the average treatment effect (ATE). If the treatment is randomly assigned, such as in lab and natural experiments, and if the subjects comply with their assigned group, then the estimated relationship is a causal effect. However, if problems of reverse causality, omitted variable bias or self-selection need to be tackled, multivariate regressions with fixed effects are an important step in the right direction. In panel data at the firm-level, firm fixed effects can control for all unobserved, time-invariant firm characteristics. If we want to quantify the productivity contribution of the adoption of a new technology in firms, we need to make sure that there is no omitted influence factor driving both the adoption decision and firm productivity. Time-varying confounding factors can be ruled out by adding relevant control variables to the regression – if we have an appropriate measure for them. Shocks, such as the financial crisis or a regulatory change, can be controlled for with year fixed effects.

In **Chapter 3**, my main specification is such a firm productivity estimation with a lagged indicator for the adoption of new technologies and fixed effects for firms and for industry-year. This way, in addition to the unobservable characteristics of firms, I can also control for contemporaneous reverse causality and industry-specific shocks. Kretschmer et al. (2012), for instance, show that regulatory change and the related competitive pressure in the car-dealer industry lead firms to increasingly adopt a new software and to raise their sales. Such an event could not bias my results. By carefully considering potential confounding factors and excluding unobservables at the firm level with the fixed effects, the estimated coefficients already come very close to the causal effect. However, a small doubt with respect to other omitted variables or reverse causality remains.

One of the most widespread and acknowledged tools for exogenous identification and causal effect estimation are instrumental variables (IV), that are correlated with the endogenous variable but not in any other way with the outcome variable. Galasso and Schankerman (2015), for example, analyze cases where patent rights were removed by court invalidation to find out whether patent rights encourage or impede follow-on innovation. The explanatory variable "patent right removal" is highly endogenous as a patent's quality is probably a driving force of both follow-on innovation (the outcome variable) and patent protection (a prerequisite for later invalidation). The authors therefore exploit the random allocation of judges to a case and use judges' propensity to invalidate patents as an instrument for actual invalidation. They find that, on average, patent invalidation leads to a 50 percent increase in citations to the respective patent.

The fixed effects model in **Chapter 3** is also complemented by an IV estimation based on broadband internet availability at the municipality level. I argue this instrument to be exogenous to the productivity of an individual firm since roll-out of the infrastructure cannot be impacted by the firm and its success. Furthermore, in our analysis of the impact of migrants on innovativeness in **Chapter 4**, my coauthors and I employ a shift-share form of the instrumental variable approach. Exogenous variation comes from a distribution of migrants at an earlier point in time that is not related to today's innovative industry structures but to the geographic distribution of migrants today.[2]

To sum up, in this dissertation, I employ a variety of empirical methods that progressively allow for causal interpretation: The study on cloud computing in **Chapter 2** is explorative and descriptive. The productivity estimations of altered communication structures in firms in **Chapter 3** are multivariate regressions with two sets of fixed effects, complemented by an instrumental variable strategy. **Chapter 4** then studies migration and innovation based on a shift-share type of instrument.

1.4 Outline of the Dissertation

The former sections already gave some insights into the chapters of this dissertation and their place in academic research and methodology. In the remainder, I will summarize each chapter in more detail.

In **Chapter 2**, my coauthors and I explore a technology that has come up in the end of the last millennium: cloud computing. First, we give a thorough insight into the market, actors and economic questions related to the new technology. Cloud Computing combines different IT components to a new service where computing and storage are virtualized and outsourced to a provider. By adopting cloud computing instead of purchasing the relevant hardware and software themselves, firms gain a great amount of flexibility and, potentially, efficiency. Storage and computing capacities are made available by the providers and only accessed and

[2] Other standard methods for causal inference in the economics of innovation are the difference-in-difference estimator and regression discontinuity estimations. The former is, for example, employed in Janssen and Mohrenweiser (2018) to compare diverging trends of a treatment group, affected by technological change after a policy change, and a control group which is not affected. Gaggl and Wright (2015) study the effect of ICT investments on firm productivity and employment exploiting a discontinuity in the eligibility for a 100 percent tax credit on ICT investments in the UK.

paid for when firms need them. Providers pool their resources, experience economies of scale and can therefore offer their services at costs that are lower than firms' inhouse solutions. This is particularly advantageous for small and medium firms who benefit from the avoided fixed costs they would incur when setting up a system of their own.

Second, an important contribution of this chapter is to propose a composite measure of a firm being technologically ready for cloud computing adoption (cloud adaptive). For the computation, we use information on the availability of network equipment and exchange software in the firm. This proxy allows ourselves and other researchers to use existing firm-level panel datasets to analyze the characteristics and outcomes of this new technology. Furthermore, we use the measure and a panel dataset with technology and balance sheet information (from the Harte Hanks technology survey and the Bureau van Dijk ORBIS database) on European firms to give first, descriptive insights into the heterogeneity of firms that are ready for the cloud. We find that large firms are more cloud adaptive than smaller firms. The differences in adoption rates are statistically significant but economically not very large. On the one hand, small firms are expected to benefit more from cloud computing, but on the other hand, many of them most likely do not need the services provided in the cloud at all. Results regarding the cloud adaptiveness of different industry sectors indicate, that the degree of firms' need of interaction with their business partners or customers could determine the adoption of cloud computing. In that case, the cloud can serve to implement a platform for data and information sharing. Furthermore, based on a simple t-test, we also find that, in manufacturing, cloud adaptive firms are more productive and that the relevant technologies are not necessarily adopted in the sectors where they allow for the highest productivity.

After this descriptive and explorative study, in **Chapter 3**, I analyze the productivity effects of a similar development in firm digitization econometrically. In the end of the last millennium, computers and phones were common, but computing and telecommunication were two different and separate things. Then, during the last two decades, IT and communication have increasingly converged: Email has become the most important communication tool in firms, often replacing the landline phone and complemented by real-time chat applications, collaboration platforms, and electronic content managements. I call the convergence of information and communication technologies "interconnectivity". The study contributes to the economic literature on the productivity effects of ICT in firms and broadband internet. I am not aware of any other research explicitly modelling the convergence of computing and telecommunication technologies within the firm. This chapter proposes a measure for interconnectivity and employs it in productivity estimations at the firm level. Analyzes of organizational and infrastructural complements to interconnectivity shed light on the economic mechanisms of the technology's impact on labor productivity.

To study the paradigm shift in firms, I refine the cloud adaptiveness indicator and complement it by Enterprise Resource Planning (ERP) software, an application that optimizes comprehensive data access for all firm departments and facilitates the exchange of information. Firms that adopt an interconnected system are likely to experience facilitated and improved communication and efficient processes which can lead to productivity gains. I test this hypothesis by augmenting a neoclassical firm production function with the indicator for interconnectivity and estimating it in a panel estimation with two sets of fixed effects. This way most of the firm heterogeneity that might be driving productivity and the variable of interest alike is controlled for. An additional instrumental variable estimation is based on broadband internet availability at the municipality level and, therefore, restricted to the German firms in my sample. Data stems, like in Chapter 2, from Harte Hanks market intelligence database on firm technology usage and from the Bureau von Dijk ORBIS database and covers firms in nine European countries in the years 2000–2007.

I find that, in my sample, the introduction of interconnectivity impacts medium and large firms differently. Labor effects are particularly robust and show that medium firms lay off staff, potentially using external business services for IT tasks instead. Large firms choose the opposite solution and employ more IT staff which speaks towards them preferring inhouse IT services. A negative impact of interconnectivity on revenues in large firms suggest that the implementation encounters difficulties in the first place. The instrumental variable approach does not yield any productivity results due to weak instrument relevance. The zero correlation between broadband internet availability and interconnectivity, however, shows that, first, the two technologies are not complementary. Second, in this sample, the availability of broadband infrastructure did not foster IT investments in interconnective resources in the firm.

In **Chapter 4**, I turn to a potential response to the big challenges of today's developed economies: Migration. My coauthors and I contribute to the recently emerged strand of literature extending the former focus of migration's impact on the labor market to migration's contribution to innovation in the host country (see, for example, Hunt and Gauthier-Loiselle, 2010, for the United States; Bratti and Conti, 2018, for Italy; and Bosetti et al., 2015, for 20 European countries). We study an immigration flow of individuals of all skill levels instead of focusing on highly qualified immigrants as most existing studies do. Furthermore, our data allow to disentangle immigrants' direct contribution to innovativeness from their spillover effects on local, incumbent inventors due to nationality information of inventors. Hence, in this chapter, I go one step back from innovation adoption and study determinants of innovation generation.

The chapter relates immigration to innovativeness focusing on the largest immigrant group from the new member states joining the EU in 2004: Poles. The major empirical challenge is that migrants with a qualification suited for patenting activities are more likely to go to cities or locations where they can find a job in an innovative firm or industry cluster. For the empirical strategy, we therefore exploit the fact that immigrants often also follow existing networks and tend to live in locations with a higher share of people of similar cultural or ethnic background. We use a historical episode in the migration history of Poles to Germany that is exogenous in our setting. It allows to analyze a causal effect of Polish immigration of all qualification-levels on the number of inventors in Germany.

The data set combines patent data from OECD's REGPAT and from the World Intellectual Property Organization with regional data from different official statistics such as the German and the Polish Statistical Offices and the Institute for Employment Research.

We find that in the years 2001-2010, in a county that receives 10 percent more Polish immigrants than another, the number of German inventors was 0.32 percent higher. So, the new arrivals do not replace locals but stimulate their work. In the study of Kerr and Lincoln (2010) for high-skilled migration to the United States there is no such significant spillover effect. We learn from the results that, first, Polish immigrants do patent in Germany. Second, spillover effects from Poles to German inventors are even slightly higher than the direct contribution. This speaks towards immigrants' innovation effect coming rather from complementary jobs than from Polish inventors. Polish migrants bring important complementary skills or knowledge, such as ideas for new products, access to new markets, or particular management or consulting capabilities, which pushed Germans to patent more. Low-skilled workers with their low reservation wage might also increase production possibilities and therefore allow for more innovative work.

The chapters of this thesis are self-contained and can be read independently.

Chapter 2

Cloud Adaptiveness Within Industry Sectors – Measurement and Observations*

2.1 Introduction

Although mention of "the cloud" or cloud computing is now ubiquitous in daily life, our understanding of what it actually is and how it changes private and corporate structures is surprisingly limited. Most people recognize cloud computing as a fairly recent development in information and communication technology (ICT). However, the wide range of opinions of what constitutes cloud computing and how it affects households and enterprises is a partial reflection of the many different uses of cloud computing and the resulting lack of a universally accepted and understood definition of it.

Beginning several decades ago, advances in processor and related technologies and the spread of the personal computer, as well as server structures and communication infrastructure like the internet, helped automatize production and supply chains and facilitate management and administration. ICT as a whole was expected to have a great influence

*This chapter is based on joint work with Tobias Kretschmer and Thomas Strobel and is published in *Telecommunications Policy* 40 (2016) 291–306.

on the productivity of industries and economies. Indeed, as suggested by Cardona et al. (2013), ICT has some of the hallmarks of enabling or general purpose technologies that are widely adopted and induce further innovations. Various authors identify positive productivity effects from ICT utilization (Jorgenson, 2001, 2005; Jorgenson and M. S. Ho, 2005; Bresnahan et al., 2002; Brynjolfsson and Hitt, 2003). These productivity effects coincided with a massive reduction in hardware prices over the last decades, which has spurred investment in IT and communication equipment(Jorgenson, 2001). Jorgenson (2005) finds that despite productivity growth rates being by far the highest in ICT-producing industries, the overall contribution of these industries to economic growth in the United States has been rather limited due to their low share of the economy. As ICT became more widely used, its main growth contribution came from total factor productivity (TFP) growth in ICT-using industries while growth rates in ICT-producing industries plateaued (Jorgenson, 2007). Similar empirical evidence is provided by Brynjolfsson and Hitt (1995, 1996, 2003) and Tambe and Hitt (2012) as to the positive effect of computers on firm-level productivity, thus corroborating the aggregate findings and painting a more nuanced picture. For an overview of the literature on the aggregate and firm-level productivity effects of ICT see Cardona et al. (2013).

The cloud, as a logical continuation of ICT-specific services, emerged as an architectural innovation (Henderson and Clark 1990) that was the result of isolated innovative processes and extended data transmission possibilities. Market research estimated the global private and corporate cloud computing market to have reached $56.6 billion (on public cloud services only) in 2014 and it is projected to more than double that by 2018 (IDC, 2014). Eurostat (Giannakouris and Smihily, 2014) reports that 19% of EU enterprises used cloud computing in 2014, mostly for hosting their e-mail systems and storing files in electronic form. The economic benefits of cloud computing adoption in the business segment of Europe's largest economies are estimated to have created 2.3 million net new jobs between 2010 and 2015 (Center for Economics and Business Research, 2010). Hence, major structural changes and productivity-enhancing effects are expected from the usage and diffusion of cloud computing.

However, frustratingly for researchers wanting to investigate and quantify the growth impact of cloud computing, data on this phenomenon continue to be scarce.

We aim to advance the understanding of enterprise cloud computing as well as of the firms using it and the potential mechanisms triggered by implementation of this innovation. One of our contributions is that we propose an indirect measure of current or prospective cloud computing adoption that allows researchers to use existing large-scale firm-level panel datasets to analyze cloud diffusion and productivity effects via a reliable and plausible proxy. This is of particular importance as many extant surveys do not employ a precisely defined or even generally accepted measure and longitudinal studies are yet to be conducted. We utilize the widely used Harte Hanks technology database for 13 European countries and the years 2000 through 2007 to develop our cloud indicator and then merge this technology data with balance sheet information from the ORBIS database. Applying our indicator to the data, we make six observations on firm-level cloud computing regarding possible correlates of adoption and the correlation between firm productivity and cloud computing in the context of structural differences in industry sectors. These observations show how the economic effects of cloud computing could be analyzed using our indicator so as to provide initial insight into empirical cloud computing economics and shape an agenda for further research on cloud computing. From our six observations we derive three suggestions for further research which are as follows:

1. As adaptiveness of cloud computing differs widely across industry sectors, studies on cloud computing should be conducted at the industry level. For example, in our sample, services exhibit especially high adoption rates.

2. It is important to understand why firms implement cloud solutions and what they actually do with the cloud. Do they intend to increase productivity or flexibility, or both?

3. Cloud adaptiveness is potentially correlated to a firm's position in the supply chain and thus suggests a linkage of cloud adaptiveness and the type of output the firm produces as well as the market in which it operates.

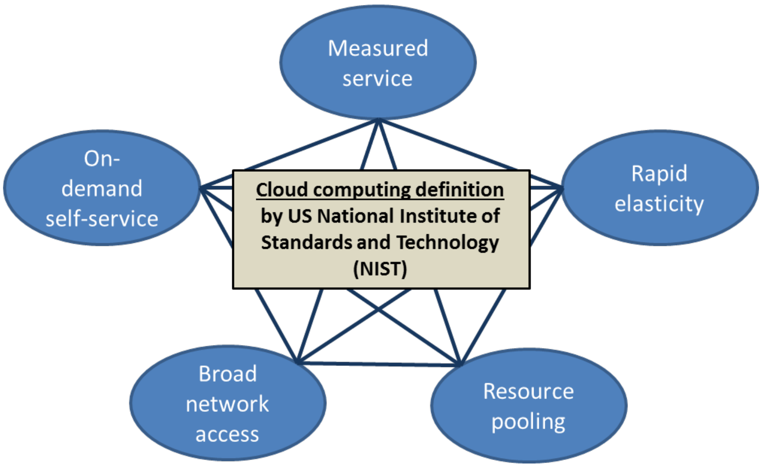
In the remainder of the paper, we first outline the concept and market of cloud computing (Section 2.2), then, in Section 2.3, compile existing first steps toward a theory of cloud computing economics and review the empirical literature on the topic. Section 2.4 introduces the data and our measure of cloud adaptiveness; Section 2.5 presents six observations from descriptive analyses of this dataset. Section 2.6 concludes.

2.2 A Primer in Cloud Computing

2.2.1 From shared infrastructure to cloud

These days, the commercial world is characterized by a trend toward sharing, for example, sharing companies, crowdsourcing, and open design platforms (Gansky, 2010). Interestingly, information technology sharing has a long tradition. The history of computing and IT begins in the late 1950s with the arrival of the first mainframe computers. These were mostly found in universities and governmental organizations, where one machine filled a large room and served all the researchers or employees of an institution, who therefore shared the infrastructure. IBM was the most important producer and developer of this kind of computing architecture Bresnahan and Greenstein (1996); Pallis (2010). Mainframes had high upfront costs for hardware and software and were therefore optimized for efficiency. The newly founded insurance company CompuServe, started renting out idle computing capacity to other companies around 1970, introducing capacity sharing across organizations. This was the first step toward a network of computers. However, hardware advances favored decentralization. Personal computers, such as the Commodore PET (introduced in 1977) and the Amiga 1000 (1985), were linked up to build a firm network, began to compete with the IBM System 360 family of mainframes (Cusumano, 2010) and eventually prevailed. PCs were easy to use and assumed some of the computing tasks, allowing for hosts to be less capable (Bresnahan and Greenstein, 1996). Operating systems and software were written and licensed by software companies, which reduced the upfront investment costs of IT-using firms and also improved the systems' agility. This type of client/server structure predominated in the 1980s and 1990s.

Figure 2.1: NIST definition of cloud computing



Source: Mell and Grance (2011).

However, the idea of using a mainframe to centralize vital functions and capacities continued to survive. While mainframes required terminals with a command-line interface, modern thin clients could run applications and services hosted by a server with a graphical user interface. Together with grid and utility computing, this thin client network system was a precursor to cloud computing (Leavitt, 2009). From the mid-1990s on, the internet spread farther and farther and became faster and faster. An early innovation quite similar to actual cloud computing involved application service providers (ASP), where thin client systems or the internet were used to provide software services to a small number of users. However, it took the development of open-source software and the adoption of Web 2.0 standards before a widely accessible system using relatively simple code was possible (Grossman, 2009). The spread of reliable, high-speed networks further drove the development of cloud computing (OECD, 2009).

2.2.2 So what is cloud computing?

Cloud computing is actually a new manifestation of an "old trend", involving preexisting computing concepts and a novel combination of established components Armbrust et al. (2009); OECD (2009); Suciu et al. (2013). The key characteristic of cloud computing is the virtualization of resources and services. Cloud computing combines the efficiency of a mainframe with the agility of a client/server system. Firms outsource their IT systems either completely or partially, renting storage space or computing power from specialized providers. This is somewhat similar to earlier hosting services, but cloud users also benefit from additional services and scalability of capacities (Lin and Chen, 2012). Grossman (2009) identifies scale, simplicity, and pricing as the key defining features of cloud relative to conventional computing. This definition mirrors the widely accepted definition of cloud computing by Mell and Grance (2011) of the US National Institute of Standards and Technology (see Figure 2.1).

As Figure 2.1 shows, in contrast to simple server usage, cloud computing involves pooling IT resources such as storage or processing in a virtual system serving multiple users. *Resource pooling* allows for specialization and the realization of economies of scale on the provider side. Capacities are assigned dynamically according to demand; users therefore cannot locate their data in a certain geographic area. Importantly, cloud users often can purchase computing resources without any human interaction and at short notice (*on-demand self-service*). While traditional computing requires heavy upfront investment with fixed capacity, cloud computing allows *rapid elasticity* (scalability) of resources and firms order and pay for only the capacity they actually need at that specific moment. The services provided are automatically measured, which not only leads to resource optimization but also facilitates billing. Cloud computing is billed based on a pay-per-use pricing scheme. Finally, *broad network access* is indispensable to access and use cloud services (Armbrust et al., 2009; Mell and Grance, 2011).

There are three deployment models of cloud computing. (1) Software as a service (SaaS), where a customer purchases access to an application, such as enterprise resource planning

(ERP) or customer relationship management (CRM), hosted and run in the cloud. (2) Platform as a service (PaaS) refers to access to platforms that allow customers, especially software developers, to test or deploy their own applications in the cloud. (3) Infrastructure as a service (IaaS) is a more basic service mostly offering access to storage capacities (National Institute of Standards and Technology 2013; Suciu et al. 2013).

2.2.3 The cloud computing market

The cloud computing market is comprised of four major groups of actors: cloud consumers, providers, carriers, and enablers or complementors (Marston et al., 2011; National Institute of Standards and Technology, 2013; Gerpott and May, 2014). The biggest consumer groups are firms, making cloud computing an important business-to-business (B2B) market, with products ranging from a complete cloud-based IT solution to select individual services. On the supply side of the public cloud market, we have vendors that own and operate the required data centers and platforms, including maintenance and upgrades of the system (Marston et al., 2011). Amazon (with Amazon Web Services) is the dominant provider, with Google (Google Drive), Microsoft (Windows Azure), and IBM (BlueCloud) distant followers (SearchCloudComputing, 2013). Cloud carriers provide interconnection from providers to consumers, so that most cloud carriers are telecommunication operators providing internet access and connection (National Institute of Standards and Technology 2013). Finally, cloud enablers "sell products and services that facilitate the delivery, adoption and use of cloud computing" (Marston et al., 2011). In other words, cloud enablers add value to bare-bones cloud services, making them cloud complementors. Cloud enablers or complementors are auditors, brokers, or additional-value service providers. A prominent example is Dropbox, which offers storage and file sharing solutions, but stores its data on Amazon's Simple Storage Service (S3) (TechTaget Glossary, 2011). Other enablers include consultancies that help firms implement cloud architecture. Moreover, cloud auditors are expected to become of increasing importance in the near future due to growing security concerns.

The cloud computing market is approaching a state of maturity, with consumers having developed a more precise idea of their needs, and suppliers refining their business models to meet them.

2.3 Cloud Computing Economics

A review of the literature on cloud computing reveals that academic research is still exploratory and generalizable results few and far between. The common view in the literature is that cloud computing enables firms to reduce their fixed investments, overall costs, and risk while gaining flexibility. Cardona et al. (2013) document that IT usage, typically measured as the number of PCs in a firm, positively affects firm productivity. To our knowledge, there are no comparable data on cloud computing; prior work studies the possible economic effects using small samples or individual firms.[1]

2.3.1 Costs, flexibility, and firm organization

One of the central economic results of cloud computing is the changing cost structure at the firm level. Cloud computing users do not have to invest in powerful personal computers and servers and hence do not incur high upfront investment and related capital costs. Instead, they incur variable expenses in the form of operating costs or pay-per-use fees (Armbrust et al., 2009; Klems et al., 2009; Bayrak et al., 2011; Etro, 2011; Yoo, 2011; Bräuninger et al., 2012). This changing cost structure is considered to chiefly benefit small and medium-sized enterprises (SME), as they have limited funds to invest in assets and suffer from unused peak capacities more than do large firms, in which tasks and peak times can be more diversified (Armbrust et al., 2009; Marston et al., 2011; Bayrak et al., 2011). Also, using cloud services

[1] In this paper, we focus on the user side of the market. On the provider side, interesting economic topics include competition and industry structure, capacity investment (Lam, 2013), and pricing.

avoids opportunity costs due to underutilization of local IT equipment and outdated software and security standards (Prasad et al., 2014).

In addition to the changing cost structure, there is consensus in the literature that cloud computing reduces total IT costs for firms or at least for SMEs. This cost advantage could originate from a specialized cloud computing vendor reaping economies of scale vis-à-vis an in-house IT solution. Hecker and Kretschmer (2010) call it "general wisdom [that] specialized outsourcing providers can produce more cost efficiently due to economies of scale, specialization,"[2] and more optimal exploitation of equipment (Brumec and Vrček, 2013). Cloud users can benefit from these efficiency gains, but have to weigh them against the transaction costs of the outsourcing process (Riordan and Williamson, 1985). However, there is as yet no empirical evidence confirming this cost advantage. Brumec and Vrček (2013) model the costs of cloud computing usage and compare them with the costs of a de-novo on-premise computing system and show that leasing computing resources from Microsoft, Google, or Amazon is cost efficient for less demanding applications, but that it is still preferable to execute highly complex applications on-premises. Hence, they identify no universal cost advantage of cloud computing over on-premises IT systems.

Flexibility gains from cloud computing also affect firm organization. First, the number of IT staff on-premises can be reduced as cloud services handle many tasks previously undertaken by traditional IT staff, such as maintenance, updates, and the like. Second, the firm can react more quickly to changing conditions in its business environment. The flexibility of cloud computing even lowers entry barriers for new firms or sectors. Etro (2009) conducted a macro-simulation and finds that by lowering entry barriers, cloud computing could create up to 1 million jobs in the European Union. A third organizational and potentially productivity enhancing effect of cloud computing is alteration of business processes, allowing for changes in corporate culture, collaboration with business partners, and customer-faced services

[2] Hecker and Kretschmer (2010) further state that markets with high scale economies tend to concentrate, which might lead clients to change their outsourcing behavior as they are losing bargaining power. Lam (2013) studies cloud providers' capacity investment incentives according to different market structures.

(Klems et al., 2009). Transformations of this kind occurred following implementation of earlier technologies such as ERP and CRM (McAfee and Brynjolfsson, 2008).

Overall, the adoption of cloud computing is expected to shift the production possibility frontier of firms outward and thus should result in higher total factor productivity.

2.3.2 Cloud computing and SMEs

As mentioned above, small and medium-sized enterprises (SME) are expected to benefit most from adopting cloud computing, which is why the literature has thus far focused on SMEs. Most of the studies on SMEs involve a fairly small sample and typically focus on one sector and/or one country.

Alshamaila et al. (2013) study cloud adoption in SMEs by conducting semi-structured interviews and analyzing the resulting data using the Technology-Organization-Environment (TOE) framework (explained in more detail in the following section). They find that except for competitive pressure, all factors of the TOE framework were relevant for the adoption of cloud services. Another interview-based study, this one of Irish SMEs, by Carcary et al. (2013) finds that the most important reasons for cloud non-adoption are security concerns, the lack of time for implementation, and a generally low level of cloud computing in the company's sector. The study did not investigate drivers of adoption but a surprising 35% of survey participants claimed to be unaware of any cloud computing benefits. Stieninger and Nedbal (2014) find that firms are afraid that their corporate image will be negatively affected if they use cloud computing and that they are also concerned about security and privacy management. While most studies assume SMEs to be more likely to adopt cloud computing, Benlian and Hess (2009) find that large firms have a head start in SaaS adoption, albeit an insignificant one. Alshamaila et al. (2013) show that among SMEs, smaller firms are more likely than larger ones to adopt cloud computing.

2.3.3 The Technology-Organization-Environment (TOE) framework applied to the cloud

Based on the findings from the above-discussed research, we structure our research along the lines of Tornatzky and Fleischer (1990), who identify three broad areas that determine a firm's adoption decision and the subsequent efficiency gains. First, the innovation has to fit the firm's existing equipment and processes, as well as its needs (technological context). If a firm already has a sufficient technological infrastructure, the firm is more likely to be able to implement the innovation successfully and to realize economic benefits.[3] An important prerequisite for cloud computing is an interconnected IT system within the firm and a broadband connection to the internet. Second, the necessity and success of an innovation adoption depends on the firm's organizational characteristics, such as size, production processes, and so forth. It is shown, especially in ICT research (Mack and Rey, 2014), that firm mechanisms and dynamics differ significantly according to size. Moreover, a firm needs to be able to assimilate the innovation, so that "alignment between the objectives of an organization's IT strategy and business strategy is directly related to IT effectiveness and overall business/organizational performance" (Carcary et al., 2013). For cloud computing, the literature focuses on small firms as the decrease in upfront investment and the increase in flexibility are of particular advantage for these firms (Kern et al., 2002; Aljabre, 2012; Stieninger and Nedbal, 2014). The third determinant identified by Tornatzky and Fleischer (1990) is the firm's environment, consisting of the industry, market structure and competition, regulation, and the like. The service sectors are expected to especially benefit from adopting cloud computing as they often dispose of huge amounts of data, need to exchange data with clients, or work from various or different locations. By contrast, firms with a security-sensitive environment might deliberately choose not to use cloud computing (Kshetri, 2013). Further, the firm's position in the supply chain, its market power, and the industry in which it is active all may (or may

[3] Note, however, that a high current level of technological infrastructure may also reduce the incremental benefits of adopting a new technology, as a well-performing substitute is already available (Shy, 1996). In the case of cloud computing, a firm's incumbent ERP system may be just such a substitute.

not) result in external pressure or requirements to adopt cloud computing. Finally, regulatory factors across countries may also matter for cloud adoption.

Prior work agrees that all three parts of the TOE framework seem to affect cloud computing adoption. However, none of the studies we found explicitly address heterogeneity between industries or discuss explicit productivity effects. With our indicator, first observations, and the resulting research agenda we take a first step toward closing this gap.

2.4 Data

2.4.1 Existing micro data

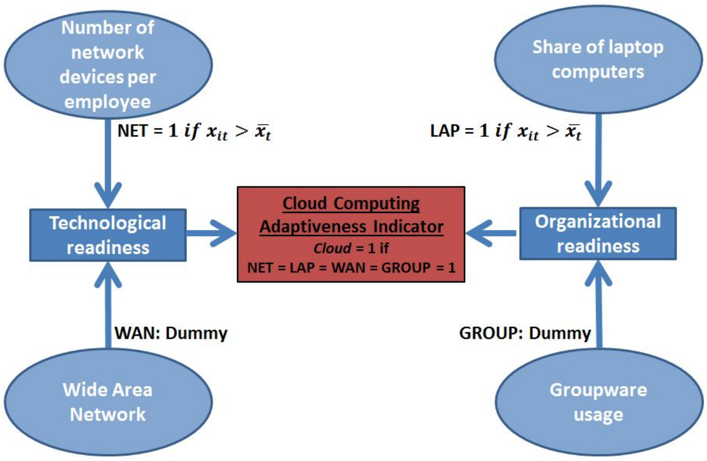
Benlian and Hess (2009) asked approximately 400 top IT executives of German firms to rate different application systems (e.g., ERM, CRM) with regard to potentially adopting them in the form of software as a service (SaaS). The survey samples of Trigueros-Preciado et al. (2013) and Stieninger and Nedbal (2014) include 94 firms from Spain and nine from Austria, respectively. Unfortunately, neither study explains how cloud computing is defined. While these first exploratory results on the drivers of cloud computing adoption and economic effects are helpful, we neither know exactly what was measured nor can we say anything about diffusion patterns given these studies are in a cross-section. The same drawbacks are found in studies conducted for or published by firm research entities such as Deutsche Bank (Heng and Neitzel, 2012), KPMG AG (2013), and Telekom AG (2010).

When studying potential drivers of innovation adoption, surveys revealing decision makers' preferences are the correct methodological choice, especially if the surveys also include non-adopters. To identify economic effects, however, we need a variable for cloud computing usage that is consistently measured and invariant to who responds to the survey.

2.4.2 Our data and measure of cloud adaptiveness

We use the CI Technology Database (CITDB), which was developed by the market intelligence firm Harte Hanks and covers more than 260,000 European firm locations. Our dataset covers the years 2000 through 2007 and includes general firm characteristics such as the number of employees and industry classification, as well as IT-specific information such as the number of desktop PCs, laptops, network devices, IT employees, and usage of different hardware and software, including producer and version. The CITDB has been used in prior studies such as Bresnahan et al. (2002), Kretschmer (2004), Forman et al. (2012), and Kretschmer et al. (2012). We merged the technology data with balance sheet data from the Bureau van Dijk ORBIS database so as to have company information on sales, assets, and so forth. The sample is largely representative, with a slight bias toward medium-sized and large enterprises.

Figure 2.2: Cloud adaptiveness indicator



Source: Authors' own diagram.

There is information on cloud computing usage in the latest Harte Hanks data waves, but the variable's informative value is limited as there is no information on the underlying definition of cloud computing or on how the technology is understood by the person interviewed. The number of observations with cloud computing information is very low in our sample. However, CITDB contains detailed information on other IT resources and elements used in firms. With this information we construct a composite indicator of cloud adaptiveness based on the concept of architectural or combinatorial innovations (Henderson and Clark, 1990) and the TOE framework (Tornatzky and Fleischer, 1990). Loebbecke et al. (2012) and Carcary et al. (2013) state that cloud computing is an evolutionary regrouping of earlier IT elements. We therefore construct our measure by studying the usage and combination of crucial IT resources that together lay the groundwork for cloud computing in a firm. Firms using this kind of IT structure are likely to introduce cloud computing at some point, in other words, they are cloud ready or cloud adaptive. Our definition of cloud adaptiveness matches the concept of architectural innovation developed by Henderson and Clark (1990), which is that an innovation is not always a departure from core concepts or a radical change of components' architecture; rather, "the essence of an architectural innovation [is] the reconfiguration of an established system to link together existing components in a new way" (Henderson and Clark, 1990). This is exactly how cloud computing came to be. Centralized computing and storage, interconnected IT resources, and the standardization of data were and are well-known components. However, the idea of virtualizing computer and server structures and offering software, infrastructure, and platforms as a service, changes the linkages between the components and therefore constitutes an architectural innovation[4]. We will define technological and organizational readiness and will assess other organizational characteristics and the firm environment in our subsequent empirical analysis.

We build our indicator of cloud adaptiveness as a dummy variable that takes the value 1 if all four variables that describe the conditions for cloud adoption take the value 1. The variables are: (1) number of network devices per employee, (2) usage of a wide-area network (WAN), (3) share of laptops among all firm PCs, and (4) usage of groupware software (see Figure 2.2).

To proxy a firm's technological readiness for cloud computing adoption we use information on the number of network devices per employee and on the existence of a wide-area network (WAN) in the firm. Network devices allow direct access to internal networks or the internet. A

[4]Varian (2010) terms this combinatorial innovation. This concept is based on the notion that existing technologies offer a vast set of components that can be combined and recombined to create new products and services.

WAN indicates that a firm has a good network connection, most likely in the form of leased priority lines and broadband, allowing particularly fast data transfers. We assume that a firm with extensive network access possibilities and a good connection infrastructure is not only ready to use cloud computing in a next step, but also likely to be particularly open to data transfer and interconnection.

We proxy a firm's organizational readiness by its usage of groupware software and the share of laptop computers. Groupware, such as Lotus Notes, helps employees communicate or share documents, thus creating a common workspace. This means that firm employees are connected via IT and use common platforms – an important feature of cloud applications. Laptops point to flexible working patterns, including mobile access to firm data, platforms, or software. Firms using groupware and with a high share of laptops have already implemented organizational patterns compatible with a centralized and flexible IT structure. For these firms, adopting cloud computing is less costly and acceptance among employees is likely to be high. A firm is considered cloud adaptive if all four criteria are met (see Figure 2.2). We transform the two continuous input measures – number of network devices per employee (1) and share of laptop computers (3) – into dummy variables. To do this, we compute the average across firms for each year and attribute a value of 1 to all firms with a number of network devices per employee or a share of laptops above the respective year's mean value. A firm that is cloud adaptive might already be using cloud computing or may adopt it in the near future.

Our measure of cloud adaptiveness contributes to the literature by allowing researchers to use existing large-scale datasets for their work. Moreover, to date, the term "cloud computing" has not been well defined – neither in academic research nor by practitioners. Firm-level surveys asking about the "usage of cloud-computing" are thus of limited explanatory power. We therefore develop a first measure of the phenomenon based on more precise firm-level data. In a survey, the questions that need to be asked to obtain our input variables can be answered clearly and unambiguously.

Clearly, a limitation of our indicator is that it does not measure cloud computing as a technology or computing paradigm, but, instead, the readiness of a firm to use it – its adaptiveness. We cannot measure the outsourcing and the scalability characteristics of a cloud and thus provide a lower bound of potential effects associated with being cloud adaptive. Furthermore, it could be argued that we are measuring a firm's technological sophistication rather than its actual cloud adaptiveness. This is a typical problem when working with proxies and cannot be entirely overcome. However, the indicator was constructed by focusing on the technological and organizational readiness for cloud computing and therefore measures a particular form of sophistication. As a robustness check, we split the sample into technologically sophisticated firms (those whose PC intensity is above the sample median of PC intensity) and non-sophisticated firms: 99% of the non-sophisticated firms are also non-cloud-adaptive, while 47% of the non-cloud-adaptive firms have a PC intensity above the median so that one does not automatically imply the other. The correlation between the sophistication dummy and the cloud dummy is 0.28. Another limitation is the equal weighting of the indicator's four input variables, implying that all four factors are equally important in classifying a firm as cloud adaptive. This is a simplification that cannot be remedied as long as there are no other studies on cloud computing and the transition from more traditional IT systems. Alternative approaches of varying weighting schemes like e.g. regression-based approaches of constructing composite indicators typically require a priori information on the selection of a dependent variable as target variable. However, as we preferably wanted to set up a general measure of cloud adaptiveness, we abstained from such an approach in our study. Our data cover the years 2000 to 2007, a period during which actual cloud services were not yet widely used. Given the variables and timeframe of our dataset, adaptiveness serves as a proxy for cloud computing. While the structure of our measure can be used for other datasets as well, a limitation of our analysis is that the Harte Hanks data were not collected by a research institution. This means that the sampling methodology does not guarantee representativeness and the questions are derived from practical point of view. However, as pointed out above, the dataset has been proven useful and reliable in a number of highly renowned studies.

We use two unbalanced panel datasets for our analysis. The first sample (adoption sample) is comprised of 73,985 observations from 25,434 companies in 13 European countries. For the paper's productivity analyses, we use a second sample (productivity sample) that is more restricted than the first sample due to the availability of variables needed to estimate the productivity measure (total factor productivity, TFP)[5].

We now apply our measure of cloud adaptiveness to the data and investigate the distribution and characteristics of cloud adaptive firms, thus providing an early set of empirical findings on cloud computing at the firm level.

2.5 Observations on Cloud Adaptiveness

Our cloud adaptiveness measure captures a firm's technological and organizational readiness to adopt cloud computing. The descriptive observations in this section follow the TOE framework by looking at correlates of cloud adaptiveness (e.g., organizational characteristics of cloud adaptive firms, such as size) and at the firm environment (such as industry or supply chain position). Additionally, we document the productivity levels of cloud adaptive firms.

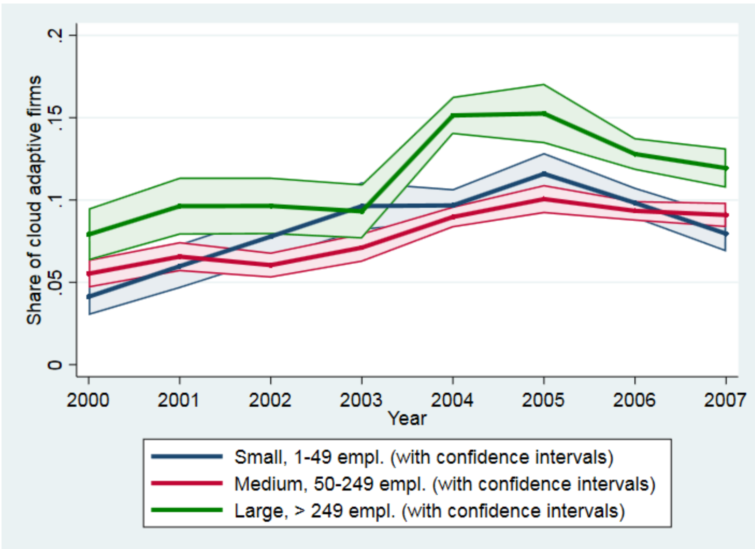
2.5.1 Large firms are early adopters but small firms catch up quickly

Differences in adoption behavior between smaller and larger firms are found in several empirical studies on general IT (Nguyen, 2009) and are expected in the case of cloud computing as well. However, our results over time are somewhat surprising (see Figure 2.3). We would expect large firms (those with more than 249 employees) to be clearly ahead of small firms (those with less than 50 employees) when implementing productivity-enhancing IT. First, at

[5]For more information on the data, see the Appendix 2.A.

the organizational level, large firms often have professional IT departments that keep abreast of trends and constantly work to optimize the company's IT structure. Second, large firms have the financial means to afford high investment in IT, while small firms are less able to make this type of investment and thus are not expected to be among the early adopters (Prasad et al., 2014; Mack and Rey, 2014). Further, there is empirical evidence that large firms imitate innovation more quickly than do small firms (Geroski, 2000). Finally, it is possible that large firms have experience with early cloud-like structures. However, this also means that they might achieve lower cost advantages from cloud computing adoption than smaller firms as large firms might already be realizing economies of scale with their original data centers and IT networks (Marston et al., 2011; Shy, 1996). While our results match our expectations at the beginning and end of our panel period, small firms catch up within several years whereas medium-sized firms do not.

Figure 2.3: Cloud adaptiveness by firm size



Data: Adoption sample. Unbalanced panel data from 2000 to 2007. Cloud adaptiveness see Figure 2.2. Source: CITDB, ORBIS.

The characteristics of cloud technology differ from those of general IT and the literature contends that SMEs benefit more from cloud computing due to its pay-per-use and scalability features, thus allowing the firm a certain degree of financial and capacity flexibility (Sultan,

2011) while avoiding high upfront investment. Our adaptiveness dummy cannot reflect this property.

However, it does capture whether firms have a highly interconnected IT structure and use central communication platforms. On the one hand, large firms tend to have a more complex task structure than small ones and thus need various types of software and hardware (Kretschmer, 2004); standardized systems often cannot satisfy the varying needs of the different firm departments. On the other hand, small firms' tasks tend to be more homogenous and generate rather uniform data. The transaction costs of becoming cloud adaptive are therefore lower for small than for large firms. Hence, the early catching up of small firms is not that surprising after all. In our panel, small firms exhibit the same level of cloud adaptiveness as large firms in 2002 and 2003. This coincides with Benlian and Hess (2009)'s finding that when it comes to SaaS adoption, there is no significant difference between small and large enterprises. However, for the years 2004 through 2007, the cloud adaptiveness of small firms plateaus, whereas the share of large-firm adopters continues to rise. Later in the sample period, firms with 249 employees and less (small and medium-sized) have similar levels of adaptiveness, which is lower than that of large firms. While the different structures and challenges of small and large firms are mostly intuitive, the situation of medium-sized firms is ambiguous. Hence, firm size seems to be associated with cloud adaptiveness, but this finding does not lead to easily interpretable stylized facts about firm adoption behavior. Rogers (1962) states that size is "probably a surrogate measure of several dimensions that lead to innovation".

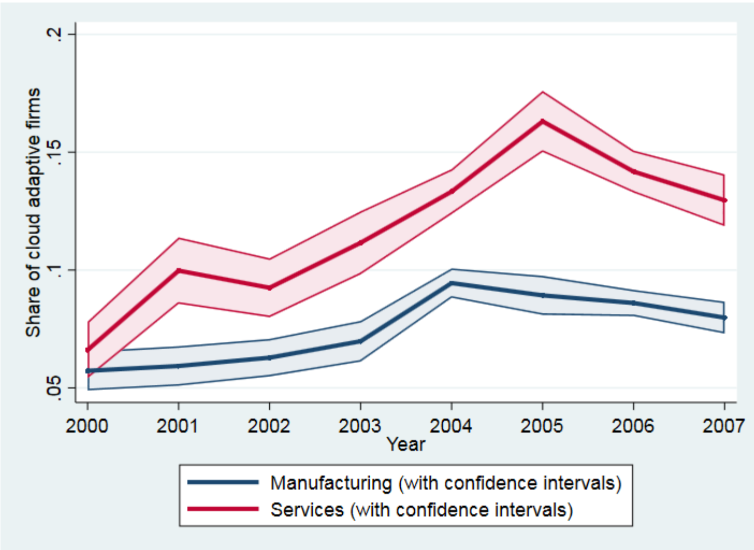
2.5.2 Service firms are more cloud adaptive than manufacturing firms

We expect to find heterogeneity across sectors in cloud adaptiveness. The industry in which a firm is active shapes the firm's technological needs as well as its organizational characteristics, and, almost by definition, the market in which it operates. The tertiary or services sector[6]

[6] Our definition of the service sector includes typical service sectors such as business and financial services as well as trade and partly privatized sectors such as health or education. It does not cover public administration or utilities.

is typically more data intensive than the manufacturing sector, which could explain this sector's high share of cloud adaptive firms (Figure 2.4). For example, financial services are highly data intensive: They process research and trading operations as well as computational algorithms for risk management; furthermore they store and transmit large amounts of data and they need time-sensitive communication with clients and trading partners. Data-intensive applications are also required in logistics and transportation, where supply-chain optimization, automated processes, and consolidation of global supply-chain providers are a source of competitive advantage. The same holds for knowledge-intensive business services (KIBS) (Musolesi and Huiban, 2010; Mack and Rey, 2014) such as consulting or IT outsourcing that create value by transferring their knowledge to clients, which requires sophisticated data management and transfer systems. In their survey of Irish SMEs, Carcary et al. (2013) find that the majority of the cloud adopters in their sample are companies active in the KIBS sector.

Figure 2.4: Cloud adaptiveness by sector



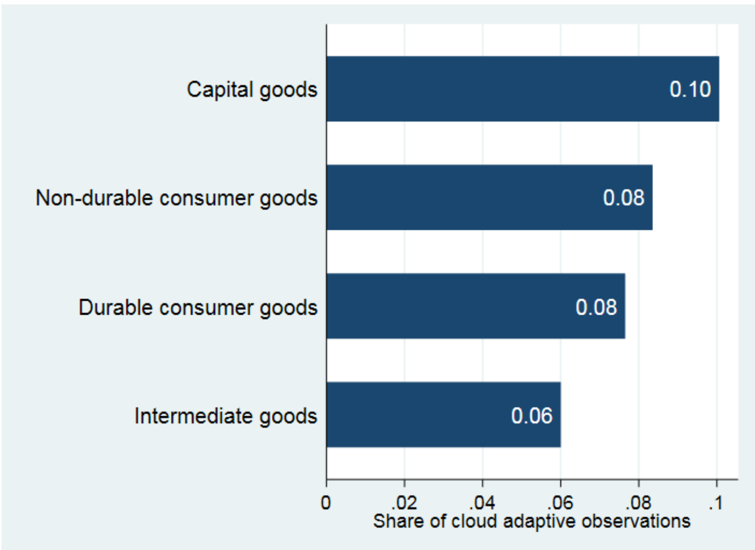
Data: Adoption sample. Unbalanced panel data from 2000 to 2007. Cloudadaptiveness see Figure 2.2. Source: CITDB, ORBIS.

Traditionally, services were viewed as technologically backward and passive adopters of technology, but this view has changed dramatically with tertiarization and information technologies (Musolesi and Huiban, 2010). Scalability and mobility are crucial in services; however, in the more stable environment of a manufacturing firm producing on-premises, a traditional server structure is often more appropriate. However, this could change with the advent of "smart factories", in which production is highly interconnected and computer optimized.[7]

2.5.3 In manufacturing, upstream capital goods industries are more cloud adaptive than downstream consumer goods industries

In production theory, factors of production – capital, labor, and materials – serve as inputs to firms' internal value chains, which link up to form an industry-wide supply chain (Porter, 1985). In manufacturing, upstream firms provide materials and intermediate inputs to firms more downstream the supply chain, which themselves produce capital goods. These are then used by firms farther down the supply chain to produce consumer goods.

Figure 2.5: Cloud adaptiveness in the manufacturing sector by main industrial groupings



Data: Adoption sample. Unbalanced panel data, pooled from 2000 to 2007. Cloud adaptiveness see Figure 2.2. Source: CITDB, ORBIS.
Notes: The pairwise mean differences between the groupings are significant at the 1%-level except for the consumer goods groupings.

In our data, firms in the capital goods sectors such as machinery, industrial electronics, and measurement equipment show higher cloud adaptiveness than firms in the consumer and

[7] In the German-speaking countries, this phenomenon has been termed "Industry 4.0" (Hermann et al., 2015).

intermediate goods industries; indeed, the latter, being upstream industries, are surprisingly non-cloud-adaptive (see Figure 2.5).[8] A possible reason for this is that upstream sectors are not incorporated into e-business operations as much as sectors in the middle and closer to the end of the supply chain.[9] Also, intermediate goods sectors are usually more specialized and therefore do not need the same flexible interconnecting capacities as businesses in the capital or consumer goods sectors, which depend more on markets and customers. More precisely, as the capital goods sector is embedded at different stages of the value chain, mostly supplying technically advanced machinery for production, it not only has high technological requirements, but also engages in marketing and sales activities. Goods are often tailored to customer needs, which can be a highly data-intensive process. The consumer goods sector is less cloud adaptive, but still has higher rates of adoption than intermediate sectors. A survey of the fashion and apparel sector discovered that one reason for limited use of e-business applications within the industry was the "lack of interoperability between the many systems in use" (European Commission, 2012). This statement applies more generally to supply chains, particularly in sectors where product lifecycles are short. More sectoral-level research is needed to better understand the role of cloud adaptiveness in single sectors.

2.5.4 In services, unregulated market sectors are more cloud adaptive than nonmarket sectors; cloud adaptiveness can differ significantly within single supply chains

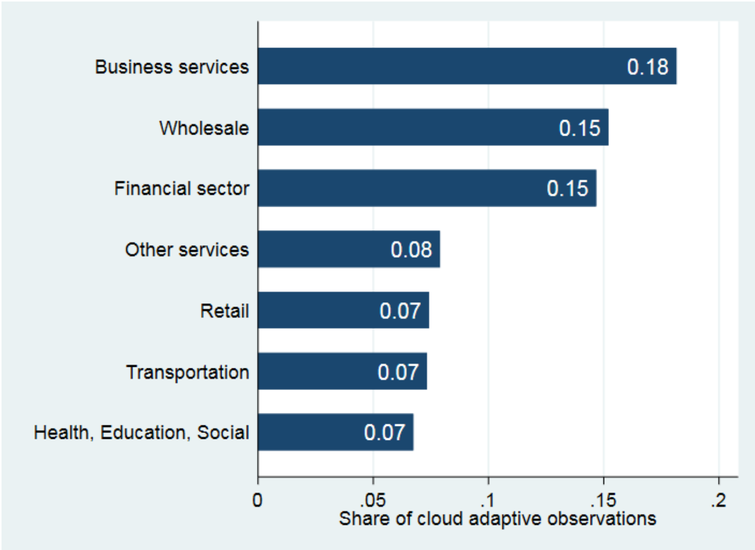
In our sample, business and financial services, as well as wholesaling, are the most cloud adaptive service sectors, while retail trade and regulated, state-dominated industries, such as health, education, and social services, are the least likely to be cloud adaptive firms (see Figure 2.6).[10] This is intuitive as business and financial services are very data-intensive sectors, requiring not only the treatment but also the exchange of data permanently and in real time.

[8] To classify industries, we use the European statistical definition of main industrial groupings according to Commission Regulation (EC) No 656/2007 of 14 June 2007.

[9] Of course, increased use of procurement platforms might result in upstream sectors catching up.

[10] Cloud adaptiveness of a sector is not correlated with firm size in the sector. For example, the highest shares of large firms are in the finance (high cloud adaptiveness) and retail (low cloud adaptiveness) sectors.

Figure 2.6: Cloud adaptiveness in the services sector



Data: Adoption sample. Unbalanced panel data, pooled from 2000 to 2007. Cloud adaptiveness see Figure 2.2. Source: CITDB, ORBIS.
Notes: 'Other services' include legal, personal and repair services and the amusement sector. The mean difference between the two subgroups (Business services, Wholesale, Financial sector versus Other services, Transportation, Retail, HES) is significant at the 1%-level.

Falck et al. (2013) analyze the diffusion of e-health, that is, interconnecting ICT applications in the health-care sector. They find that doctors and hospitals use some ICT applications, but that information exchange and teleconferencing are not widespread. Data security and quality of services are requirements a health-care network or cloud system needs to fulfill. Hence, the low cloud adaptiveness of these sectors could be due to insufficient service stability, a still incomplete legal framework for (international) cloud services, and the absence of widespread cloud certification services – the lack of each of which leads to a lack of trust and security in cloud computing.

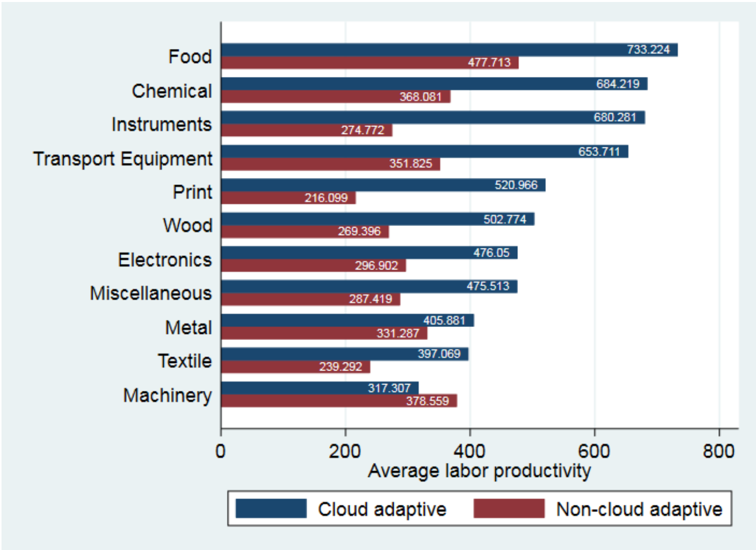
Wholesale firms work closely with producers but they do not produce goods themselves. They resell to retailers, who in turn sell the goods to private consumers. A characteristic of the retail and wholesale businesses is that, in contrast to other service sectors, they have not only a flow of information, but also a flow of goods, along the supply chain (Prajogo and Olhager, 2012). In our data, the wholesale sector is one of the most cloud adaptive service industries, whereas retail shows a very weak disposition toward cloud computing (Figure 2.6).

This is surprising at first sight as both are closely vertically related and basically execute very similar tasks. Their operations differ in scale and complexity though. Retail business is generally locally oriented; wholesale tends to operate at a global scale and therefore faces a much greater challenge in organizing both the flow of information and the flow of goods. A global wholesale company needs to be constantly in touch with geographically dispersed producers, not only communicating and negotiating, but also observing and analyzing the development of international markets. Looking downstream, these companies manage and maintain a large distribution network. By contrast, a locally operating retail firm requires less e-business interaction. Still, it is surprising that companies upstream and downstream the supply chain can cooperate without being fully integrated, that is, without using the same IT structure and communication channels, especially since integrated logistics system can help reduce shortages and optimize inventories (Prajogo and Olhager, 2012). Cachon and Fisher (2000) conducted an empirical study on the value of information sharing in a grocery supply chain between supplier and retailer. They find that implementing information technology such as scanners and electronic data interchange (EDI), that allows quicker order processing and sharing of demand and inventory data, can reduce supply chain costs by as much as 10%. Cloud computing could further enhance these advantages. However, IT integration of a supply chain is not costless. The retail trade market is currently experiencing the emergence of large players that pressure smaller suppliers into the adoption of their specific IT systems (European Commission, 2012). Standardized cloud computing solutions might be cheaper and more widely compatible. We therefore expect retail companies to catch up, with regard to cloud adaptiveness, in the near future.

2.5.5 In manufacturing, cloud adaptive firms are more productive

Evidence on the productivity-enhancing effects of adopting cloud applications is scarce. Employing our cloud adaptiveness measure for two different types of productivity measures separated by industries provides some initial observations on the productivity of cloud adaptive and non-cloud-adaptive firms in manufacturing sectors.[11]

Figure 2.7: Labor productivity in industries



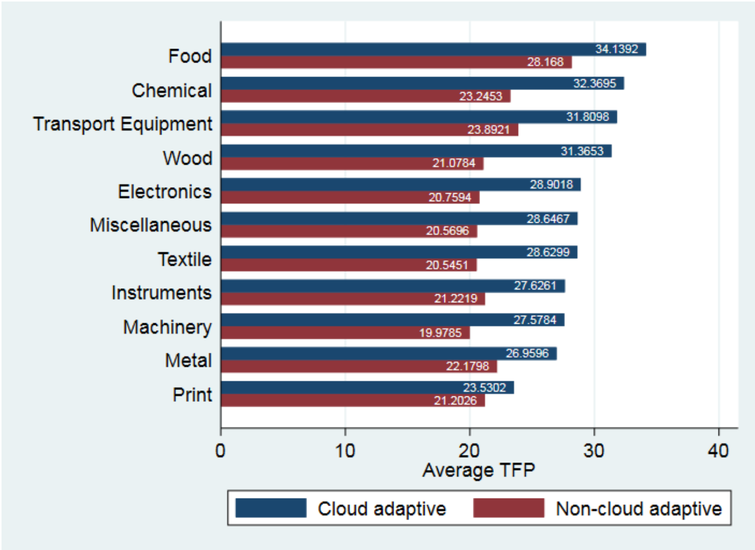
Data: Productivity sample. Unbalanced panel data, pooled from 2000 to 2007. Cloud adaptiveness see Figure 2.2. Source: CITDB, ORBIS.
Notes: Mean differences between Y/L of cloud adaptive and Y/L of non-cloud adaptive observations are significant at the 1%-level except for Metal and Machinery.

In Figure 2.7, cloud adaptive manufacturing firms generally exhibit higher average labor productivity[12] compared to manufacturing firms that are not as cloud adaptive, except for the machinery sector. Sectors with large differences in labor productivity are instruments, chemicals, and transport equipment. As labor productivity is only a partial productivity measure, it reflects the joint influence of a host of factors and therefore it is easily misinterpreted as technical change. An alternative productivity measure is total factor productivity (TFP), the residual in the firm's output function after having controlled for capital and labor as physical inputs. Hence, as TFP abstracts from the effect of inputs, it is a more appropriate measure of technical change, which further allows for the incorporation of spillovers and therefore

[11] We find the same qualitative results in the services sectors, but the picture is less clear. In all service sectors, cloud adaptive firms are more productive than non-cloud-adaptive ones and we also find significant mean differences for almost every sector. However, these improvements are either in labor productivity or in TFP, not necessarily both. We find no significant differences in the financial sector or in the health/education/social sector. The partly insignificant differences might be due to higher within-sector firm heterogeneity.

[12] Labor productivity is measured as sales divided by employment.

Figure 2.8: TFP in manufacturing industries



Data: Productivity sample. Unbalanced panel data, pooled from 2000 to 2007. Cloudadaptiveness see Figure 2.2. Source: CITDB, ORBIS.
Notes: Mean differences between TFP of cloud adaptive and TFP of non-cloud adaptive observations are significant at least at the 5%-level.

proxies for cloud computing as a general purpose technology.[13] According to our estimates (Figure 2.8), there are TFP differences throughout all manufacturing sectors. These findings underline the importance of accounting for the specific nature of cloud computing as it is incorporated in technical change.

Our analysis does not allow drawing causal conclusions on the productivity effects of cloud computing or cloud adaptiveness. However, there is empirical evidence that cloud computing and firm productivity are highly correlated. Not only do cloud adaptive firms achieve higher sales per employee, they also are more successful in the choice and employment of technologies, measured by total factor productivity. A causal specification needs to resolve whether these productivity differences are driven by cloud adaptiveness. IT-driven intra-industry productivity differences are found in several studies controlling for various other factors (e.g., Brynjolfsson and Hitt (1996); Tambe and Hitt (2012). In their meta-study, Cardona et al. (2013)

[13] To estimate TFP at the firm level, we follow Levinsohn and Amil (2003). This method accounts for biased coefficients of the production function originating from unobserved productivity shocks by explicitly modeling capital and intermediates within the estimation. This method ensures consistent estimates of inputs in the production function and thus enables unbiased calculation of total factor productivity by subtracting estimated input contributions from output. For further explanation, see also Van Beveren (2012).

confirm that most studies use either PC intensity or IT capital as a measure for IT, which was reasonable in the 1990s, the time period most productivity studies focus on (Tambe and Hitt, 2012). We would expect similar intra-industry effects driven by modern ICT like cloud computing and its direct precursors, which can no longer be measured based on capital as services became an essential part of it.

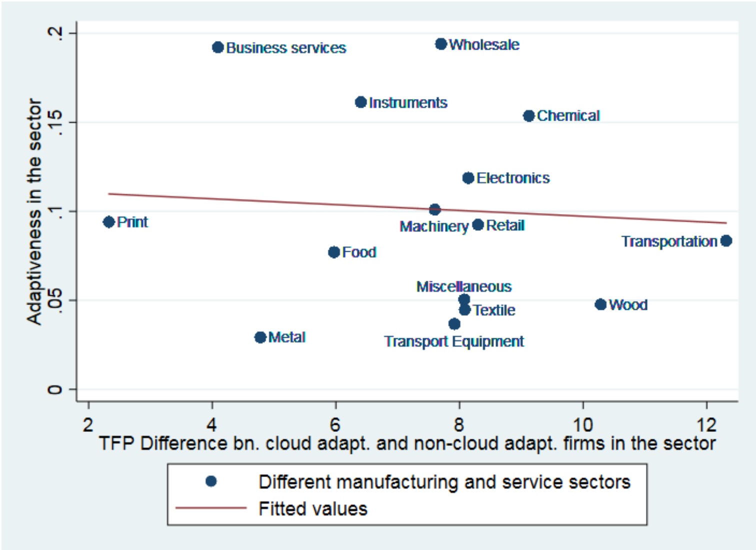
2.5.6 Cloud-similar technologies are not necessarily adopted in the sectors where they allow for the highest productivity

We would expect industries in which cloud adaptive firms have a large productivity advantage to also have a high adaptiveness rate. Interestingly, this is not what we find in the data (Figure 2.9). The correlation between a sector's cloud adaptiveness and the productivity difference between adaptive and non-adaptive firms in this sector is slightly negative.[14] This finding shows a strong heterogeneity among a sector's cloud adaptiveness and its firm-level productivity performance. While e.g. a given adaptiveness in the print sector is associated with relatively low TFP differences between cloud adaptive and non-cloud-adaptive firms, the same given adaptiveness is associated with high TFP differences between firms in the retail sector.

One potential explanation why firms' productivity advantages are not necessarily associated with its cloud utilization across all sectors is reverse causality. That is, more productive firms might be more cloud adaptive in general, so that TFP differences between cloud adaptive and non-cloud-adaptive firms in a sector only weakly correlate with the adaptiveness share. Further, recall that the productivity measure of TFP is not input driven. If a firm observes a cloud productivity potential in its sector, it might take a while to catch up, become cloud adaptive and realize the productivity advantage. Another explanation of the low adaptiveness in sectors with a high productivity potential is the first-mover advantage meaning that the firms that became cloud adaptive first realize productivity advantages other firms cannot.

[14] Note that in this section we consider both manufacturing and service sectors.

Figure 2.9: TFP differences and cloud adaptiveness



Data: Productivity sample. Unbalanced panel data, pooled from 2000 to 2007. Cloud adaptiveness see Figure 2.2. Source: CITDB, ORBIS.
Notes: The Financial sector, Other services and Health/Education/Social are not represented as their mean differences are insignificant.

This can be due to limited needs of this technology in the sector, bounded growth potential of the industry or particular market characteristics. However, adoption of the software and hardware that readies firms for cloud computing might be driven by factors other than direct productivity gains. One driver of adoption is flexibility gains (see Section 3). Another reason for adoption is pressure from business partners or the necessity of integrating into a supply chain (see Section 5.4). While these measures might not be productivity-enhancing in the short run, they can secure the survival of the firm in the medium or long run. Moreover, particularly at the start of an innovation adoption lifecycle, firms often choose to adopt for non-economic reasons, for example, a manager's interest in technology, innovativeness as an important part of corporate image, or IT departments that are autonomous and agile in their adoption decisions.

2.6 Conclusion

Cloud computing is expected to generate productivity effects in firms and growth in the economy. We develop a measure of cloud computing that lets us examine its diffusion pattern and its association with firm productivity across industries. Our measure builds on an existing panel of firm-level data and takes into account the genesis of cloud computing as an architectural innovation. We thus observe firms' cloud computing adaptiveness over time and study adoption and productivity patterns at a stage where comprehensive firm-level panel datasets on cloud computing are not yet available. Our six observations allow us to suggest an agenda for further research.

Our findings show that firm size is not a good predictor of cloud adaptiveness per se; rather, it is other firm characteristics that are correlated with the adoption decision. We also find that the service sector is more cloud adaptive than the manufacturing sector and that it is especially business services and the financial and wholesale sectors that are most cloud adaptive. Interestingly, in the manufacturing sector we find positive productivity differences between cloud adaptive and non-cloud-adaptive firms. This productivity advantage, however, does not necessarily benefit a large fraction of the firms in this sector.

With a view to the currently still poor data situation, we suggest employing our cloud adaptiveness dummy in future empirical research on cloud computing and the underlying economics of it. Our approach enables scholars to work on diffusion and productivity and to establish appropriate econometric identification strategies that help test theoretical predictions. In the long run, data-collection efforts should focus on a representative panel, be based on a precise and thorough definition of cloud computing, survey firms on their business and production processes that use a cloud service, and collect information on how cloud computing affects firm costs, communication, and organization. With the help of the TOE framework and based on this paper's observations, future work should attempt to discover the key characteristics that prompt firms to adopt cloud computing and result in successful, productivity-enhancing implementation. More specifically, studies on cloud computing should be conducted at the industry level due to massive heterogeneity. Further, given that the concept of cloud computing is very broad, care should be taken to discover which elements of cloud computing firms actually implement (e.g., IaaS, SaaS, PaaS, or even more fine-grained aspects), and what they actually do with it, in order to understand the underlying potentially productivity-enhancing mechanisms. Finally, cloud computing adoption varies based on a firm's position in the supply chain and thus suggests a linkage of cloud adaptiveness and the firm's type of output or its market power in addition to its industry.

By modeling and quantifying such underlying mechanisms, the economic effects of cloud computing can be understood and a consistent framework of cloud computing economics can be developed, especially at the firm and industry level.

Appendix 2.A Data and Samples

We use a dataset with data from two sources: (1) the Harte Hanks CI Technology Database (CITDB) and (2) Bureau Van Dijk's ORBIS. Harte Hanks, a market intelligence firm, conducts annual telephone surveys to take stock of specific IT types used by individual sites (establishments) of more than 10,000 German firms. As the CITDB data are collected at the establishment level while the ORBIS database covers the company level, we aggregated the Harte Hanks dataset to the company level or extrapolated where required. The first step was the identification of all establishments that belong to one company. We matched *bvd* (Bureau van Dijk) *company IDs* to the CITDB *site IDs* using the company name, the zip code, and the three-digit SIC code of every observation. Next, we had two types of technology variables to aggregate: dummy variables were set to 1 at the firm level if any of the company's establishments used this technology, for example GROUP, and 0 otherwise. Integers, such as the *total number of PCs*, were summed and expressed as relative numbers (per employee). As the data structure is rather complicated and sometimes misleading, the results were cross-checked carefully and in some cases weighted.

In this paper we use two different extracts from the resulting panel dataset:

1. the adoption sample for Sections 2.5.1 through 2.5.4 of the paper and

2. the more restricted productivity sample for Sections 2.5.5 and 2.5.6.

We chose this approach because of the high number of missing data points for the balance sheet variables required for the productivity analysis. Refer to Tables 2.1 through 2.4 for sample statistics.

Table 2.1: Sample statistics and distribution of cloud adaptiveness in the adoption sample

Adoption sample	Num. of obs.	%	Num. of firms	% of cloud adaptive firms	
				in 2000	in 2007
Total sample	73,985	100.00	25,434	5.71	9.58
Firm size					
Small (< 50)	17,526	23.69	7,194	4.13	7.95
Medium (50–249)	39,396	53.25	14,076	5.53	9.09
Large (≥ 250)	17,063	23.06	6,671	7.91	11.94
Industries					
Manufacturing	41,761	56.44	13,698	5.73	7.98
Services	25,072	33.89	9,143	6.61	12.96
Other	7,152	9.67	2,593	2.13	7.30

Data: Harte Hanks CI Technology Database, ORBIS balance sheet data, unbalanced panel data from 2000 to 2007.
Notes: A firm can grow or shrink throughout the panel. The service sectors include Retail, Wholesale, Business Services, Financial Sector, Transportation, Health/Education/Social, and Other Services (legal, personal, and repair services, amusement sector). "Other sectors" include the primary, construction, public utilities, and public administration sectors.

Table 2.2: Descriptive statistics of input variables in the adoption sample

Adoption sample	Num. of obs.	Mean	Std. dev.	Median	Min.	Max.
Employees	73,985	457.04	4090.23	105	1	260,070
Num. of network devices per employee (NET)	73,985	0.74	1.69	0.53	0	177.4
Wide-area network (WAN)	73,985	0.53	0.50	1	0	1
Share of laptops among all firm PCs (LAP)	73,985	0.16	0.20	0.1	0	1
Groupware (GROUP)	73,985	0.90	0.30	1	0	1
Cloud adaptiveness (Cloud)	73,985	0.09	0.29	0	0	1

Notes: Descriptive statistics are based on firm-year observations.

Table 2.3: Sample statistics and distribution of cloud adaptiveness in the productivity sample

Productivity sample	Num. of obs.	%	Num. of firms	% of cloud adaptive firms	
				in 2000	in 2007
Total sample	32,608	100.00	11,091	5.93	11.18
Firm size					
Small (< 50)	8,270	25.36	2,909	3.65	9.05
Medium (50–249)	16,567	50.81	5,995	6.17	10.36
Large (≥ 250)	7,771	23.83	3,328	8.05	14.51
Industries					
Manufacturing	20,451	62.71	6,545	5.51	9.43
Services	9,559	29.31	3,552	7.68	14.65
Other	2,598	7.97	994	2.14	11.48

Data: See Table 2.1.
Notes: See Table 2.1.

Table 2.4: Descriptive statistics of input variables in the productivity sample

Productivity sample	Num. of obs.	Mean	Std. dev.	Median	Min.	Max.
Employees	32,608	342.62	2035.49	112	1	105,261
Sales (in mio. $)	32,608	110.93	775.12	24.95	1	62,900
Labor productivity (in mio. $)	32,608	457.08	3,524.67	216.21	0.03	317,083
TFP	32,608	25.54	30.41	20.45	0.0016	3,370
Num. of network devices per employee (NET)	32,608	0.73	1.18	0.53	0	120
Wide-area network (WAN)	32,608	0.51	0.50	1	0	1
Share of laptops among all firm PCs (LAP)	32,608	0.13	0.15	0.09	0	1
Groupware (GROUP)	32,608	0.90	0.30	1	0	1
Cloud adaptiveness (Cloud)	32,608	0.10	0.30	0	0	1

Notes: See Tables 2.1 and 2.3.

Chapter 3

Moving Communication to the Digital Space: Productivity and Organizational Effects of Interconnected ICT in Firms

3.1 Introduction

During the last two decades, computing and telecommunication merged into one single system leading workplaces to be increasingly digitized. A central feature of digitized workplaces is that communication and collaboration is moved from face-to-face interaction to IT-based tools. Thus information flows and knowledge sharing across the organization, between employees, teams and different hierarchical levels are changed in unprecedented ways (Deloitte, 2011; Dery et al., 2017). The new, integrated information and communication technologies can therefore heavily impact firms' processes, organization and, eventually, economic success.

The productivity effects of IT in firms have been a major topic in the economics and information systems literature since the 1990s and continue to be of great interest: On the one hand, it is because the productivity effects of IT are generated in a complex ecosystem including task specialization, firm organization, competition, industry structure, and public infrastructure. On the other hand, the technologies are evolving and continuously creating new opportunities and challenges. Measuring IT or ICT (Information and Communication Technologies) is therefore a challenge with respect to methodology and data availability. Many micro-founded studies use the number of PCs per employee or IT capital stock in the firm as their IT variable for productivity function estimations (Cardona et al., 2013). Another, more recent, strand of empirical literature focuses on a related infrastructure, that is, broadband internet access (see for example Atasoy, 2013, and Akerman et al., 2015). However, neither the conventional nor the more recent measures account for the evolution of IT structures inside the firms where computing and telecommunication resources merged into a single system.

In this paper, I fill this gap and propose a measure of the convergence of computing and telecommunication which I call *interconnectivity*. After the introduction of PCs, this convergence is a major step in firm digitization as it moves collaboration and communication in the firm to the digital space. For the interconnectivity indicator, I exploit information on the availability of interconnecting software (ERP and groupware) as well as hardware (network devices and laptops) at the firm level. The baseline approach are labor productivity estimations augmented by the indicator. Then, I improve the understanding of the productivity mechanisms of the new ICT by providing evidence on complementary changes in the firm that have not been identified as such in the literature before. I study the impact of interconnectivity, first, on employment and displacement of IT workers (an organizational complement) and, second, in the context of broadband internet availability (an infrastructural complement). For the estimations, I use a cross-country firm-level panel dataset including technology information and balance sheet data from 2000 to 2007.

I find heterogenous effects with respect to firm size. Across all firms in the sample, there are no statistically significant productivity effects of a firm's change to an interconnective IT system. Medium-sized firms, however, show positive productivity effects of interconnective IT systems, whereas productivity effects of interconnectivity are negative in large firms.

Furthermore, I find that negative productivity effects in large firms can be attributed to decreasing sales, which suggests technical or organizational start-up difficulties, and economic adjustment costs after the introduction of interconnectivity. Positive productivity effects in medium-sized firms are driven by changes in the number of employees. More specifically, medium-sized firms seem to choose to outsource parts of their IT departments when adopting interconnective systems, whereas large firms seem to opt for in-house solutions. The results are robust to a number of controls and alternative specifications. I also implement an instrumental variable estimation based on broadband availability which, however, shows zero effects. Intuitively, broadband internet is likely to be a complementary technology to interconnectivity because it allows the interconnected resources in the firm to be linked up to the outside. This is not confirmed by my estimations on this sample. The merge of computing and communication resources in firms has heterogenous effects on productivity and organization. A fast internet connection is not driving the adoption and the effects, though.

This work contributes to three strands of literature. First and foremost, to the best of my knowledge, the merge of computing and communication to what we call ICT and therefore the transfer of communication to the digital space has not been quantitatively addressed in the productivity literature to date. In contrast, ICT in its broadest sense is the subject of various productivity studies in non-parametric approaches such as growth accounting (Jorgenson, 2001; Stiroh, 2002) and in econometric production function estimations. In their meta-study on ICT and productivity, Cardona et al. (2013) find a large range of output elasticities of different technologies but identify a clear cluster around the values of 0.05–0.06. This means that a 10 percent increase in ICT investment translates into output growth of 0.5–0.6 percent. The reviewed studies mostly use traditional technology measures such as IT capital or the number of (workers using) PCs in firms (e.g., Brynjolfsson and Hitt, 2003; Black and Lynch, 2004; Bloom et al., 2012).[1] Hitt et al. (2002) consider advances in IT by looking at enterprise resource planning (ERP) software, whereas Atasoy (2013) and Akerman

[1] Other work, such as Beaudry et al. (2010) and Autor et al. (2013), also refers to PCs as a measure of ICT adoption for research questions other than productivity.

et al. (2015) analyze the impact of broadband access on output and labor. In contrast to my work, these examples are focusing on a single technology, namely an IT application or telecommunication infrastructure. Closest to the present analysis is the study of Gaggl and Wright (2015) on wage inequality and skill-demand in small U.K. firms as a result of investments in IT and communication equipment that was high-tech in the period of analysis, 2000 through 2004. Also Gaggl and Wright (2015) do not specifically focus on the convergence of IT and CT though.

Second, the literature on ICT and organizational change shows that the impact of ICT on workers' wages, tasks or jobs varies, for instance, by hierarchy (e.g., Bloom et al., 2014) or skill group (e.g., Akerman et al., 2015; Gaggl and Wright, 2015). I contribute to these studies by looking at the group of employees that is directly concerned, namely IT employees in general and developers in particular.

The third strand of literature related to this study is still developing. The relationship between broadband adoption and productivity is subject to a number of publications (e.g., De Stefano et al., 2014; Canzian et al., 2015; Akerman et al., 2015). Most of them also provide a discussion of potential complementary technologies as the impact channel. To the best of my knowledge, this paper is, however, the first to empirically test the complementarity between broadband infrastructure and a certain firm ICT.

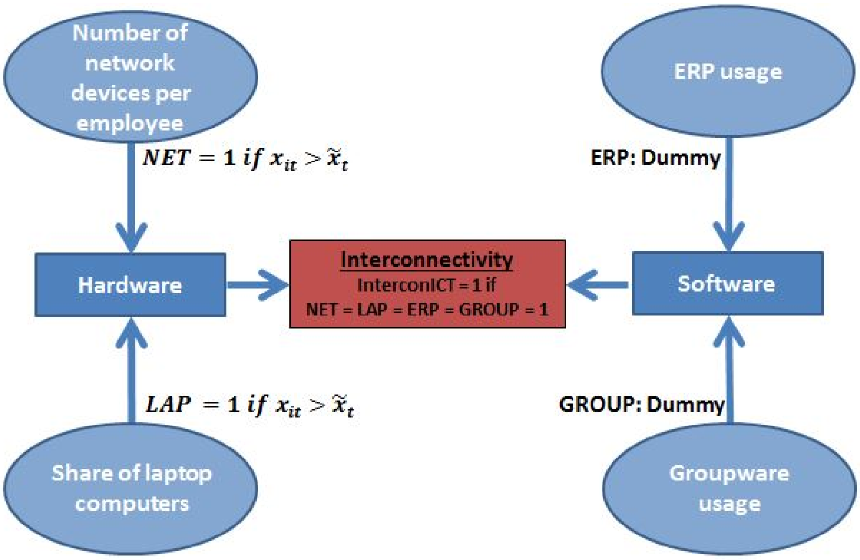
The remainder of the paper is structured as follows: Section 3.2 explains the construction of the interconnectivity variable and potential mechanisms of the effect. The empirical specification as well as the idea of the instrumental variable approach are explained in Section 3.3. Section 3.4 presents the data for the analysis and descriptive statistics. Sections 3.5 and 3.6 show and discuss the results and robustness checks for the fixed effects and for the IV approach. Section 3.7 concludes.

3.2 Interconnectivity in Firms

3.2.1 The InterconICT Indicator

Interconnectivity is the integration of computing and communication in the firm into a single system. I construct a composite indicator of interconnective IT systems in firms based on the idea of Candel-Haug et al. (2016) including information on software and hardware such as network devices, enterprise resource planning (*ERP*), groupware, and laptops. *Network devices* are a necessary condition for interconnection as they build the appropriate backbone and provide access to servers and the Internet. *ERP* systems are large software packages that are integrated across the firm and allow processing the organization's core transactional data (Staehr, 2010) within and beyond a firm's boundaries (Hitt et al., 2002). They reflect the company's organizational structure and are used by most departments (Schubert and Adisa, 2011), not only to access data, but also to enter data only once. These systems ensure that data is harmonized and data storage is centralized and accessible for different departments. *Groupware* provides an explicit platform for communication and collaboration, some of the most well-known examples being Lotus Notes and MS Outlook. These applications help employees communicate internally and externally via email or live chat and to share documents and calendars, thus creating a common workspace. Last, I use the *share of laptops* among all firm PCs as another indication of the firm's interconnectivity. Laptop computers can only be used efficiently if access to internal resources is portable and available when away from the desk, e.g. in meetings or with a client. For this reason, a high share of laptop computers in the firm is a further proxy for interconnectivity. I define firms that use ERP and groupware and that employ a significant number of network devices and laptops in a given year to be interconnected.

Figure 3.1: Construction of the InterconICT indicator



Source: Own diagram.

For each firm, I calculate the number of network devices per employee as well as the share of laptops among all of the firm's personal computers. Then, for both variables, I identify the 50th percentile among all firms for each year and attribute the value 1 to all firms that have a number of network devices per employee or a share of laptops above the respective year's median. To represent the software part of interconnective IT systems, the dummies for ERP and groupware usage in the firm are included. The measure is constructed by adding up information from the four input variables. A firm's IT system is denoted as being interconnected (*InterconICT*= 1) if all four conditions are met (see Figure 3.1). A firm that switched to interconnectivity once will remain interconnective for the rest of the sample period.[2]

My data allow identifying firms that invested in the respective hardware or software, but this does not always mean that resources are actually used by employees. On the one hand, it seems reasonable to assume that at least in smaller firms the IT department's activities are closely related to the actual needs of the employees. In large firms, on the other hand, there is

[2]The construction of the dummy with *NET* and *LAP* being measured depending on the equipment of other firms theoretically allows a firm to switch back from *InterconICT*= 1 to *InterconICT*= 0. This is the case for 1091 firms. Robustness checks excluding these firms yield very similar results.

the risk that resources might be purchased and available but not used by (most of) the staff. In the case of interconnectivity, however, I expect the input components to be widely used. They involve crucial changes to the firm's communication and collaboration processes that can hardly be circumvented by individual employees.

3.2.2 Potential Mechanisms of the Productivity Impact of Interconnectivity

Switching to an interconnected IT system means moving firm communication and collaboration to the digital space. Consequently, the concept is not purely technical, but has wide-ranging implications on a firm's work processes and potentially also on firm employment and productivity.[3]

In the first place, every single input technology of the interconnectivity indicator impacts firm processes with respect to collaboration, communication and cost efficiency. The simple connection of several IT systems via network devices in the firm can improve capacity utilization with regard to storage and computing, and therefore decrease operating costs (Grance et al., 2002). Furthermore, the technical interconnection is a precondition of the integration of communication and IT. Standardized data entry, storage, and access, such as provided by an ERP, significantly decreases frictions related to the parallel execution of tasks in different departments of the company or the absence of up-to-date information where it is required for business and decision-making. Structured data collection and sharing allows, for example, the computation of indicators on firm performance, customers and competitors thereby supporting sales, marketing and management tasks (Hitt et al., 2002). Collaboration is also encouraged and improved with the usage of groupware applications by providing a platform for document sharing and electronic communication. Employees can work on a

[3] According to Galbraith (1974), an organization needs to adapt its information processing capabilities to the uncertainties it faces in its activities. Galbraith predominantly refers to changes in the organizational structure to make information processing more efficient, but the same argumentation applies to the adoption of ICT. Interconnectivity is very likely to provide a firm with efficient tools for information processing.

document together and exchange with their colleagues. Laptop computers need the access to an internal firm system and then allow consulting data and documents in real-time.

In the second place, taking the indicator's inputs together, the implementation of an interconnective system can have implications beyond improvements and efficiency gains in single work processes. Interconnectivity can, for instance, be a driver, a complement or an outcome of modifications in firm strategy or organization. Enhanced data treatment and communication in the firm can help the management to fine-tune or change the firm's business strategy. When extended from administrative processes to the production process, the interconnectivity across firm departments would also allow for the customization of products or better service quality (Bartel et al., 2007). Moreover, the literature agrees that altering fundamental ICT structures implies organizational change in the firm "around the new technology" (Draca et al., 2006). Bresnahan et al. (2002) explicitly find that IT and workplace reorganization complement each other in their contribution to higher firm productivity. Bloom et al. (2014) find that information technologies (IT) have a decentralizing effect and shift decision making to lower hierarchical levels whereas communication technologies (CT) have the opposite – centralizing – effect, shifting decision making to higher hierarchical levels. Along the same lines, several studies conclude that IT decreases vertical integration and therefore average firm size (Brynjolfsson et al., 1994; Hitt, 1999; Im et al., 2012). The new technologies can also alter job skill demand in the firm (Autor et al., 2003). On the one hand, the introduction of interconnectivity requires the skills to handle the applications and platforms. On the other hand, the new system needs to be appropriately managed and maintained. Furthermore, related changes in business strategy potentially require new qualifications in the firm. Research on firm effects of broadband internet access finds that the new technology complements workers in executing problem-solving, complex communication and information-intensive tasks (Akerman et al., 2015). This could also apply to interconnectivity.

The implementation of new IT resources and the related strategic or organizational changes incur costs. In a model on the productivity contribution of general purpose technologies, Helpman and Trajtenberg (1998) find that a new long-run cycle starts with each new generation of technologies: During the first phase after the introduction, output and productivity growth slow down, whereas the positive effects only appear in the second phase. Empirical evidence on firm IT supports this idea: Yang and Brynjolfsson (2001) list the costs related to the implementation of an ERP suite in a firm such as consultants, training, process engineering and testing. These implementation and deployment costs sum up to four time the cost of the necessary hardware and the software license. Further economic costs are frictions in the administration and production routine or even production downtimes, as well as management time.

Interconnectivity is likely to combine the effects of its constituent technologies. The inputs suggest efficiency gains from shifting communication and collaboration to digital tools. Furthermore, it is likely that the implementation of interconnectivity as a set of technologies is related to a change in strategy or organization. However, the work of Bloom et al. (2014) explicitly shows that IT and CT can even have contrasting effects on firms. Hence, the productivity and organizational effects of interconnectivity are not obvious in advance. Overall, I argue that the implementation of an interconnective system allows for more efficient processes at many stages, better decision making and enhanced competitiveness, and is consequently increasing labor productivity in the firm in the long run. The adoption process, however, most like goes along with organizational change which might enhance start-up costs and problems. I expect the economic reorganization costs and frictions to be lower in small and less complex firms. Furthermore, interconnectivity might not be such a radical change in small organizations where regular communication and interaction in person is easier and therefore more common even without the interconnecting ICT resources.

3.3 Empirical Model

3.3.1 Fixed Effects Specification

I estimate an augmented Cobb-Douglas production function in the style of Black and Lynch (2004) or Bloom et al. (2012). The baseline specification is:

$$y_{it} = \alpha + \beta_1 k_{it} + \beta_2 m_{it} + \beta_3 \text{InterconICT}_{i(t-1)} + \alpha_i + \delta_t * \gamma_{ind} + \varepsilon_{it} \tag{3.1}$$

where i denotes the specific firm, t the year of the observation and ind the firm's industry at the 2-digit level of the SIC classification. y_{it} represents logged company sales per employee; k_{it} and m_{it} represent logged capital per employee and logged materials (intermediate inputs) per employee respectively. *InterconICT* is the dummy denoting the adoption of interconnective IT resources in the year $t-1$ by the firm. α_i denote firm fixed effects and $\delta_t * \gamma_{ind}$ the two-way fixed effects of year and the two-digit industry of the firm. ε_{it} is the error term.

The ICT investments are included in the capital variable and represent embodied technological change (Jorgenson, 1966). The interconnectivity indicator (*InterconICT*), however, combines information on the availability of software and hardware resources that are crucial to the new paradigm and hence measures the value of the system for given inputs (disembodied technological change or a shift in the production function). The interconnectivity effect can be thought of as evaluating a markup on general and ICT capital. *InterconICT* enters the equation with a one-period lag so as to exclude contemporaneous reverse causality. Furthermore, it is intuitive to assume that if a firm upgrades its IT system to an interconnected one in year t, productivity effects are not likely to appear before $t+1$.

The model is estimated with two sets of fixed effects. Firm fixed effects allow controlling for unobserved firm characteristics that are constant over time and that might be correlated with interconnectivity adoption and productivity at the same time, such as the industry, management strategy, or location of the firm. Note that, in contrast to other studies, in this analysis interconnectivity is not a firm characteristic but a dummy that can switch from 0 to 1 during the panel period. This allows to add fixed effects and therefore to control for considerable firm heterogeneity. I thus measure the variation within the firm and identify the effect of the adoption of interconnectivity on labor productivity. My identification strategy is based on firms that change their IT system from a regular one to interconnectivity. Two-way industry-year fixed effects at the two-digit industry level ($\delta_t * \gamma_{ind}$) control for industry-specific developments and shocks, such as innovations or technological progress in the years 2000 through 2007.[4]

The measure of labor productivity detects how revenue and employment are developing relative to each other. However, a positive coefficient on *InterconICT* does not reveal whether revenue is rising relative to employment in the firm or whether firm employment is disproportionately decreasing when introducing interconnectivity. The numerator or the denominator could also remain unchanged. Hence, to better understand the drivers of potential productivity effects, I follow Acemoglu et al. (2014) and estimate the impact of interconnectivity on productivity's two constituent variables separately. First, the numerator, revenue (Y):

$$Y_{it} = \alpha + \beta_1 K_{it} + \beta_2 M_{it} + \beta_3 L_{it} + \beta_4 \text{InterconICT}_{i(t-1)} + \alpha_i + \delta_t * \gamma_{ind} + \varepsilon_{it} \tag{3.2}$$

where Y_{it} are the logged firm sales in the respective year t, K_{it} is logged capital, M_{it} logged materials and L_{it} the logged number of employees. The dummy, fixed effects, and error term are as described for Equation 3.1.

And, second, the denominator, employment (L):

$$L_{it} = \alpha + \beta_1 \text{InterconICT}_{i(t-1)} + \alpha_i + \delta_t * \gamma_{ind} + \varepsilon_{it} \tag{3.3}$$

[4]Kretschmer et al. (2012), for instance, exploit an exogenous regulatory shift in the French automobile distribution market and find that higher competitive pressure increases dealers' likelihood of adopting innovative software. In my setting, this would be controlled for by the industry-year fixed effects.

where L_{it} is the number of employees in firm i and year t, the fixed effects and the error term correspond to what has been described above.

The employment regressions are conducted several times with different outcomes: For the baseline results, I estimate the effect of interconnectivity on the total number of employees. For a deeper insight into organizational change, I then focus on the composition of staff and re-estimate Equation 3.3 with the logged number of different IT employee groups, namely total IT employees and developers, in the firm.

As the technology data stem from a survey on ICT investment and not on ICT usage, *InterconICT*= 1 measures an intention-to-treat effect. Generally, this is the effect of interest to decision makers in firms or, by extension, policy: They can decide to invest in a particular IT resource but the new equipment might not be used by employees. In this case, I would underestimate the effect of interconnectivity as I would assign firms to the treatment group that did not comply in reality and therefore did not experience the effects.

3.3.2 Instrumental Variable Approach

The fixed effects model controls for time-invariant unobserved firm characteristics (firm fixed effects) and for time-specific shocks or particularities in 2-digit industries (industry fixed effects interacted with year dummies). Furthermore, a set of robustness checks is conducted. Still, remaining endogeneity issues cannot be completely excluded.[5] To get closer to the ideal setting of an experiment and causal interpretation, I employ an instrumental variable (IV) approach exploiting exogenous variation in interconnectivity adoption by firms. The IV is based on the idea that a reliable and fast outside connection is likely to drive the adoption of interconnective IT structures in the firm. As I expect active broadband internet adoption by

[5] For instance, the (time-varying) factor inputs of the productivity function or investments in research and development could be correlated with both interconnectivity adoption and productivity. The former can, in parts, be tackled not only by an instrumental variable approach but by following the methodology proposed by Levinsohn and Amil (2003). Estimation results (available upon request) point towards a positive and significant revenue effect of interconnectivity in all firm-size groups with returns increasing in firm size. However, the algorithm exhibits some problems when applied to this sample, rendering the IV approach more appropriate.

firms to be endogenous in this setting, I use broadband availability at the municipality level instead. The availability of broadband (that is, high-speed) internet at the municipality level is therefore the regressor in a first stage estimation preceding the estimation of the productivity effect of interconnectivity at the firm level in the second stage. Based on the related literature, I argue that interconnectivity and broadband internet are important complements and that the productivity effect of broadband internet access only runs through this complementary set of technologies.

Complements to Broadband Internet in Firms

The impact of broadband internet roll-out on firm productivity is an important question for public infrastructure policy as well as subject to a number of analyses in the economics of innovation and labor. Results are mixed and range from zero effects to some positive productivity contributions of the technology.[6] Given the various and partly inconclusive results, it is crucial to pay attention to the economic mechanisms behind the productivity impact of broadband internet.

For instance, Akerman et al. (2015) do not find any evidence that, on average, firms' inputs became more productive with the adoption of broadband. They then use individual-level data and show that broadband adoption in firms complements skilled workers in efficiently executing nonroutine abstract tasks. Similar results are found by Atasoy (2013). However, a broadband connection in itself cannot create this kind of effect. The simplest example of the advantage of broadband over low-speed internet is sending an email with a large data file attached. Even in this case, a firm would need a corresponding email application (groupware) to process the email. The mechanism of the productivity contribution of broadband neces-

[6]Haller and Lyons (2015) for Ireland and Bertschek et al. (2013) for Germany, estimate the productivity effects of broadband internet with different instrumental variable strategies and both do not find any significant impact at the firm level. Evidence for New Zealand suggests a positive productivity contribution of conventional broadband adoption in firms (Grimes et al., 2012) whereas ultrafast internet does not significantly impact firm productivity (Fabling and Grimes, 2016). Canzian et al. (2015) exploit a quasi-experimental local policy intervention in the rural area of Trentino (Italy) and find a positive impact of ADSL2+ broadband availability on firm's total factor productivity (1.4 percent for 100 days of ADSL2+ exposure). With a regression discontinuity design, De Stefano et al. (2014) study firm productivity effects of broadband internet in the Northeast of England and do not find any statistically significant outcome.

sarily runs through complementary technologies such as interconnectivity. This is important for the exclusion restriction of my instrumental variable analysis to hold.

The following two studies build on complementarities between advanced internet and IT resources in the firm. Forman et al. (2012) explore the impact of “advanced internet” on regional wages and argue that usage of technologies similar to those in the interconnectivity indicator is a proxy for an advanced internet connection in the firm. Furthermore, they state that “advanced internet involves frontier technologies”. Colombo et al. (2013) also consider technologies that are complementary to broadband internet and group them in four categories: Basic, advanced communication, supply chain and customer management, and management systems. They find that the adoption of supply chain management software together with a strategic change at the firm level yields positive effects for manufacturing firms. Similarly, advanced communication tools paired with organizational change in the firm have a positive productivity effect in service firms. Even though the study’s empirical strategy does not explicitly model complementarity of broadband with particular IT resources in the firm, the authors’ conclusion is intuitive: Broadband internet is an enabler, rather than a directly productivity enhancing technology. In line with Forman et al. (2012) and Colombo et al. (2013), I consider broadband internet as an enabler of interconnectivity in the firm and therefore a relevant instrument.

Broadband Availability as an Instrument for Interconnectivity

The local average treatment effect (LATE) spells out the complementarity of interconnectivity and broadband internet: I estimate the productivity effect of interconnectivity for those firms where broadband availability drove the implementation of an interconnected IT system (the compliers). Thereby, on the one hand, I can get a causal relationship between interconnectivity and firm productivity and, on the other hand, I can provide a potential mechanism for the productivity impact of broadband internet in the firm.

More specifically, in the two-stage least-squares (2SLS) analysis, I deal with two types of endogeneity problems: First and most important, I want to instrument for my variable of interest, namely interconnectivity adoption. Second, if I used broadband usage in the firm as an instrument, this variable would likely be correlated with the productivity level of the firm in both directions: Successful firms are also more prone to adopt a high-speed outside connection. Furthermore, the adoption of interconnectivity and broadband in the firm could be motivated by similar strategic considerations. I therefore follow the literature discussed above (especially Bertschek et al., 2013, and Akerman et al., 2015) and instrument broadband adoption in the firm by broadband availability at the municipality level. In order to avoid a three-stage estimation and because I do not have information on firms' broadband adoption or usage, I directly employ the availability measure as the instrument for interconnectivity adoption in the two-stage least-squares (2SLS) analysis.

Broadband availability in Germany in the early years 2000 depended on a historical relict in the structure of today's telephony network. Municipalities that were close enough to a relevant node in the network, called main distribution frame, could be provided with broadband internet at low cost and soon after deployment started, that is, in 2000 or 2001 (Falck et al., 2014). This way, cities were among the first to have near to 100 percent broadband availability. In other, mostly more rural, municipalities, broadband availability gradually increased over the following years. Broadband availability is determined at the municipality level and deployment can therefore not be influenced directly by the firm. The firms in my sample do not relocate during the period of analysis. However, roll-out by a telecommunication carrier is still partly driven by cost and benefit considerations, so municipalities with a high concentration of very productive and successful firms might be given earlier broadband access as demand is expected to be high. This could be a threat to my identification strategy. It is therefore helpful that the variation in broadband availability in the period of analysis was not only determined by telecommunication carriers but also by government programs (mostly at the state or municipality level). Furthermore, in the municipalities with the strongest and most productive firms, namely cities and metropolitan regions, there is not much variation left in the period of analysis (2005 through 2007) that could bias my coefficients. The firm and industry-year fixed effects are also applied to the IV model.

3.4 Data

3.4.1 Data Sources

For my analysis, I use two different samples combining firm and regional information from three different data sources. Sample A spans the years 2000 through 2007 and nine European countries. Sample B is a subset of Sample A, complemented with regional information from Germany and unique in the literature.

Commercial data on firms' ICT adoption stem from the CI Technology Database (CITDB) constructed by the market intelligence firm Harte Hanks. The company conducts annual telephone surveys collecting information on IT types used by firms such as the number of desktop PCs, laptops, network devices, IT employees, and usage of various software and hardware. Information is gathered below the firm/company level, i.e. Harte Hanks surveys one or more establishments of a company on the IT used by this or these establishments. Harte Hanks produces this survey primarily to sell the information to large IT producers and suppliers for the purpose of sales and market research (Mahr and Kretschmer, 2010). But the CITDB has also been employed in academic ICT research, including Bresnahan et al. (2002), Bloom et al. (2012), Forman et al. (2012), or Kretschmer et al. (2012). For this analysis, the technology data were aggregated from the establishment to the firm level. I construct the interconnectivity indicator based on variables from Harte Hanks.

The second data source is the Bureau van Dijk ORBIS database. ORBIS covers information on public and private companies on a yearly basis mostly collected from balance sheets and profit and loss statements. It includes economic output measures such as sales, operating revenue and EBIT as well as economic input measures such as the values of different assets, materials and labor cost. Data providers vary across countries (e.g. for Germany it is Creditreform, a debt collection and credit bureau), but ORBIS reports are standardized and therefore comparable. They also contain firms' primary and secondary industry codes and information on business activities, products and services.

Information for the 2SLS approach (Sample B) stems from the German *Breitbandatlas Deutschland* that reports annual broadband availability at the municipality level. It is published by the Federal Ministry of Economics and Technology and is based on reports by telecommunication operators (Fabritz, 2015; Falck et al., 2014). More precisely, the data contain the percentage of households in the municipality that had access to broadband internet in the respective year. The threshold is set at a minimum downstream data transfer rate of 384 kbit/s. Broadband (DSL) internet deployment in Germany started slowly in the year 1999, but the annual data was collected starting in 2005. Hence, I combine it with a subset of observations of Sample A restricted to Germany and covering the years 2005 to 2007. Note that the broadband measure in this analysis does not cover actual broadband adoption of firms, but, instead, the availability of a high-speed internet connection. From a policy maker's point of view this is particularly interesting as infrastructure roll-out is an investment decision problem she is facing.

3.4.2 Samples

With this data I construct two different samples (a third sample will be described and used in the Appendix):

Sample A: European Sample

The main sample is an unbalanced panel spanning the years 2000 through 2007 and containing 41,094 firm-year observations from 9,083 companies across nine European countries. It is constructed by merging the technology information from Harte Hanks' CITDB to the financial data from ORBIS. Values are conservatively imputed[7] and remaining records with incomplete information are dropped. I use this sample for all fixed effects productivity estimations and numerous robustness checks.

[7] Missing technology dummies are imputed by setting them one or zero respectively in t if the firm's records in $t-1$ and $t+1$ are available and of the same values. Missing continuous variables are imputed by setting them to the mean of firm's corresponding values in $t-1$ and $t+1$. The number of imputed values in the sample is very limited.

Sample B: German Sample

The European sample (A) is reduced to the German sample (B) by dropping all firms that are not located in Germany. The restriction to Germany is due to the scope of the data on local broadband availability. I also lose some German observations, because the German broadband atlas started to collect data at the municipality level only in 2005. Hence, Sample B contains 1,685 firm-year observations from 764 German firms and the years 2005 through 2007. Broadband data, which are at the municipality level, are added to the CITDB and ORBIS firm information by matching via a municipality-postcode correspondence table. None of the firms in the sample relocates during the period of analysis. I can therefore exclude that firms follow broadband infrastructure in this sample.

3.4.3 Descriptive Statistics

The European sample (A) runs from 2000 to 2007 and is unbalanced. As firms are allowed to exit the sample, a potential survivor bias can be limited. Around 2,000 firms are only represented in two periods, 1,265 firms are covered during the entire period of analysis. Half of the firms in the sample are medium-sized firms with 50 to 249 employees. This is not an entirely representative sample, as most firms in the European Union (96 percent according to Eurostat) and also in the group of countries covered in the sample (90 percent according to OECD data) are micro or small enterprises with up to 49 employees. However, since needs and processes inside the firm differ largely across firm sizes, most results in this paper are based on sample splits into groups of small, medium and large firms. 45 percent of the firm-year observations in Sample A are interconnective and the percentage of interconnective firms increases from 14 percent to 39 percent during the panel period (see Table 3.1). Taking into account the decade being investigated by this analysis, one could expect that large firms are ahead of smaller firms in the adoption of modern IT systems. Yet, the data show similar adoption patterns in the three firm size groups. Furthermore, the diffusion curves of interconnectivity in the sample have some properties of the classic S-curve (Figure 3.2). Also,

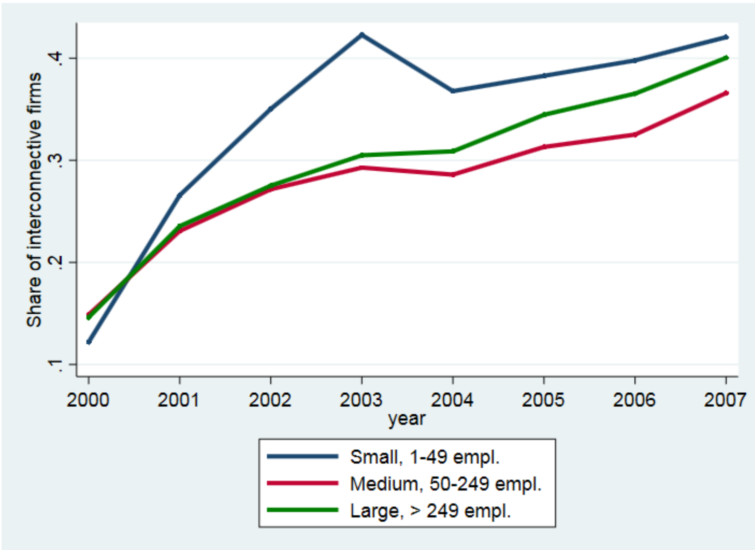
Table 3.1: Sample statistics and distribution of interconnective IT

	Num. of obs	%	Num. of firms	% of intercon. firms in 2000	% of intercon. firms in 2007
Total sample	41,094	100.00	9,083	14	39
Firm size					
Small (< 50)	10,886	26.49	2,361	12.20	42.07
Medium (50 – 249)	20,621	50.18	4,433	14.89	36.59
Large (> 250)	9,587	23.33	2,289	14.62	40.04
Industries					
Primary (01-14)	452	1.10	119	8.33	40.00
Construction (15-17)	1,779	4.33	421	11.90	32.95
Food (20)	2,589	6.30	594	15.73	39.24
Textile/Apparel (22-23)	2,136	5.20	467	13.25	28.20
Print (27)	1,182	2.88	247	14.71	35.14
Chemical (28)	2,301	5.60	477	26.37	58.57
Stone, Glass, ... (32)	1,209	2.94	271	9.89	30.33
Metal (33-34)	3,346	8.14	725	7.84	21.50
Machinery (35)	4,215	10.26	870	14.85	51.90
Electronics (36)	2,067	5.03	419	17.03	53.27
Transport Equipment (37)	1,437	3.50	305	6.96	29.69
Wholesale (50-51)	4,877	11.87	1,076	17.50	51.54
Retail (52-59)	1,870	4.55	451	10.71	27.27
Financial sector (60-67)	233	0.56	63	9.09	46.43
Business services (73)	1,468	3.57	354	17.48	53.29
Other services	1,075	2.62	236	10.00	32.73
Public Admin. (91-99)	114	0.28	25	16.67	38.46
Countries					
Spain	11,929	29.03	2,434	14.08	33.61
Italy	11,615	28.26	2,123	20.32	43.15
France	4,359	10.61	1,373	-	31.64
Sweden	4,095	9.96	652	11.90	49.28
Finland	3,810	9.27	632	4.86	54.79
Germany	2,627	6.39	990	-	32.28
Poland	1,305	3.18	424	-	17.05
The Netherlands	680	1.65	178	-	36.36
Austria	674	1.64	277	-	50.67

Data: Sample A. Unbalanced panel data from 2000 to 2007. Source: CITDB, ORBIS.
Notes: The listed industry groups are the most relevant in the sample, two-digit SIC codes in parentheses. Empty cells do not yield sufficient observations. The last columns indicate the percentage of firms with interconnective ICT in the respective category and year. A firm's ICT structure is interconnective if the firm adopted ERP and Groupware and if it owns more network devices and laptops than the median firm in the respective year (distribution of input variables see Table 3.A.1).

all industries represented in the sample show a clear increase in interconnectivity usage. The expectation that particular industries such as the financial sector or business services would be the driving forces behind this increase is not met. Adoption rates in Sweden and Finland are remarkably high (Table 3.1). 1,639 firms are interconnective throughout the sample, 5,909 firms never adopt an interconnective ICT paradigm. 1,535 firms switch during the period of analysis.

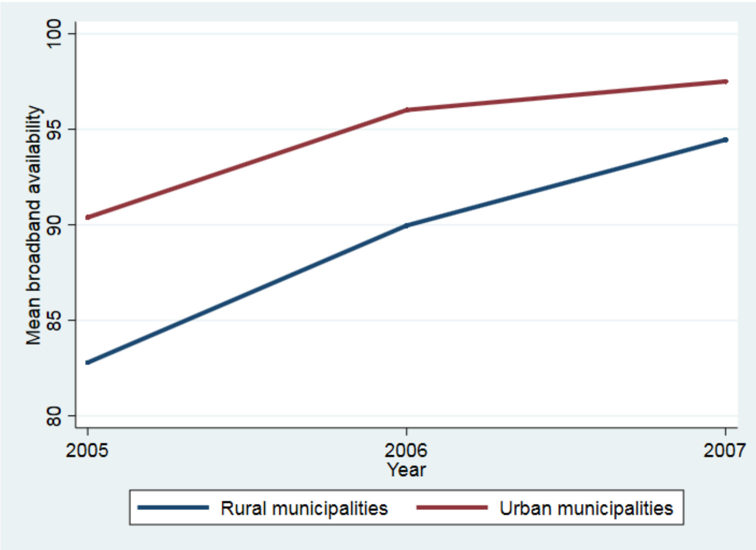
Figure 3.2: Diffusion of interconnectivity in Sample A



Data: Sample A. Unbalanced panel data from 2000 to 2007. For the measure of interconnectivity see Figure 3.1. Source: CITDB, ORBIS.

The German sample (B) runs from 2005 to 2007 and is also unbalanced. 607 firms span two time periods; for 157 firms are covered through all three years. The large firms account for 60 percent of the firms in the sample and are therefore clearly overrepresented. With only 36 small firms, I do not present results for this group. Broadband roll-out in Germany started in 1999. In 2005, the first year the *Breitbandatlas* observed availability at the municipality level, it was already widely spread. Figure 3.3 plots the mean availability at the municipality level for the firms in the sample in these years. It shows that mostly rural areas caught up, but also in more urban areas, there was still variation. Availability levels mostly range between 70 and 99 percent (which are the 5th and the 95th percentile of the distribution). Take-up in firms increased quickly: In 2004, 32 percent of German firms used local DSL infrastructure for a broadband connection, whereas in 2005 it was already 40 percent of the firms. Other technologies, such as cable or leased lines (mostly relevant for large firms) account only for a small share, namely around 10 percent of all broadband using firms[8]. This analysis' instrumental variable for interconnectivity adoption does not capture alternative technologies.

Figure 3.3: Diffusion of broadband availability in Sample B



Data: Sample B. Unbalanced panel data from 2005 to 2007 for Germany. Source: CITDB, ORBIS, Breitbandatlas.

3.5 Fixed Effects Results

3.5.1 Productivity Effects of Interconnectivity

A pooled OLS regression with different control variables (see Table 3.B.1 in the Appendix) shows a highly significant association of interconnectivity with labor productivity and output independent of firm size. Employment effects, however, are negative across all firm sizes and particularly so for medium-sized firms. Now, these results do not take into account

[8]Statistisches Bundesamt, Wiesbaden (2006) Informationstechnologien in Unternehmen, Ergebnisse für das Jahr 2005. Tabellenband.

unobserved characteristics of the firms which can drive productivity and interconnectivity at the same time, so the interconnectivity variable is likely to be endogenous. Consequently, the baseline specification of this analysis is a firm fixed effects model: I conduct the regression for the total Sample A and, in particular, for sample splits by firm size (see Table 3.2). The model also controls for shocks to the economy and particular industry-specific developments (year-industry fixed effects) that might drive the adoption of interconnective IT structures and labor productivity alike. I do not find any significant average effect of interconnective ICT across all firm sizes (Column 1). However, the split sample shows that the results in the total sample masks contrasting effects in firms of different size groups: For medium-sized firms (50–249 employees; Column 3) I find a positive average effect of interconnectivity on labor productivity and for large firms I find a negative effect (Column 4). If a medium or large firm implements interconnective IT structures, this is associated with a 2.29 percent increase or a 3.78 percent decrease in labor productivity, respectively.

To better understand these intention-to-treat effects on labor productivity (Y/L), Table 3.2 also shows the effects on the components of the productivity measure – revenue (Y) in a standard production function and employment (L) in a simple fixed effects regression. Large firms' negative productivity effect is driven by a significantly negative effect of interconnectivity on revenue (Column 8). In medium-sized firms, however, it is the negative employment effect that drives the (positive) productivity effect (Column 11). On average across all firm sizes, the employment effect is significantly negative, suggesting a decrease of 2.6 percent in staff on average over all observed years following the introduction. For the average firm in the sample, that is, one with 325 employees, this is a shrinkage by 9 workers. Note, furthermore, that the coefficients on capital, materials and labor in the revenue production function estimations do not sum up to one (0.75), suggesting decreasing returns to scale in firms.

Table 3.2: Two-way fixed-effects estimation: Interconnectivity and labor productivity with its drivers

	Labor productivity: ln(Y/L)				Sales: ln(Y)				Employment: ln(L)			
	All sizes (1)	Small (2)	Medium (3)	Large (4)	All sizes (5)	Small (6)	Medium (7)	Large (8)	All sizes (9)	Small (10)	Medium (11)	Large (12)
L.InterconICT	0.00114	0.00500	0.0229**	-0.0378*	-0.00403	-0.00688	0.0147	-0.0370*	-0.0263**	-0.0426*	-0.0467***	0.00925
	(0.00803)	(0.0164)	(0.0100)	(0.0199)	(0.00721)	(0.0136)	(0.00953)	(0.0191)	(0.0120)	(0.0255)	(0.0159)	(0.0262)
ln(K/L)	0.137***	0.135***	0.108***	0.179***								
	(0.0163)	(0.0182)	(0.0262)	(0.0430)								
ln(M/L)	0.483***	0.453***	0.481***	0.551***								
	(0.0231)	(0.0327)	(0.0365)	(0.0556)								
ln(K)					0.0884***	0.0838***	0.0552**	0.149***				
					(0.0180)	(0.0183)	(0.0226)	(0.0525)				
ln(M)					0.451***	0.421***	0.452***	0.518***				
					(0.0227)	(0.0313)	(0.0354)	(0.0618)				
ln(L)					0.211***	0.193***	0.244***	0.165***				
					(0.0337)	(0.0351)	(0.0650)	(0.0455)				
Constant	2.967***	3.250***	3.035***	2.426***	4.469***	4.603***	4.540***	3.745***	4.726***	3.403***	4.749***	6.234***
	(0.127)	(0.157)	(0.213)	(0.300)	(0.315)	(0.306)	(0.356)	(1.080)	(0.00789)	(0.0194)	(0.00948)	(0.0169)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year*Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
r2	0.683	0.724	0.717	0.646	0.700	0.770	0.710	0.672	0.0347	0.0613	0.0796	0.0719
Observations	31870	8490	16109	7271	31870	8490	16109	7271	31877	8493	16111	7273
N. of firms	9083	2361	4433	2289	9083	2361	4433	2289	9083	2361	4433	2289

Data: Sample A. Unbalanced panel data from 2000 to 2007. InterconICT see Figure 3.1. Source: CITDB, ORBIS.
Notes: The specification is an augmented production function in intensive form estimated across all firm sizes and in a split sample for small, medium-sized and large firms seperately. InterconICT is included with a one-year-lag. Models (1) through (4) show the baseline specification with labor productivity as dependent variable. Models (5) through (12) use the components of labor productivity (*sales* in a revenue production function and *employment* in a simple fixed effects regression) as dependent variables. All models include firm fixed-effects and year*industry fixed effects. Standard errors are clustered at the firm level and noted in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The results suggest quite different channels for the impact of interconnectivity on the firm conditional on initial firm size. Large firms seem to experience the biggest problems to smoothly introduce the new technology and the related changes with respect to administrative or production processes. This is in line with findings by Hitt et al. (2002) who show that the implementation of an ERP system is related to a slowdown in firm productivity in the short-run but that financial markets consistently reward the adopters with higher market valuation.

3.5.2 Organizational Change

The heterogeneity of productivity effects across different firm sizes suggests diverging internal mechanisms triggered by firm's adoption of interconnectivity. Furthermore, the (mostly negative) employment effects point towards organizational change as a complement or an outcome of this technological change. The first department and skill group to be affected by the adoption of the new technologies are, by nature, the IT department and employees specialized in ICT. The employment specification is therefore modified to particularly investigate IT employment. The first dependent variable of the fixed effects regressions is the number of IT employees, the second the number of workers specialized in programming and web development, and the third of the share of IT employees among total staff (see Table 3.3). For medium-sized firms, the effects are negative both for the number of IT employees in general and for developers in particular: their numbers decrease by 6.87 percent and 7.62 percent respectively, which, for the average medium-sized firm with 4 IT employees including 1.5 developer jobs, corresponds to a third of an IT job and 10 percent of a developer position. Large firms extend their IT department with, on average, six more IT employees and, among them, two developers and the share of IT employees with respect to total staff increases significantly (Column 12).

These results show that firms react differently to new information technologies: In medium-sized firms, adoption of an interconnective IT structure is accompanied by a reduction in both IT and non-IT staff. IT departments can be scaled down because centralized and linked-up

IT systems can be managed more efficiently and reduce the need for on-site maintenance. Furthermore, IT consulting firms offer to set up and maintain whole IT systems as a business service. Similarly, improved communication and information flows in the firm can allow for substitution between labor and technology. The insignificant effect in Column 11 of Table 3.3 speaks towards such a substitution effect: The negative total employment effect for medium-sized firms (Table 3.2 Column 11) seems not to be driven only by the reduction in IT staff but also by layoffs of non-IT employees in the firm. Also large firms decrease the number of non-IT staff, but employ IT workers instead. The positive coefficients in Table 3.3 and the insignificant total employment effect lead to this conclusion. These results point towards in-house IT solutions specifically tailored to the company's needs.

The coefficients for small firms are inconclusive since results are mostly insignificant or only weakly significant. On average across all firms, the total negative employment effect seems not to be driven by restructuring the IT department but by laying off non-IT staff (see Columns 1 and 9). The data allow distinguishing IT workers from other staff, but they do not allow distinguishing between qualification levels.

Heterogeneity analyses by industry groups show that negative employment effects are mostly found in service firms.[9] Splitting the sample further according to firm size reveals that among the medium-sized firms it is the manufacturing firms that lay off staff (see Table 3.4). Service firms can outsource numerous IT-based tasks, which is facilitated by an interconnected IT structure and particularly important to small firms. The effect in manufacturing, however, points toward the introduction of interconnective components into the production process as being required by ongoing automatization and robotization.

[9]The definition of the manufacturing industry is intuitive and well-defined in industry classifications (SIC: Division D, WZ 2008 for Germany: Division C) However, due to the wide spread across subindustries in my dataset, the service industries are defined in a very broad sense for the sample splits. The group not only includes typical service subindustries such as finance, IT and business services but also the utilities and transportation as well as wholesale and retail. Mining, Construction and Public Administration are excluded when the sample is split into manufacturing and services.

Table 3.3: IT employment effects

	Number of IT employees: $\ln(L_{IT})$				Number of IT developers: $\ln(L_{DEV})$				Share of IT employees: $\ln(L_{IT}/L)$			
	All sizes	Small	Medium	Large	All sizes	Small	Medium	Large	All sizes	Small	Medium	Large
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
L.InterconICT	0.000910	-0.0534	-0.0687**	0.119**	0.0124	0.0306	-0.0762*	0.145**	0.0308*	-0.0140	-0.0122	0.119***
	(0.0217)	(0.0393)	(0.0316)	(0.0493)	(0.0311)	(0.0934)	(0.0421)	(0.0585)	(0.0181)	(0.0273)	(0.0268)	(0.0437)
Constant	1.386***	0.950***	1.213***	2.239***	1.341***	0.921***	1.182***	1.741***	-3.434***	-2.520***	-3.572***	-3.977***
	(0.0155)	(0.0369)	(0.0193)	(0.0333)	(0.0247)	(0.0854)	(0.0307)	(0.0416)	(0.0131)	(0.0244)	(0.0163)	(0.0288)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year*Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
r2	0.156	0.290	0.208	0.159	0.130	0.409	0.225	0.158	0.227	0.432	0.288	0.190
Observations	25359	5907	13358	6094	10694	1439	5591	3664	25359	5907	13358	6094
N. of firms	7809	1870	3909	2030	3910	571	1956	1383	7809	1870	3909	2030

Data: Sample A. Unbalanced panel data from 2000 to 2007. InterconICT see Figure 3.1. Source: CITDB, ORBIS.
Notes: Compare with models (9) through (12) in Table 3.2. Here the dependent variables are different IT employee groups and their share among total staff. Standard errors are clustered at the firm level and noted in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.4: Heterogeneity of employment effects

	Coefficient on L.InterconICT			
Dep. var.: ln(L)	All sizes (1)	Small (2)	Medium (3)	Large (4)
Manufacturing sample	-0.0162 (0.0154)	-0.0141 (0.0290)	-0.0534*** (0.0204)	0.0191 (0.0322)
Service sample	-0.0375* (0.0208)	-0.0662* (0.0399)	-0.0419 (0.0269)	0.0307 (0.0485)
Firm FE	Yes	Yes	Yes	Yes
Year*Industry FE	Yes	Yes	Yes	Yes

Data: Sample A. Unbalanced panel data from 2000 to 2007. InterconICT see Figure 3.1. Source: CITDB, ORBIS.
Notes: Compare with models (9) through (12) in Table 3.2. Here the sample is further split to the manufacturing and service sectors. Standard errors are clustered at the firm level and noted in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.5.3 Robustness Analysis

To test the robustness of the results, I explore potential confounding factors in the following.

Country Characteristics

The results might be driven by country-specific characteristics of the sample firms. Indeed, IT infrastructure development, such as broadband internet roll-out, does vary across countries. Furthermore, some countries are more IT affine than others, suggesting the introduction of favorable framework conditions for the adoption of innovations such as interconnectivity. Similarly, public funding schemes for firms largely depend on a country's specific industrial policy and are likely to change after elections.

First, the sample is split by country (Table 3.B.2 in the Appendix), which allows to explore whether effects differ for different countries and whether a particular country is driving the whole effect. This seems not to be the case, as none of these countries exhibits qualitatively similar and significant productivity effects. Poland is an exception: I find significant productivity effects for the 673 large Polish firms but the sign is opposite to the effect in the European sample. Polish large firms are therefore not the sole source of the negative productivity effects found in Sample A. Consequently, the firms experiencing the positive (for medium firms) and negative (for large firms) significant effects of interconnectivity on the ratio of sales and employment are distributed across the sample countries.

Second, the results might also be biased by time-varying country-specific characteristics of the sample firms. Indeed, the time schedule of IT infrastructure development, such as broadband internet roll-out, does vary across countries. Also, the introduction of better (legal) framework conditions for the adoption of innovations such as interconnectivity could be a threat to my identification. Similarly, public funding schemes for firms largely depend on a country's specific industrial policy and are likely to change after elections. To control for such potential time-varying drivers of the results, country-year fixed effects are included in the baseline specifications. Table 3.B.3 in the Appendix shows that the qualitative results remain unchanged and that the quantitative results change by 0.32 percentage points at most.

Trade Exposure

Next, the baseline specification with firm fixed effects and year-industry fixed effects already controls for many elements of observable and unobservable heterogeneity. The interconnectivity variable might accidentally capture a related development which also drives productivity and might therefore bias the results. Bloom et al. (2016) find that increasing exposure to trade, particularly to Chinese imports, enhanced productivity of European firms in the early years 2000, which corresponds to the geographic and time scope of the present study. Econometrically, this could be a problem if a firm significantly increased its exports at the same time as it adopted interconnectivity or if it was exposed to a large increase in import competition at that very moment. The following robustness check deals with this objection. As trade exposure is generally measured at a higher-digit industry level (see Dauth et al., 2014, and Bloom et al., 2016) than the controls in the baseline specification, the year-industry fixed effects are now constructed considering the three-digit SIC level. The qualitative results do not change in comparison to the two-digit fixed effects, whereas the quantitative effect is marginally higher (1 percentage point at most) in the robustness test than in the baseline regression (Table 3.B.3).

IT-Intensive Firms

The interconnectivity indicator might also reflect a firm's general IT affinity instead of the sole adoption of an innovative computing paradigm. In case this is industry-specific or a constant property of the firm, the two sets of fixed effects control for this. If, however, a firm builds up all of its IT equipment at the same time, the coefficients could be biased. I therefore make use of information on PC intensity (number of PCs per employee) in the sample and construct a dummy using the same methodology as for *InterconICT*: a firm that has a PC intensity above the median in year t is designated as PC intensive with a dummy = 1. A PC intensive firm is assumed to be IT affine and might be successful due to IT effects not directly related to interconnectivity. Consequently, the first specification (Table 3.B.4) tests the effects of PC intensity as the only IT measure and yields very different results from those for interconnectivity. In small firms, high PC intensity enhances sales and, by extension, labor productivity. Other samples do not exhibit significant effects. Of course, a firm can be both PC intensive and interconnective. Therefore, in a second step, both IT measures are included in the regression controlling for historical IT affinity of the firm and allowing for a "horse race" between the two IT resources. The coefficients remain the same for both variables (Table 3.B.5), thus demonstrating that *InterconICT* clearly measures an innovation that goes beyond traditional IT equipment. These results suggest that the integration of communication and IT is an important firm strategy.

Table 3.B.6 explores the components in more detail. First, the four input variables of the indicator are tested for their contribution to the overall effect and mostly yield insignificant coefficients. Only the negative employment effect for the total sample in the baseline specification seems to be driven by groupware and the number of network devices per employee. ERP never yields any significant effect on labor productivity or its inputs. Interestingly, the few significant coefficients on the input dummies do not reflect the total results of interconnec-

tivity. The robustness analysis therefore suggests and confirms that the computing paradigm of interconnectivity incorporates different components with their specific characteristics and cannot be reduced to one single IT resource.

Indicator Construction

As a further robustness check, I vary the construction of the indicator. This way, I make sure that the assumptions made when developing the computation methodology are not too restrictive. Instead of using the median as a cutoff point for the number of network devices and the share of laptops, the cutoff points are now the 75th and 25th percentiles, respectively (Table 3.B.7). This first new cutoff point implements stricter rules for attributing the characteristic of interconnectivity to a firm's IT structure compared to the baseline cutoff at the 50th percentile. Qualitatively, the pattern of results remains unchanged and the effects are even stronger and more significant: Small and medium-sized firms have positive productivity effects with the introduction of interconnectivity. The effects for medium-sized firms are simultaneously driven by positive output and negative labor effects. Like in the baseline results, large firms experience a negative productivity effect, driven by a negative output effect of interconnectivity. The cutoff at the 25th percentile yields no significant effects. In conclusion, a stricter, more specific attribution of the interconnectivity status better identifies the firms that benefit most from the innovation. If the definition is more generous and therefore a larger fraction of the firms in the sample is assumed to be interconnective, no specific productivity effect of interconnectivity can be identified.

3.6 Two-Stage Least-Squares Results

The two-stage least-squares estimations use broadband availability at the municipality level as the instrument. Due to restricted data availability, I reduce the sample to the firms located in Germany (Sample B).

3.6.1 The Local Average Treatment Effect on Productivity and Employment

The results for the instrumental variable estimations are presented in Tables 3.5 (all firms) and 3.B.8 (medium and large firms).[10] The IV specification does not yield any significant productivity or employment results. Across all firm sizes as well as for large firms, the direction of the effect is, however, the same as in the fixed effects estimations.

Table 3.5: Two-stage least-squares: All firm sizes

	All sizes					
	(1) ln(Y/L)	(2) ln(Y)	(3) ln(L)	(4) ln(Y/L)	(5) ln(Y)	(6) ln(L)
Second stage						
L.InterconICT	0.362	0.186	-0.667			
	(0.418)	(0.229)	(0.591)			
	[-0.47,1.19]	[-0.27,0.64]	[-1.84,0.50]			
InterconICT				2.375	1.745	-4.596
				(2.823)	(1.880)	(6.487)
				[-3.17,7.92]	[-1.95,5.44]	[-17.34,8.15]
First stage						
Broadband	-0.0032	-0.0042	-0.0036	-0.0005	-0.0006	-.00001
availability	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
	[-0.009,0.003]	[-0.010,0.002]	[-0.010,0.003]	[-0.0018,0.0008]	[-0.0019,0.0007]	[-0.002,0.001]
F stat	1.066	1.746	1.326	0.653	0.801	0.750
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Ind*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	314	314	314	1685	1685	1685
N. of firms	157	157	157	764	764	764

Data: Sample B. Unbalanced panel data from 2005 to 2007 for Germany. Source: CITDB, ORBIS, Breitbandatlas.
Notes: This table presents two-stage least-squares estimations, instrumenting interconnectivity with broadband availability in the municipality. Standard errors are therefore clustered at the municipality level and presented in paratheses. The 95% confidence intervals in square brackets. F-statistic is Kleibergen-Paap.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The first stage results with the insignificant coefficient on broadband availability and, more importantly, the extremely low F-statistic reject the relevance of the instrument and show that broadband availability does not significantly impact interconnectivity adoption. The scientific discussion is mostly focusing on statistical significance of the parameters of interest (Abadie, 2018). Insignificant results are rarely discussed even though they also provide

[10]The size of the small firm subsample is not sufficient for estimating the fixed effects model.

valuable information. When a parameter is not significant, it means the data provide little or no evidence that the null hypothesis is false. The effects could be zero or just very small. Here, I argue that the impact of broadband availability on the adoption of interconnectivity is not only statistically insignificant, but also zero in economic terms: First, the coefficients of the first stage are extremely small in all different sample splits, ranging from 0.00001 to 0.004 in absolute values. Second, the confidence intervals of the estimates allow to quantify the effect size that can be excluded. Take, for example, the first stage of the productivity effect for all firm sizes (Table 3.5, Column 1): We can reject declines of the likelihood of interconnectivity adoption due to an increase in broadband availability from 0 to 100 percent coverage by more than 0.9 percentage points and increases by more than 0.3 percentage points. Consequently, the effect is most likely economically zero.

Broadband internet was introduced in the year 2000 and very rapidly available for municipalities close to a main distribution frame in the telephony. It might therefore be the case that the variation of the broadband availability variable is too small for the estimations to have sufficient statistical power. Although the descriptive statistics suggest important variation from 2005 to 2007, I further explore this point by splitting the sample at the population median into rural and urban municipalities. Figure 3.3 shows that variation in the time period of my data is rather observed in rural areas. However, also for firms in rural municipalities only, the IV regression effects remain insignificant (see Table 3.B.9).

As the German sample contains a limited number of firms and could lack representativeness, I also conduct the first stage estimations on a larger sample containing broadband and Harte Hanks technology information. The coefficients are comparably small and insignificant (see Table 3.C.1 in the Appendix).

The second stage results are less clearly zero than the results of the first stage: As the coefficients are larger and the confidence intervals wider, I could only exclude quite large effects. Anyhow, the interpretation of these LATE-coefficients is not meaningful due to the weak first stage of the estimation.

3.6.2 Zero-Effect of Broadband as an Enabler of Interconnectivity

The non-significant effects in the first and in the second stage give some interesting insights into the nature of interconnectivity and the mechanisms of broadband internet in the firm. Before I discuss the different conclusions that can be drawn from the 2SLS results, it is important to recollect that my dataset does not contain information on individual broadband adoption of firms and that broadband availability at the municipality level is used instead. This measure cannot be influenced by the firm directly and can therefore – in contrast to firms' broadband take-up – be considered exogenous in this setting. I exploit this property in the 2SLS estimations aiming for causal identification. From the zero effects found, we can learn the following:

First, the first stage estimations yielding non-significant estimates confirm that interconnectivity is a paradigm inside the firm. It does not implicitly include a broadband component that would have been omitted when building the indicator. Interconnectivity is the integration of information technology and communication technology in the firm, which moves communication and collaboration to the digital space. The number of network devices per employee is one of the input variables of the indicator and from my results I conclude that medium-sized firms use interconnective IT structures to outsource IT-related tasks. The endowment of a firm with network equipment as well as the execution of tasks outside the firm make it very likely that a high-speed connection is required to benefit entirely from interconnectivity. The firm would need to stay in touch with their IT services provider or even with software-as-a-service platforms. *InterconICT* could therefore implicitly account for an internet connection. I cannot control for low-speed internet access and I do not have sufficient observations for small firms, but I can show that a high-speed connection above 384 Mbit per second is not a complement of the interconnectivity paradigm in medium and large firms. This finding supports the computation of the indicator.

Second, the 2SLS-estimation measures a Local Average Treatment Effect (LATE) of interconnectivity on productivity, where the broadband instrument identifies those interconnectivity implementations that are due to broadband availability in the municipality. However, the results show that interconnectivity is not a productive complement to broadband internet in the firm. The literature does not (yet) agree on the existence and size of productivity effects of broadband internet and the mechanisms of the productivity contribution of broadband internet are only marginally disentangled. To the best of my knowledge there is no study identifying IT resources that are complementary to the broadband productivity effect. With my German sample (B), I implement exactly this setting and find that interconnectivity does not provide the complementary mechanism to broadband productivity. Interconnectivity is an internal firm system, that stands for itself and generates productivity effects and organizational change in the firm. These effects are not enabled by broadband, but are independent of the availability of a fast internet connection.

Table 3.6: Interaction of interconnectivity and broadband

	*Coeff. on InterconICT*BroadbandAvail*		
	All sizes	Medium	Large
Dep. var.:	(1)	(2)	(3)
ln(Y/L)	0.000281	-0.000413	0.000596
	(0.000360)	(0.000389)	(0.000570)
ln(Y)	0.000389	-0.000319	0.000654
	(0.000351)	(0.000387)	(0.000570)
ln(L)	.000408*	0.000606*	0.000506**
	(0.000215)	(0.000346)	(0.000211)
Firm FE	Yes	Yes	Yes
Year*Industry FE	Yes	Yes	Yes
Observations	1685	589	1023
N. of firms	764	273	455

Data: Sample B. Unbalanced panel data from 2005 to 2007 for Germany. InterconICT see Figure 3.1. Source: CITDB, ORBIS, Breitbandatlas.
Notes: This table presents the baseline estimations with the interaction of InterconICT and broadband availability. Standard errors are clustered at the firm level and presented in paratheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Complementary influence could, however, also run the other way: Interconnectivity could push broadband adoption in the firm. I cannot directly measure this because I do not have information on broadband take-up. To still get an idea of the mutual impact of interconnectivity and broadband, I run the baseline analyses including an interaction term of interconnectivity and broadband availability. This specification assumes that all firms adopted broadband internet according to the availability distribution. In this case, the interaction accounts for potential mutual interferences of these two resources. However, also this estimation does not yield any significant coefficients for productivity and output (Table 3.6). Only for employment, there is a very small but (weakly significantly) positive impact of the joint implementation of interconnectivity and broadband. Note that the baseline employment effect of interconnectivity is negative (see Table 3.2). Bringing these different results together, it could mean that broadband internet can turn around the negative employment effects of interconnectivity – but without broadband being the driving force behind the adoption.

To sum up, the first stage estimation of the IV suggests that broadband infrastructure does not drive the implementation of an interconnective IT system in the firm. It would be interesting to limit this analysis to multi-establishment firms. Firms with multiple sites would benefit particularly from interconnectivity and the adequate broadband infrastructure to link up their systems. Broadband in the municipalities where the establishments are located would be more likely to be an enabler of interconnectivity. In the present sample, however, interconnectivity is clearly an intra-firm paradigm that stands for itself and is impacting productivity without broadband internet as a potential mediator. In policy debate, it is often argued that network infrastructure is an important prerequisite for IT investments in the firm. This cannot be confirmed in my sample.

3.7 Conclusion

The convergence of computing (IT) and telecommunication (CT) to ICT is a crucial step in the process of digitization in firms. This work proposes an indicator measuring whether a firm has already transitioned to this new paradigm I call "interconnectivity". I find heterogenous productivity effects of interconnectivity with respect to firm size. Medium firms benefit from the new technologies whereas large firms presumably experience implementation difficulties. The coefficient of around 0.02 in this log-linear model is of about the same size as the elasticity cluster identified by Cardona et al. (2013). The numbers are, however, not directly comparable: A switch of the interconnectivity indicator from 0 to 1 is associated with a 2 percent increase in firm productivity, whereas a 1 percent increase in IT capital, the IT measure of the analyses reviewed in the meta-study, leads to a productivity increase of 0.5 percent. The difference is not surprising because implementing an interconnective IT system is a much larger intervention in the firm than slightly increasing IT investments.

The employment effects of interconnectivity are particularly robust in my analyses and suggest, among other things, that medium-sized firms use the new technology to outsource IT tasks and services. They could, for instance, use cloud computing to switch to a pay-as-you-go computing scheme that can be beneficial by reducing IT capital, labor and maintenance costs in the firm (see for example Candel-Haug et al., 2016, for a discussion of the economic benefits of cloud computing). Building on these results, it would be interesting to analyze whether these jobs are lost to the economy or whether the IT employees go to the IT services sector. My results suggest that the IT employees of medium firms are employed by larger firms. However, the sample is not entirely representative in its firm size and industry composition. A fine-grained industry-level analysis could much better inform on employment relations in the industry and the IT service sector. It could also be the case that large firms that choose inhouse solutions for their interconnected IT structures also provide IT services to other firms. I consider my work a valuable starting point for further research in this direction.

In my sample, I also identify a zero-relationship between broadband infrastructure and the implementation of interconnectivity at the firm level. This result gives suggestive evidence on an important policy topic: Policy makers can take the decision whether to roll-out broadband in a certain region. However, they cannot control take-up by firms and the investment in complementary technologies, that, according to the literature, are crucial for broadband to exhibit positive productivity effects. Evidence on complementary investments to broadband availability is therefore urgently required. This analysis can only give some indications on a restricted sample and for a broadband connection speed that is considered very low nowadays. The question definitely deserves further research and discussion.

Appendix 3.A Additional Summary Statistics

Table 3.A.1: Summary statistics Sample A (European countries)

	Num. of obs	Mean	Std. dev.	Median	Min.	Max.
Employees	41,094	324.70	1717.99	119	1	105,261
IT Employees	36,985	13.12	164.65	2.07	0	19,278
Share of IT Employees	36,985	0.04	0.12	0.02	0	14
Sales (in million $)	41,094	106.071	676.81	26.74	0.001	62,851
Capital (in million $)	41,094	27.65	517.49	3.36	0	81,604.35
Materials (in million $)	41,094	60.06	386.02	12.53	0.0005	37,824.12
ERP	41,094	0.90	0.30		0	1
Groupware	41,094	0.92	0.28		0	1
Num. of network devices per employee	41,094	0.74	1.05	0.55	0	94.07
Share of laptops among all firm PCs	41,094	0.13	0.15	0.09	0	1
Num of PCs per employee	40,006	0.63	1.501	0.38	0	62.5

Data: Sample A. Unbalanced panel data from 2000 to 2007 for nine European countries. Source: CITDB, ORBIS.
Notes: Summary statistics are based on firm-year observations.

Table 3.A.2: Summary statistics Sample B (Germany)

	Num. of obs	Mean	Std. dev.	Median	Min.	Max.
Employees	1,685	1158.71	5007.01	309	3	105,261
IT Employees	1,001	66.91	494.4	5.53	0	12,910
Share of IT Employees	1,001	0.04	0.07	0.02	0	1
Sales (in million $)	1,685	459.31	1,706.06	105,165	1.57	33,000
Capital (in million $)	1,685	130.18	855.72	12.83	0.01	16,805
Materials (in million $)	1,685	261.63	829.68	56.88	0.039	12,894
ERP	1,685	0.89	0.31	1	0	1
Groupware	1,685	0.84	0.37	1	0	1
Num. of network devices per employee	1,685	0.92	0.9	0.75	0	21.25
Share of laptops among all firm PCs	1,685	0.13	0.16	0.09	0	1
Num of PCs per employee	1,539	0.68	0.62	0.55	0	9
DSL avail (munic. level)	1,685	90.88	10.65	94.59	0	99.99
DSL avail rural	844	87.70	12.68	91.22	0	99.99
DSL avail urban	841	94.07	6.75	96.73	57.37	99.69

Data: Sample B. Unbalanced panel data from 2005 to 2007 for Germany. Source: CITDB, ORBIS, Breitbandatlas.
Notes: Summary statistics are based on firm-year observations.

Appendix 3.B OLS and Robustness Checks

Table 3.B.1: OLS with different fixed effects

	Coefficient on L.InterconICT							
	All sizes	Small	Medium	Large	All sizes	Small	Medium	Large
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(Y/L)	0.218***	0.177***	0.216***	0.236***	0.144***	0.0677***	0.155***	0.186***
	(0.00669)	(0.0146)	(0.00858)	(0.0138)	(0.00638)	(0.0136)	(0.00810)	(0.0134)
ln(Y)	0.217***	0.174***	0.217***	0.239***	0.145***	0.0688***	0.156***	0.189***
	(0.00664)	(0.0144)	(0.00856)	(0.0138)	(0.00634)	(0.0136)	(0.00809)	(0.0134)
ln(L)	-0.0785***	-0.0229	-0.0459***	0.0164	-0.0732***	-0.00247	-0.0441***	-0.00893
	(0.0101)	(0.0167)	(0.00958)	(0.0187)	(0.00970)	(0.0167)	(0.00949)	(0.0175)
Firm FE	No	No	No	No	No	No	No	No
Ind FE	No	No	No	No	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	Yes	Yes	Yes	Yes
N. of obs	31870	8490	16109	7271	31870	8490	16109	7271

Data: Sample A. Unbalanced panel data from 2000 to 2007. InterconICT see Figure 3.1. Source: CITDB, ORBIS.
Notes: The specification is an augmented production function in intensive form estimated across all firm sizes and in a split sample for small, medium-sized and large firms seperately. InterconICT is included with a one-year-lag. Each cell is a seperate regression. The first line shows the baseline specification with labor productivity as dependent variable and with different fixed effects. Line (2) and (3) use the components of labor productivity (Sales and Number of employees) as dependent variables. Standard errors are clustered at the firm level and noted in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.B.2: Robustness: Country-split of sample

	Coefficient on L.InterconICT			
Dep. var.:	All sizes	Small	Medium	Large
ln(Y/L)	(1)	(2)	(3)	(4)
Spain	0.00173	-0.0249	0.00421	-0.0138
	(0.0120)	(0.0237)	(0.0118)	(0.0475)
	[0.773]	[0.841]	[0.832]	[0.720]
Italy	-0.000915	-0.0395	0.0321	-0.0198
	(0.0175)	(0.0448)	(0.0215)	(0.0326)
	[0.673]	[0.785]	[0.721]	[0.639]
France	-0.0244	-0.0625	-0.0164	0.0297
	(0.0234)	(0.0563)	(0.0284)	(0.0465)
	[0.702]	[0.792]	[0.691]	[0.828]
Sweden	0.0180	0.0184	0.0116	0.0552
	(0.0138)	(0.0209)	(0.0220)	(0.0406)
	[0.802]	[0.842]	[0.801]	[0.961]
Finland	0.0323	0.0430	0.0298	-0.0405
	(0.0242)	(0.0474)	(0.0250)	(0.0619)
	[0.686]	[0.686]	[0.747]	[0.970]
Germany	-0.00916		-0.0131	-0.0338
	(0.0264)		(0.0653)	(0.0266)
	[0.898]		[0.823]	[0.922]
Poland	0.0747	0.255	0.0775	0.117**
	(0.0912)	(0.266)	(0.0849)	(0.0482)
	[0.742]	[0.914]	[0.914]	[0.900]
Netherlands	-0.0493		-0.00328	-0.0558
	(0.0392)		(0.0515)	(0.0607)
	[0.826]		[0.967]	[0.831]
Austria	-0.00281		-0.0702	-0.00173
	(0.0275)		(0.0540)	(0.0263)
	[0.981]		[0.998]	[0.984]
Firm FE	Yes	Yes	Yes	Yes
Year*Industry FE	Yes	Yes	Yes	Yes

Data: Sample A. Unbalanced panel data from 2000 to 2007. InterconICT see Figure 3.1. Source: CITDB, ORBIS.
Notes: Robustness check for the baseline specification (see Table 3.2). Here the sample is split according to the country of firm headquarters. Each cell is a seperate regression. Empty cells stand for insufficient size of the subsample. Standard errors are clustered at the firm level and noted in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.B.3: Robustness: Countries and trade exposure

	Coefficient on L.InterconICT							
	Country-Year FE				Three Digit Industry-Year FE			
	All sizes	Small	Medium	Large	All sizes	Small	Medium	Large
Dep. var.:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(Y/L)	0.00126	0.000681	0.0206**	-0.0342*	0.00545	0.00535	0.0268**	-0.0486**
	(0.00802)	(0.0166)	(0.0100)	(0.0195)	(0.00823)	(0.0158)	(0.0108)	(0.0224)
ln(Y)	-0.00402	-0.0114	0.0134	-0.0346*	-0.00114	-0.0104	0.0185*	-0.0461**
	(0.00727)	(0.0139)	(0.00954)	(0.0188)	(0.00757)	(0.0134)	(0.0104)	(0.0220)
ln(L)	-0.0265**	-0.0295	-0.0444***	0.00725	-0.0265**	-0.0379*	-0.0492***	0.0213
	(0.0103)	(0.0213)	(0.0139)	(0.0228)	(0.0106)	(0.0229)	(0.0143)	(0.0230)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind2digit-Year FE	Yes	Yes	Yes	Yes	No	No	No	No
Country-Year FE	Yes	Yes	Yes	Yes	No	No	No	No
Ind3digit-Year FE	No	No	No	No	Yes	Yes	Yes	Yes
Observations	31870	8490	16109	7271	31870	8490	16109	7271
N. of firms	9083	2361	4433	2289	9083	2361	4433	2289

Data: Sample A. Unbalanced panel data from 2000 to 2007. InterconICT see Figure 3.1. Source: CITDB, ORBIS.
Notes: Robustness check for the baseline specification (see Table 3.2). In Columns 1 to 4 country-year-fixed effects are added as further controls, in Columns 5 to 9 industry-year-fixed effects are extended to the 3-digit SIC level, controlling for changing trade structures in the industries. Each cell is a seperate regression. Standard errors are clustered at the firm level and noted in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.B.4: Robustness: Traditional IT measure – PC intensity

	Coefficient on L.InterconICT			
	All sizes	Small	Medium	Large
Dep. var.:	(1)	(2)	(3)	(4)
ln(Y/L)	0.00706	0.0359**	0.00480	-0.0215
	(0.00887)	(0.0152)	(0.0116)	(0.0290)
ln(Y)	0.00572	0.0343**	0.00443	-0.0275
	(0.00872)	(0.0157)	(0.0117)	(0.0252)
ln(L)	-0.0107	-0.0309	-0.00286	-0.00684
	(0.0107)	(0.0249)	(0.0133)	(0.0213)
Firm FE	Yes	Yes	Yes	Yes
Year*Industry FE	Yes	Yes	Yes	Yes
Observations	31870	8490	16109	7271
N. of firms	9083	2361	4433	2289

Data: Sample A. Unbalanced panel data from 2000 to 2007. InterconICT see Figure 3.1. Source: CITDB, ORBIS.
Notes: In this table, InterconICT is replaced by PC intensity, a traditional ICT measure in firms. The continuous variable *Number of PCs / Number of employees* is transformed to a dummy: $Dummy(PCs/empl)_{it} = 1$ if PCintensity_{it} is larger than the median across firms in t. Each cell is a seperate regression. Standard errors are clustered at the firm level and noted in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.B.5: Robustness: Control for IT affinity

	All sizes (1)	Small (2)	Medium (3)	Large (4)
Dep. var.: ln(Y/L)				
L.InterconICT	0.00109	0.00610	0.0228**	-0.0375*
	(0.00803)	(0.0164)	(0.0100)	(0.0199)
L.Dummy(PCs / empl)	0.00705	0.0362**	0.00441	-0.0209
	(0.00887)	(0.0153)	(0.0116)	(0.0290)
Dep. var.: ln(Y)				
L.InterconICT	-0.00407	-0.00585	0.0147	-0.0366*
	(0.00721)	(0.0136)	(0.00950)	(0.0191)
L.Dummy(PCs / empl)	0.00575	0.0340**	0.00418	-0.0268
	(0.00871)	(0.0157)	(0.0117)	(0.0251)
Dep. var.: ln(L)				
L.InterconICT	-0.0239**	-0.0293	-0.0480***	0.0107
	(0.0105)	(0.0216)	(0.0144)	(0.0225)
L.Dummy(PCs / empl)	-0.0105	-0.0320	-0.00204	-0.00703
	(0.0106)	(0.0250)	(0.0132)	(0.0214)
Firm FE	Yes	Yes	Yes	Yes
Year*Industry FE	Yes	Yes	Yes	Yes
Observations	31870	8490	16109	7271
N. of firms	9083	2361	4433	2289

Data: Sample A. Unbalanced panel data from 2000 to 2007. InterconICT see Figure 3.1. Source: CITDB, ORBIS.
Notes: This table reports the results of the baseline specification augmented by PC intensity. Each panel (!) is a seperate regression. Standard errors are clustered at the firm level and noted in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.B.6: Robustness: Input dummies of InterconICT_{it}

	All sizes (1)	Small (2)	Medium (3)	Large (4)
Dep. var.: ln(Y/L)				
L.ERP	-0.00520	-0.000579	0.00172	-0.0462
	(0.0101)	(0.0158)	(0.0101)	(0.0456)
L.Groupware	-0.000310	0.000965	-0.00193	-0.00557
	(0.0102)	(0.0197)	(0.0106)	(0.0346)
L.Dummy(Netw dev / empl)	0.0139	0.0350**	0.0189	-0.0244
	(0.00940)	(0.0172)	(0.0136)	(0.0209)
L.Dummy(Share of laptops)	-0.0152*	-0.0129	-0.00794	-0.0326
	(0.00808)	(0.0183)	(0.00983)	(0.0204)
Dep. var.: ln(Y)				
L.ERP	-0.00513	0.00680	-0.00356	-0.0461
	(0.00946)	(0.0148)	(0.00910)	(0.0454)
L.Groupware	-0.00795	-0.0218	-0.00604	-0.00753
	(0.00911)	(0.0166)	(0.0102)	(0.0319)
L.Dummy(Netw dev / empl)	-0.0277**	-0.0445	-0.0272	-0.0294
	(0.00891)	(0.0146)	(0.0133)	(0.0212)
L.Dummy(Share of laptops)	-0.00786	0.00162	-0.00255	-0.0295
	(0.00766)	(0.0170)	(0.00937)	(0.0200)
Dep. var.: ln(L)				
L.ERP	0.00591	0.0176	-0.00266	-0.00382
	(0.0111)	(0.0220)	(0.0137)	(0.0217)
L.Groupware	-0.0238*	-0.0398	-0.0209	-0.00102
	(0.0123)	(0.0243)	(0.0153)	(0.0278)
L.Dummy(Netw dev / empl)	-0.0277**	-0.0445	-0.0272	-0.0294
	(0.0128)	(0.0287)	(0.0169)	(0.0231)
L.Dummy(Share of laptops)	0.0113	0.0344	0.00870	-0.0239
	(0.0103)	(0.0222)	(0.0122)	(0.0259)
Firm FE	Yes	Yes	Yes	Yes
Year*Industry FE	Yes	Yes	Yes	Yes
Observations	31870	8490	16109	7271
N. of firms	9083	2361	4433	2289

Data: Sample A. Unbalanced panel data from 2000 to 2007. InterconICT see Figure 3.1. Source: CITDB, ORBIS.
Notes: InterconICT is replaced by its four input variables as dummies. Each panel is a seperate regression. Standard errors are clustered at the firm level and noted in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.B.7: Robustness: Alternative computation of the interconnectivity indicator

	Coefficient on L.InterconICT (p75)				*Coefficient on L.InterconICT (p25)*			
	All sizes	Small	Medium	Large	All sizes	Small	Medium	Large
Dep. var.:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(Y/L)	0.0237*	0.0483*	0.0531***	-0.0676**	0.00289	0.00532	0.00770	-0.0187
	(0.0136)	(0.0278)	(0.0159)	(0.0322)	(0.00695)	(0.0135)	(0.00939)	(0.0178)
ln(Y)	0.0140	0.0259	0.0416***	-0.0696**	0.0000842	-0.00546	0.00567	-0.0175
	(0.0120)	(0.0227)	(0.0137)	(0.0303)	(0.00640)	(0.0118)	(0.00914)	(0.0165)
ln(L)	-0.0224	-0.0268	-0.0477**	0.0142	-0.00318	-0.0182	-0.00199	0.00481
	(0.0175)	(0.0369)	(0.0224)	(0.0360)	(0.00867)	(0.0199)	(0.0113)	(0.0176)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year*Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31870	8490	16109	7271	31870	8490	16109	7271
N. of firms	9083	2361	4433	2289	9083	2361	4433	2289

Data: Sample A. Unbalanced panel data from 2000 to 2007. InterconICT see Figure 3.1. Source: CITDB, ORBIS.
Notes: In this table, the method of computation of the interconnectivity indicator was modified: Instead of the median as a cutoff point for the dummies for network devices and share of laptops, the 75th and 25th percentiles were used respectively. Standard errors are clustered at the firm level and noted in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.B.8: Two-stage least-squares: Medium and large firms

	Medium			Large		
	(1) ln(Y/L)	(2) ln(Y)	(3) ln(L)	(4) ln(Y/L)	(5) ln(Y)	(6) ln(L)
Second stage						
InterconICT	0.890	0.759	0.0417	-3.336	-3.724	2.775
	(1.195)	(1.016)	(0.440)	(8.537)	(11.112)	(6.873)
	[-1.47,3.25]	[-1.24,2.76]	[-0.83,0.91]	[-20.14,13.47]	[-25.59,18.14]	[-10.75,16.30]
First stage						
Broadband avail	-0.0012	-0.0012	-0.0013	0.0004	0.0003	0.0004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	[-0.003,0.001]	[-0.004,0.001]	[-0.004,0.001]	[-0.001,0.002]	[-0.002,0.002]	[-0.001,0.002]
F stat	1.042	1.171	1.171	0.172	0.125	0.163
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Ind*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	589	589	589	1023	1023	1023
N. of firms	273	273	273	455	455	455

Data: Sample B. Unbalanced panel data from 2005 to 2007 for Germany. Source: CITDB, ORBIS, Breitbandatlas.
Notes: This table presents two-stage least-squares estimations, instrumenting interconnectivity with broadband availability in the municipality. The sample is split into medium and large firms. The group of smaller firms is too small to be analyzed in a split sample. Due to the variation level of the instrument, standard errors are clustered at the municipality level and presented in parentheses. The 95% confidence intervals in square brackets. F-statistic is Kleibergen-Paap. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.B.9: 2SLS on subsamples of urban and rural municipalities

	Coeff. on L.InterconICT		*Coeff. on InterconICT*	
	Rural	Urban	Rural	Urban
Dep. var.:	(1)	(2)	(3)	(4)
ln(Y/L)	0.836	0.189	3.903	1.509
	(0.920)	(0.253)	(7.358)	(3.187)
ln(Y)	0.689	-0.00930	3.273	1.031
	(0.756)	(0.134)	(5.953)	(1.775)
ln(L)	-1.288	-0.261	-7.531	-1.253
	(1.491)	(0.210)	(13.671)	(3.596)
Firm FE	Yes	Yes	Yes	Yes
Year*Industry FE	Yes	Yes	Yes	Yes
Observations	144	170	844	841
N. of firms	72	85	383	378

Data: Sample B. Unbalanced panel data from 2005 to 2007 for Germany. InterconICT see Figure 3.1. Source: CITDB, ORBIS, Breitbandatlas.
Notes: This table presents the two-stage least-squres estimations on the subsamples of urban municipalities (population above the Sample B median) and rural municipalities (equal to or below the Sample B median). The F-statistics of the first stages are below 1. Standard errors are clustered at the municipality level and presented in paratheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix 3.C First Stage on the German Technology Sample

The German technology sample (C) serves for a robustness check of the first stage of the two-stage least-squares estimations. It is restricted to CITDB technology data of German firms and the broadband variable. The sample does not comprise ORBIS financial information and therefore does not suffer from the restricted overlap of CITDB and ORBIS. The German technology sample includes all complete firm-year observations from the Harte Hanks database in Germany and broadband information from Breitbandatlas. It covers 15,463 firm-year observations from 6,069 firms in an unbalanced panel structure over the years 2005 through 2007. Due to the small size of sample B, I use sample C to test the first stage of the 2SLS estimation: Table 3.C.1 reports the regression of the interconnectivity measure on the broadband availability instrument. Note that I do not have information on broadband adoption of firms. So, to be precise, broadband availability is already an instrument for broadband usage and, again, I estimate an intention-to-treat effect. The coefficients and confidence intervals on the large sample confirm the results on the German sample (B) and the zero-effect of broadband internet on interconnectivity.

Table 3.C.1: 2SLS on Sample C

	All sizes	Small	Medium	Large
	(1)	(2)	(3)	(4)
	InterconICT	InterconICT	InterconICT	InterconICT
DSLavail	-0.000123	0.000412	0.000169	-0.000396
	(0.000)	(0.001)	(0.001)	(0.001)
	[-0.00,0.00]	[-0.00,0.00]	[-0.00,0.00]	[-0.00,0.00]
Firm FE	Yes	Yes	Yes	Yes
Year*Industry FE	Yes	Yes	Yes	Yes
r2	0.145	0.179	0.193	0.143
Observations	14722	1223	6541	6958
N. of firms	5777	517	2613	2647

Data: Sample C. Unbalanced panel data from 2005 to 2007 for Germany. Source: CITDB, Breitbandatlas.
Notes: This table presents the first stage of the 2SLS specification in Tables 3.5 and 3.B.8 estimated on the larger Sample C. Standard errors are clustered at the municipality level and presented in paratheses. The 95% confidence intervals in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chapter 4

Immigrants' Contribution to Innovativeness: Evidence from a Non-Selective Immigration Country*

4.1 Introduction

Integration of migrants into the labor market and their contribution to economic growth is an important topic of public debate. Economic research has largely been analyzing the impact of immigration on natives' wages and employment opportunities and is increasingly interested in the impact of migration on innovation and growth in the host country. We add to this literature by studying how the number of inventors of German nationality was impacted by the arrival of Polish immigrants in the time period around the Eastern enlargement of the European Union. A particularity of this immigration wave is that entry and the permission to work were not conditional on a university degree.

Several studies, like Kerr and Lincoln (2010) or Moser et al. (2014) look at high-skilled immigration and its impact on patenting. Other work analyzes the effects of immigrant

*This chapter is based on joint work with Alexander Cuntz and Oliver Falck.

shares or ethnic diversity on innovation (Hunt and Gauthier-Loiselle, 2010; Ozgen et al., 2013; Bosetti et al., 2015). This paper uses historical migration patterns in a shift-share instrumental variable approach to quantify the contribution of migration, both high- and low-skilled, to innovativeness by incumbent inventors in Germany in 2001–2010. The expansion of the European Union by 10 countries, mostly from Eastern Europe, in 2004, generated one of the greatest migration waves in Europe in the first decade of the millennium and was accompanied by a great amount of uncertainty concerning labor market integration and growth potential in the destination countries.

One of the central empirical papers on high-skilled immigration and innovation in the United States is Kerr and Lincoln (2010). In contrast to that US case, migration from Eastern Europe to Germany around the enlargement was not regulated based on immigrants' qualifications. We therefore apply the Kerr and Lincoln (2010)-approach to the German case so as to directly compare the effects of a skill-based immigration system to an immigration policy that is not based on qualifications.

From a unique dataset developed by Miguelez and Fink (2013), we obtain disaggregated information on patenting inventors in Germany, such as their nationality and place of residence. We count the inventors indicated in patent applications by nationality, aggregate these counts to the county (*Kreis*) level, and add information on the local Polish immigrant group as well as county characteristics. In our two baseline estimations at the county level, we relate the number of Polish immigrants to the number of inventors of, first, Polish and, second, German nationality. We control for migrants' endogenous location choice by employing a shift-share prediction of the number of Polish immigrants to the county. Among the immigrants from new EU member states to Germany, Polish citizens comprise by far the largest group and their particular migration history to Germany after the Solidarnosc movement in the 1980s allows the construction of our instrument. They came as political refugees and were allocated to German municipalities based on a quasi-random distribution system. We therefore focus on Polish immigration to Germany and, rather than referring to the year before our period of analysis, our shift-share instrument is backed by a conclusive historical immigration story in the 1980s. We set the period of our analysis around the enlargement, that is from 2001 to 2010.

Our results suggest a positive and statistically significant impact of Polish immigration on the number of inventors in Germany. Some of these migrants became inventors themselves: Counties that received 10 percent more Polish immigrants than other counties experienced a 0.28 percent higher number of Polish inventors. This effect size is quite small but still one-tenth of what was found for high-skilled immigration in the United States. The spillovers from Polish migrants to inventors of German nationality have a slightly higher point estimate ($\beta = 0.032$) and, in contrast to the results for the United States, are statistically significant. We conclude that some Polish immigrants are inventors, but that a greater number of them are – independent of their qualification level – complements to incumbent inventors in Germany.

More in detail, Kerr and Lincoln (2010) build a shift-share instrument exploiting regional variation in the count of noncitizen immigrant scientists and engineers at an earlier point in time and estimate a reduced-form IV specification. They find that more high-skilled immigration leads to more science and engineering employment as well as more patents by Indian or Chinese inventors. The point estimates for Anglo-Saxon inventors and total patenting are also positive but not statistically significant. Hunt and Gauthier-Loiselle (2010) use a similar identification strategy and find positive effects of skilled immigrant shares on total patents per capita. These results confirm that skilled immigrants make a positive contribution to local innovativeness in total. Spillovers on incumbent inventors cannot be tested directly with their data. However, Hunt and Gauthier-Loiselle (2010) conclude from the difference between their individual- and state-level results, that there are positive spillovers from immigrants in this domain. Moser et al. (2014) find that the arrival of German Jewish emigrants to the United States in the 1930s significantly increased the number of patents in the immigrants' specialized fields. This result, however, is neither driven by the immigrants' contribution to patenting nor by an increase in the patent productivity of incumbent researchers; rather the arrival of German Jewish researchers attracted new domestic inventors to the particular research fields in which the immigrants were successful. We learn from Moser et al. (2014) that migrants can also have an indirect innovation effect by changing a firm's or a field's specialization.

Turning to Europe, Bosetti et al. (2015) conduct a macro-level analysis for a panel of 20 European countries and find that the share of foreign workers in the skilled labor force explains increases in patent counts. According to Ozgen et al. (2013)'s study using Dutch firm-level data, the share of foreigners in a firm has a negative effect and cultural diversity (variance of ethnicities) among employees has a positive effect on firm innovativeness. In contrast to the US-papers and in line with our study, Bratti and Conti (2018) analyze the impact of immigrants of all skill-levels on innovation in Italy. They do not find any significant effects in various specifications. Finally, we are aware of a single study for Germany on this topic: Jahn and Steinhardt (2016) exploit the immigration of ethnic Germans from Eastern Europe to Germany and find that their presence has a positive impact on total patenting at the regional level. These studies on Europe provide interesting insight into the total effect of immigration on patent counts. However, the data do not allow disentangling migrant and resident contributions to patenting. Our paper, in contrast, gives more information on the mechanism of the effect and on whether immigrants are substitutes or complements to incumbents in the host country. Furthermore, we do not limit our analysis to high-skilled immigrants.

In the following section, we explain our identification strategy in more detail. We present our data set in Section 4.3 and our results in Section 4.4. Section 4.5 concludes.

4.2 Identification and Empirical Specification

We are interested in the impact of Polish immigration on innovativeness in Germany over a 10-year-period around the Eastern enlargement of the European Union (2001-2010).[1] For our empirical model, we follow the literature by exploiting regional variation and choose the county (*Kreis*) level for analysis. Furthermore, innovativeness is proxied by (patenting) inventor counts. The effect of immigrants on the number of inventors is subject to different potential mechanisms: On the one hand, Polish immigrants can be inventors and patent in Germany without impacting incumbent patentees. On the other hand, when immigrants are complements, they push patenting activities of German inventors and have a positive impact on total patenting whether they patent themselves or not. But immigrants can also be substitutes to incumbent inventors and crowd them out if the new arrivals are more successful. We shed light on these mechanisms by separately analyzing the impact of Polish immigrants on inventors of Polish nationality and on inventors of German nationality.

4.2.1 Empirical Model

We estimate the following equation:

$$log(\text{Num of inv})_i = \beta_0 + \beta_1 * \widehat{Mig}_i^{POL} + \beta_2 * \boldsymbol{x}_i + \beta_3 * (\text{Agglo FE}) + \beta_4 * (\text{State FE}) + \varepsilon_i \quad (4.1)$$

where i indicates the county level and *log(Num of inv)* denotes, in separate regressions, the logged number of inventors of Polish or German nationality aggregated across the ten years of our period of analysis 2001–2010. **x** is a set of county-specific controls relating to the distance to Poland, the industry structure of the county and the presence of a university. *Agglo FE* represents the agglomeration type or settlement structure of the county, *State FE* the federal state the county is located in, and ε_i the error term. The key coefficient of interest is β_1. It

[1] Choosing this time frame also avoids confusion in the context of the reform of the German nationality law in 2000.

gives us the effect of Polish immigration to German counties on the number of inventors in the counties. In an estimation with the actual Polish immigration numbers at the county level, the coefficient would most likely be biased because we expect the distribution of Polish immigrants across German counties to be endogenous in our setting. We therefore implement a shift-share type approach.

The Shift-Share Instrument

Relating regional immigration to regional innovativeness would suffer from a serious selection problem: Polish inventors, that is, immigrants with the relevant qualifications, are likely to choose their residence according to the structure of innovative (i.e., research and patenting intensive) industries in Germany. The development of the number of Polish migrants and inventors in county i are therefore both potentially driven by the density of innovative industries. To overcome this problem, we employ a shift-share type of instrument, such as can be found in earlier work of Card (2001), Hunt and Gauthier-Loiselle (2010), and Lewis (2011), in order to use exogenous variation of the number of migrants.[2] The instrument consists of two parts: A regional distribution and a macro trend. The macro trend is then disaggregated to the regional level based on an exogenous migrant share of an earlier point in time. In this analysis, we use Polish emigration flows around the EU enlargement ($Mig_{t=2001-2010}$) and disaggregate them to the regional level in Germany based on each county's share of Polish citizens in 1989 ($(\frac{Mig_i^{POL}}{Mig_D^{POL}})_{t=1989}$). In fact, the instrument is a prediction of the migration flows to the respective county in the period of analysis and looks as follows:

$$\widehat{Mig}_i^{POL} = ln(Mig_{t=2001-2010}^{POL \rightarrow World}) * (\frac{Mig_i^{POL}}{Mig_D^{POL}})_{t=1989}^{norm} \tag{4.2}$$

The idea underlying this approach is that immigrants tend to live in locations with a higher share of people of similar background. This phenomenon is partly due to the presence of cultural or religious institutions such as, in our case, Polish cultural centers, Polish-speaking Catholic masses, and restaurants or supermarkets with Polish cuisine and products. Social

[2] This instrument is also known as a *Bartik*-type instrument because it was first applied in Bartik (1991).

ties also play a big role in immigrants' location choice. Burchardi and Hassan (2013) and Hoisl et al. (2016) show that social ties are persistent over a long time period. There is extensive empirical evidence of the advantages of being integrated in this kind of network, especially for job search (e.g., Edin et al., 2003 for Sweden; Damm, 2009 for Denmark; Hoisl et al., 2016 for Germany). The shift-share instrument structure is widely used and acknowledged in the economic literature on migration and has also been applied in research on trade (e.g., Autor et al., 2013) and technological change (e.g., Acemoglu and Restrepo, 2017).

Among all 10 new EU member states of 2004, we limit the analysis to migrants from Poland. Restricting our analysis to a particular group is motivated by the idea of our instrument that allocates migrants based on their ethnic and cultural network: as the new member states are culturally and language-wise very heterogeneous, we do not expect immigrants from these countries to form "new member states networks" but to join existing networks of migrants with the same country of origin. We are aware, that other papers use the aggregate of predicted immigration from all source countries, hence avoiding a restriction to a particular migrant group. However, it has recently been pointed out by Goldsmith-Pinkham et al. (2018) that the shifts in the Bartik-type instrument affect an instrument's relevance but do not automatically solve the endogeneity problem. Consequently, authors need to explain why the earlier shares are exogenous.[3] The particular immigration history of Poles to Germany in the 1980s allows us to use an earlier distribution that we argue is exogenous in our setting. In Section 4.2.2 we explain why this is the case. Furthermore, Poles are and have been one of the largest group of foreigners living in Germany and they also were the largest group of immigrants after the EU Eastern enlargement, which makes them an economically relevant group.

For the macro trend we use the total emigration flow from Poland ($Mig^{POL \rightarrow World}_{t=2001-2010}$) instead of Polish migration to Germany. The presence of innovative industries in Germany might be a pull factor impacting Polish migrants' destination decisions. By using total emigration to all countries in the world, we account for push factors of migration from Poland, such as

[3]A summary of the recent discussion on shift-share instruments can be found at `http://blogs.worldbank.org/impactevaluations` (last viewed on July 16, 2018).

unfavorable labor market conditions, which we consider to be exogenous in our setting. Furthermore, in contrast to most existing studies, we measure the total migration flow and do not restrict the analysis to high-skilled individuals or occupations demanding high qualifications.

In addition, for the computation of the instrument, we follow Kerr and Lincoln (2010) and take the log of the macro trend and normalize the 1989-share. It is a reduced-form instrumental variable approach.

Controlling for Confounding Factors

The distribution of Poles across Germany in 1989, which is the relevant share for our instrument, is not entirely unrelated to the number of inhabitants of a county (see Figures 4.1 and 4.A.1). Besides, big agglomerations with their concentration of highly qualified workforce and excellent infrastructure could be more likely to host innovative firms than rural counties. We therefore add fixed effects for the settlement structure of the respective county (*Agglo FE*), distinguishing between agglomerations, urbanized zones, rural counties with some more densely populated spots, and rural areas. With this approach, we avoid our results to be confounded by county population or population density. As a result of the settlement structure fixed effects, we identify our effect only within these groups, which means we compare, for example, densely populated counties with other densely populated counties.

Furthermore, we weight our regressions by county population. This way, counties with many residents have a higher impact than counties with low population. Consequently, our estimates cannot be disproportionally driven by a few small counties. Our results are not representative for the average county, but for the population average in Germany.

Variables measuring structural characteristics of the counties in our sample control for remaining factors that could potentially impact the immigration destination and the inventor count alike. These include the industry quota (Number of employees in the industrial sector in county i devided by the total number of employees in the county) as a proxy for the structure of the county's economy. A dummy for the presence of a university (*Universität* or *Fachhochschule*) in the county serves as a proxy for the presence of scientific research.

One could also argue that Polish immigration and an increasing inventor count in a county are a result of increasing trade and, therefore, more intense cooperation between Germany and Poland. As a consequence of the EU enlargement, German firms might, for example, replace their former French suppliers with Polish suppliers and consequently also employ more Polish staff. We control for the relevance of trade and cooperation with Poland by adding the road distance to the next Polish border crossing to our estimation. As we only consider West Germany, there are no counties in our sample that are located directly at the border to Poland.

We add state fixed effects to the equation because our instrument might also be slightly correlated with the economic situation of the German federal states (*Bundesländer*) and therefore potentially with the location of innovative industries. In Section 4.2.2 we will show that Polish political refugees in the 1980s were, in a first step, allocated to German federal states according to the *Königsteiner Schlüssel* which is partly based on economic characteristics. However, in a second step, refugees were distributed according to state-specific criteria, which we will argue to be nearly random. Still, we are cautious and add state fixed effects so as to control for any remaining correlation of the distribution criteria of the refugees and our outcome variable. The fixed effects cover only territorial states and exclude the city-states Hamburg, Berlin, and Bremen.

4.2.2 A Brief History of Polish Immigration to Germany

Polish immigration has a long-standing tradition in Germany. At the end of the 19th, beginning of the 20th, century, around 300,000 ethnic Poles, generally called the *Ruhr-Polen*, moved to Western Prussia to work in mining and other industries (Kaluza, 2002).[4] Due to assimilation to the German environment, return migration after foundation of the Polish national state in 1918, and persecution by the Nazi regime, their descendants cannot be identified as such

[4] Technically speaking, these were internal migrants from the Eastern provinces of Prussia and therefore had the German citizenship. For our setting, however, it would be crucial, that they were culturally Polish.

today. Directly after World War II, hundreds of thousands of Polish-speaking forced laborers and concentration camp prisoners were still in Germany but most of them soon left the country. According to Kaluza (2002), approximately 40,000 of them stayed on (*displaced persons*).

Polish immigration in the 1980s

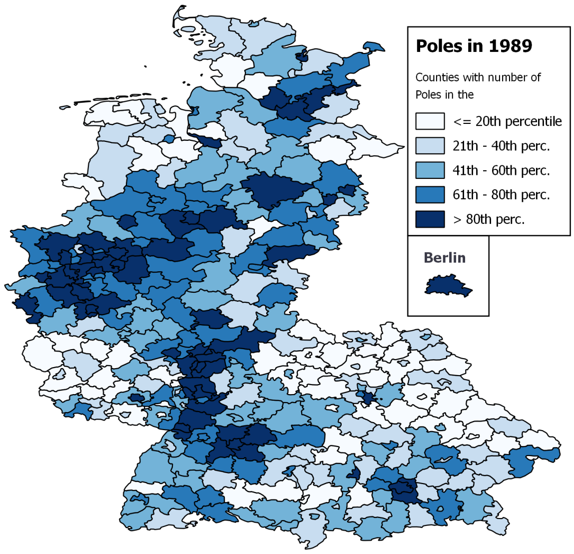
We base our shift-share identification strategy on political refugees from Poland to Germany in the 1980s. In this context, it is crucial to distinguish the political refugees from two other, larger, Polish immigrant groups arriving during the same time period: ethnic Germans and economic refugees. The three groups differed with regard to their legal situation. In the aftermath of the war and up until 1990, a great number of ethnic Germans from Poland moved to the Federal Republic of Germany (*Aussiedler*). They were not considered asylum seekers but were awarded German citizenship immediately after their arrival and do not enter immigration statistics as Polish nationals.

However, German statistics on asylum seekers (see Table 4.A.1) document an increasing number of Poles at the end of the 1980s. Economic refugees from the deteriorating economic situation in socialist Poland account for a large share of these asylum seekers. Their chances of being granted asylum were extremely low, though. Most of them were only granted an exceptional leave to remain (*Duldung*), meaning that they could stay on because West Germany would not send refugees back to a socialist country. These immigrants did not have access to the labor market and had to cope with an uncertain residence permit. In the years 1986 and 1987, immigration laws were liberalized and refugees from the Soviet Bloc who were not granted asylum had the right to apply for a temporary work permit after a one-year waiting period. In reality, however, few work permits were issued and the immigrants' situation remained extremely tenuous[5] (Meister, 1992).

[5]Work permits could only be issued for a particular job and under the condition that there was no German worker available for the job. Furthermore, a survey among German firms in 2017 shows that employers generally hesitate to recruit refugees due to their uncertain residence permit situation (ifo Personalleiterbefragung 1. Quartal 2017). With the fall of the Iron Curtain, German authorities proceeded to expel this group from the country. However, many Polish nationals received a permanent right of residence by referring to customary law, albeit their access to the legal labor market remained restricted (Kaluza, 2002; Meister, 1992).

The third largest group of immigrants arriving from Poland in the 1980s and a small fraction of the asylum seekers were political refugees. The construction of this analysis' instrument is based on their regional distribution (see Figure 4.1). The failure of the Solidarnosc movement and the imposition of martial law in Poland in 1981 drew many activists and workers to Germany. In West Germany, they could pursue their political activities and publish their work. These people were granted asylum ex officio and had immediate access to the labor market.

Figure 4.1: Geographic distribution of Polish employees in 1989 across Germany in percentiles of counties



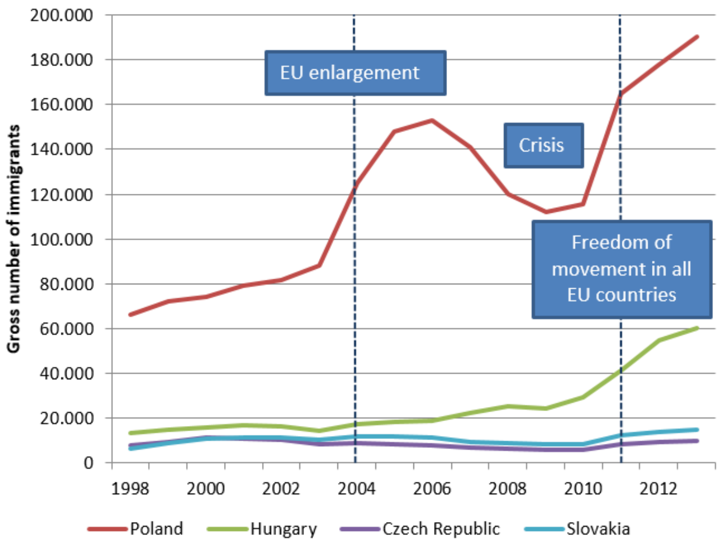
Source: Own presentation based on data from German Social Security Records provided by the Institute for Employment Research, Nuremberg.

We consider the distribution of these political refugees across German counties in the 1980s (here: 1989) to be exogenous to today's innovative industry structures, which qualifies this variable for the construction of our instrument (see Equation 2). First, these immigrants did not leave their home country so as to improve their work and economic situation and, second, refugees were distributed across West German states (NUTS1 level) according to an allocation key called *Königsteiner Schlüssel* based on tax revenue and population. The distribution within the states and to the district (NUTS3) level, however, followed state-specific criteria and was mostly affected by factors such as the availability of adequate real estate for the accommodation of the refugee groups or the negotiation skills of the governing mayor. Due to the structure of the state-level allocation key, we add federal state fixed effects to the equation. Furthermore, we have to exclude the Eastern German counties, which joined the Federal Republic only in 1990, from our analysis.

Polish immigration in the 2000s

Migration from Poland to Germany in 2001–2010, the period of our analysis, was subject to different legal limitations. After the fall of the Iron Curtain, migration from Poland stopped (except for the late *Aussiedler (Spätaussiedler)*) due to strict new asylum legislation in Germany but also partly to improved living conditions in the former Soviet Bloc. Before the Eastern enlargement of the European Union in 2004, Poles mainly could migrate temporarily as seasonal workers; other possibilities were very restricted.[6] With Poland's accession to the

Figure 4.2: Immigration from new member states to Germany 1998–2012



Source: Own presentation based on data from the German foreigners registry (German Ausländerzentralregister) provided by the Bundesverwaltungsamt, Köln.

European Union, the freedoms of the single market did not apply entirely and immediately in the case of moving to Germany. Temporary transition rules in force until 2011 can be

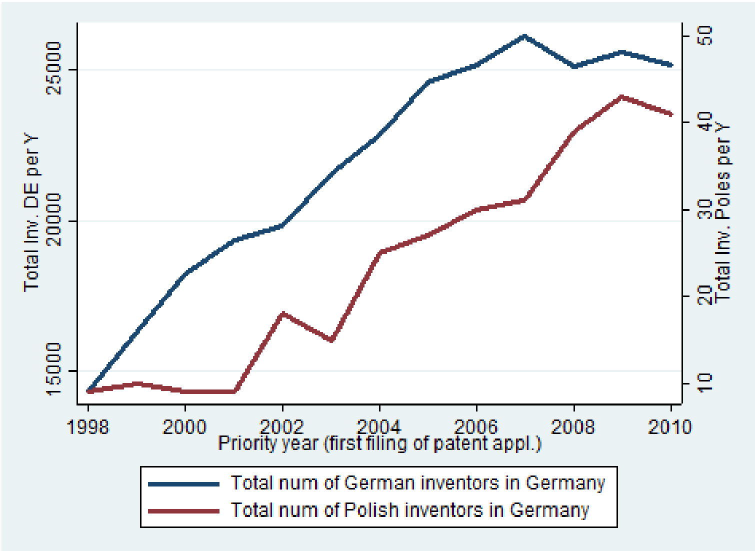
[6]From 2000 to 2004, a German Green card system was in place and facilitated hiring IT experts from countries outside of the European Union for jobs with a salary above 51,000 Euros per year. A total of 17,931 Green cards were granted, but only around 13,000 of them were finally issued. Indians and Eastern Europeans such as experts from the Baltic states, the Czech, and the Slovak Republic were the largest groups benefitting from this system. Poles accounted only for a very small fraction (Bundesamt für Migration und Flüchtlinge, 2006). The European Blue Card was only introduced in 2012 and therefore does not coincide with our period of interest.

summarized as follows: First, Poles willing to take a job in Germany needed a work permit, which was granted upon proof of a concrete job proposal by the employer and after checking whether job-seekers with a prior claim (e.g., EU 15 citizens) were available on the labor market (*Vorrangprüfung*). However, this last regulation did not apply to highly qualified job-seekers. Managers, researchers, and scientific staff could be employed in their domain without requiring a *Vorrangprüfung* (Bundesamt für Migration und Flüchtlinge, 2006). Second, freedom to provide services across borders was restricted in some areas such as construction or cleaning. In other sectors, established entrepreneurs from Poland could offer their services in Germany. Third, freedom to establish a business was unrestricted and so Poles could found firms in Germany right after the accession on May 1, 2004.

According to numbers from the German foreigners registry (see Figure 4.2) around 1.16 million Polish citizens migrated to Germany from 2001 to 2010 and 913,000 of them after the EU enlargement[7]. The increase in immigration after the accession is surprising at first sight because labor market access remained very restricted. The freedom to establish a business, however, was effective immediately and is one important reason for this development. German Mikrozensus data show that the self-employment rate of Polish citizens in Germany increased from around 6 percent before 2004 to more than 20 percent afterward. Dietz (2005) collected data on 11 German regions and reports that, after the enlargement, 3,157 new businesses were founded by Polish nationals, whereas only 275 new businesses were founded previously by nationals of all new member states together. The new entrepreneurs after the enlargement were mostly operating in non-innovative craftsman professions. The accession also made migration to Germany easier for inventors: they were free to travel to Germany and use this geographic proximity to firms and the German innovative industries to find a job. Furthermore, employers no longer had to give priority to German citizens: highly qualified job-seekers from the new member states had the same rights.

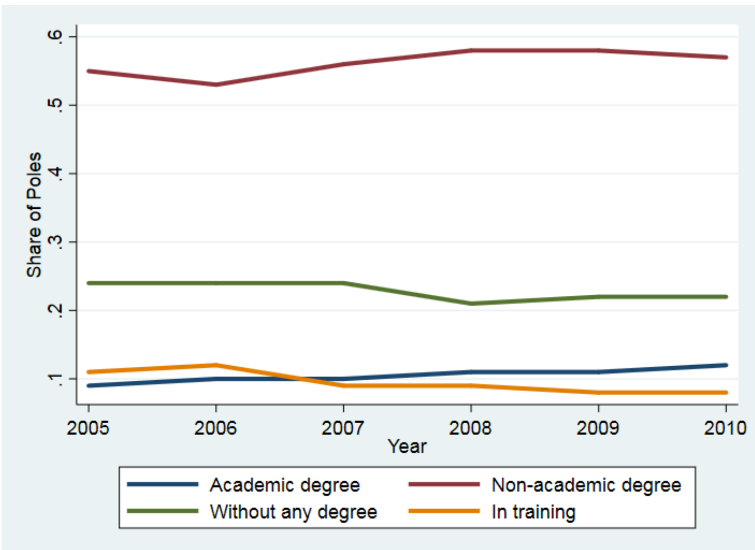
[7]In contrast to the Polish emigration data we use for our instrument, German immigration data also include temporary migration. Seasonal workers immigrating only for some months represent a large share of the 1.16 million.

Figure 4.3: Number of German and Polish inventors in Germany 1998–2010



Source: Our dataset with data provided by REGPAT and WIPO.

Figure 4.4: Education of first-generation Poles in Germany 2005–2010



Source: Own presentation based on data provided by the German Statistical Office in: Ergebnisse des Mikrozensus 2005–2010, Fachserie 1 Reihe 2.2.

In our data as in most official socio-economic statistics, we cannot distinguish Polish residents in Germany according to their time of arrival.[8] Still, the available data allow some insightful conclusions regarding the Polish immigrants arriving in our time period of interest, 2001–2010. In 2010, 419,435 Polish nationals were living in Germany, most of them (96 percent) were born in Poland, and a big share (55 percent) had arrived between 2001 and 2010[9]. The Polish inventors in Germany we measure are likely to belong to this group: The number of Polish inventors in Germany did not increase at the same pace as the number of German inventors before the enlargement (see Figure 4.3). Some of them might already have come as students: In 2001, 7,586 young Poles with Polish schooling were studying at a German university and planning to graduate there[10](Deutscher Akademischer Austauschdienst (DAAD) and Institut für Hochschulforschung (HIS), 2012).

Figure 4.4 plots the qualification levels of first-generation Poles in Germany in 2005 through 2010 (the earliest years the data is available) and show a slight increase in qualification levels: The share of Poles without any degree decreased, whereas the share of academically trained increased. The largest qualification group are those with non-academic degrees, such as technicians or craftsmen. Dustmann et al. (2012) show in a longer time frame that the education level of Polish emigrants, that is, Poles leaving Poland, increased significantly during the first decade of the new millennium: the share of high-skilled emigrants from Poland rose from 13 percent in 1998 to 20 percent in 2007, the share of low-skilled shrank from 12 to 5 percent. Furthermore, compared to the Polish population, emigrants had higher qualification levels. Still, Poles in Germany are overrepresented in the construction sector and underrepresented in manufacturing or in finance (see Figure 4.A.2). It must also be noted that the recognition of foreign degrees is sometimes difficult in Germany and that it is quite likely

[8]An exception, but not directly relevant for our analysis, is a survey by Luthra et al. (2014) on migration motives of recently-arrived Polish immigrants living in one of the following German cities: Berlin, Hamburg, Munich, Cologne in 2010 and 2011. Out of the 1516 respondents, 23 percent came for family reasons (marriage or following a partner that moved), 66 percent came for work, 15 percent for education and 7 percent "just because", i.e., by cultural interest or for self-development (note that multiple reasons for migration could be reported).

[9]Source: Destatis Fachserie 1 Reihe 2, Stand 31.12.2010.

[10]The numbers even increased to 11,588 in 2004 and slightly decreased to 10,289 in 2008.

to find also Poles with a degree working in the construction sector. Overall, we retain from these figures that, in the 2000s, the largest share of Polish immigrants was medium-skilled, whereas high-skilled immigrants represent a small but growing fraction of this group.

4.2.3 Mechanisms of the Impact of Immigrants on Local Innovation

In our causal analysis, we focus on Polish immigrants that came to Germany between 2001 and 2010 and break down their overall effect into two components: In the first estimation, we measure the direct contribution of Polish immigrants to Polish innovativeness in Germany by using the log number of Polish inventors as the dependent variable. We expect a non-negative effect for two reasons. First, immigration to Germany was not restricted to a specific qualification level and it is certain that there were inventors among the new arrivals, which would imply a positive contribution from the immigrants.[11] Second, however, among the Polish inventors we also measure Poles who came to Germany a longer time ago. New arrivals (i.e., within our time window) could have positive or negative spillover effects on these incumbents: they could crowd them out or the two groups could cooperate due to their social or ethnic ties and support and encourage each others' work, as discussed by Lissoni (2018).

In the second estimation, we analyze how Polish immigration impacts the innovativeness of German nationals and whether the immigrants are substitutes or complements. Several potential spillover mechanisms seem feasible. Immigrants of any qualification can contribute to an innovative environment even though they might not be implicated in the innovation process per se. Immigrants with special skills, knowledge, or contacts with new markets can change a firm's strategy or specialization. Influential positions for accomplishing this include management, entrepreneurship, and consulting. Increased or altered research and

[11] Individuals self-select into migration. According to Borjas (1994) the push and pull effects of migration are based on the wage distribution and unemployment rates in the host and the destination country and determine the (skill) composition of immigrants. Luthra et al. (2014) extend this neoclassical focus on labor migration by identifying different Polish emigrant types such as Temporary, Settler, Family, Student or Adventurer. For our setting, the selection mechanism is not crucial, but Section4.2.2 gives some indications on the composition of the Polish immigrants group.

development activities can enhance job creation (Kerr and Lincoln, 2010) and/or patenting. Ozgen et al. (2013) discuss the impact of diversity, finding that an international working environment can boost inventor creativity. Peri and Sparber (2009) find that low-skilled immigration leads native workers to reallocate their task-supply. In our setting, low-skilled immigrants might replace German workers and thus give them the opportunity for promotion to more inventive occupations. Due to a lower reservation wage, low-skilled immigrants can also be employed in the production process thereby increasing production capacities and making it profitable for the firm to advance innovations in the pipeline. In addition to the mechanisms described, high-skilled immigrants who are inventors themselves can help achieve critical mass in a specialized research area and lead to a breakthrough reflected in new patents and patentees (Hunt and Gauthier-Loiselle, 2010). Immigrating inventors can also have a competitive effect on their teammates with German or other citizenship. Competition can drive innovative productivity by challenging incumbents and pushing them to work more or better. Or, competition can lead to a substitution of German inventors and therefore a negative effect on inventor counts of German nationality. Hence, by regressing the number of German inventors on Polish immigration we capture a number of mechanisms and we cannot predict which effect will prevail and which sign the effect might have.

Taken together, if spillovers to incumbents are positive, then we expect a higher point estimate for the total effects on Polish inventors than for the spillover effects on German inventors: the effect on Polish inventors consists of the direct contribution of immigrants and of spillovers to Polish incumbents in Germany, whereas the German effect has only one dimension.

4.3 Data and Descriptive Statistics

We construct our core dataset at the county level (*Kreis*, corresponds to NUTS3) using various data sources: patent data provided by OECD and the World Intellectual Property Organization

(WIPO), migrant statistics by German and Polish Statistical Offices, and employee social security records from the German Institute for Employment Research (IAB). Due to the structure of our instrument we focus data collection entirely on counties in West Germany and thus have 326 observations in our sample.

Table 4.1: Summary statistics of variables

Variable	Obs	Mean	Std. Dev.	Min	Max	P50
Polish inventors	326	.85	2.78	0	36	0
German inventors	326	721.39	1041.12	14	9208	375.5
Non-Polish inventors	326	758.35	1121.47	14	10321	386.5
Polish employees 1989	326	78.48	192.88	10	2753	36
Pole share 1989	326	0.0031	0.0075	0.0004	0.1076	0.0014
Emigration from Poland	1	258368				
Predicted Polish immi (=instr)	326	0.00	12.48	-4.43	173.04	-2.79
ln(Pol inv)	326	.3	.62	0	3.61	0
ln(Ger inv)	326	5.96	1.14	2.71	9.13	5.93
ln(Non-Pol inv)	326	5.99	1.15	2.71	9.24	5.96

Data: Inventor data from REGPAT and WIPO, emigration data from the Polish Statistical Office, distribution of Poles in 1989 from German social security statistics.
Notes: This table reports summary statistics for the inventor and migration variables used in the main estimation.

We obtain inventor records on patent applications via the Patent Cooperation Treaty (PCT) route from OECD's REGPAT database (Maraut et al., 2008). In a first step, they are linked to inventor and nationality records from WIPO's recently published micro dataset on mobile inventors (Miguelez and Fink, 2013), using unique application IDs and inventor names. The latter dataset exploits particular features of the PCT system, specifically that non-US PCT applications needed to list inventors as applicant-inventors if they indicated the United States as a designated state (which was the case for most applications; see Miguelez and Fink, 2013). All applicant-inventors were then required to document their nationalities in the applications. Matched data are then aggregated to counties in West Germany and applications filed in a given year, using REGPAT's regional county codes. The latter code derives from the residence address of the inventor recorded on applications. More precisely, we apply fractional counting when an application involves more than one inventor resident in different counties. Say, for example, when two inventors are assigned to a single application, one from county A and one from B, each county's total number of patent applications increases by only .5. In a last step, we identify the set of unique inventors in a given county and year using parsing and filtering techniques suggested by Raffo and Lhuillery (2009), disambiguating inventor names (as individual inventors can be listed on several patent applications in a given year), and segregate the latter into groups by nationality of unique inventors. We cumulate unique inventor counts as well as Polish emigration and all control variables over our 10-year period (2001–2010). We use the standard approach of taking the log of the number of inventors +1 in order to keep all observations in the sample.

For computation of our instrument, we use the distribution of Polish employees across German counties in 1989, which we take from IAB social security records. Individuals only show up in social security records when they are or have been employed and they are registered with their nationality. For anonymization reasons, numbers below or equal to 15 in a county are not reported; for these 65 counties, we set the number of Polish employees at ten[12]. Note, that we capture only those Poles who did not acquire German citizenship. In our setting, this allows us to distinguish political refugees of the 1980s from the group of *Aussiedler*, because the latter appear as Germans in our social security statistics (Salentin, 2007). We also can essentially exclude that we are measuring economic refugees from Poland. Recall that migrants who were granted asylum, such as political refugees, received a work permit right away, whereas other migrants from Soviet Bloc countries encountered a more difficult situation. As they could not be expelled, at least not until the fall of the Iron Curtain, they were allowed to apply for a work permit after a certain waiting period, which varied across the 1980s and by states (Bundesländer) and ranged from one to two years. However, even after the waiting period, most applicants were not granted a work permit (Meister, 1992). We are therefore confident to measure the intended political refugee group of Poles with social security statistics.

The distribution of Polish employees per county in 1989 is right-skewed with a mean of 78.48 and a median of 36 (see Table 4.1). In total, there were 25,586 Polish employees in West Germany in 1989. According to Table 4.A.1, the number of Polish asylum seekers increased

[12] In a robustness check, we choose a uniform distribution of these numbers and obtain qualitatively and quantitatively very similar results.

significantly in 1988 and their total number from 1980 to 1989 was over 100 thousand. If we apply the 20 percent share of recognized refugees reported by Meister (1992), we find that most of the Poles we capture with the social security statistics must have been recently arrived immigrants.

The information on total emigration from Poland in 2001 to 2010 stems from the Polish Statistical Office and includes only emigrants who leave for at least one year, thus excluding temporary and seasonal emigration. The Polish statistics report 258,368 permanent emigrants during our period of analysis. This corresponds with the German Statistical Office's report of a net immigration of 224,374 Poles. The gross emigration information from Polish statistics and the net immigration number from German statistics are comparable because the German statistics also count immigrants who do not have the intention or possibility of a permanent stay and, therefore, to a large majority, leave the country after a while. The Polish emigration statistics only report longer stays. Therefore, our instrument does not measure short-term immigrants, which are the biggest group of Polish emigrants from Germany. As we standardize the share of Poles in 1989, which acts like a weight in the construction of our instrument, the predicted immigration has a mean of zero.

The statistical offices do not report Polish immigration to Germany at the county level and for our main, reduced-form instrumental variable model, we do not need these actual (endogenous) immigration numbers. For the 2SLS-specification, we compute Polish net migration per county i by taking the yearly difference in the stock of Polish citizens in i, which we then sum up for the 10-year period[13]. There are 21 of our 326 counties that have a negative net migration (*Pol immi*). As our specification is in logarithms, we set these counties' Polish migration to zero. Descriptive statistics of this variable can be found in Table 4.A.3 in the Appendix.

[13] Seasonal workers are generally obliged to register with the municipality authorities but migration researchers and even the German Statistical office agree that the majority of these workers are not found in the official statistics (Dietz, 2005). We therefore measure more permanent migrants. Note, furthermore, that for the federal state of Saarland, the number of foreigners is not reported at the county level. We therefore distribute this state's Polish citizens across the counties based on their total population.

The settlement structure (agglomeration type) fixed effects as well as the time-invariant controls in the specification are added from INKAR database.[14] Descriptive statistics of the two sets of control variables can be found in Table 4.A.2 in the Appendix.

4.4 Immigrants' Contribution to Innovativeness in Germany

4.4.1 Main Results

Table 4.1 shows the reduced-form instrumental variable estimations. Polish immigration to Germany positively and significantly impacts the number of Polish inventors and the number of German inventors. In Columns 1 and 2 we present the results without county-specific controls, but with settlement structure fixed effects. In Columns 3 and 4, controls for the industry structure, the distance to the Polish border and the presence of a university are added. Alternative controls are used in Columns 5 and 6. Over the different specifications, the results are very robust and they only change at the third decimal. We take Columns 5 and 6 as our main results.

In counties with 10 percent more Polish new arrivals compared to other counties, there are 0.28 percent more Polish inventors and 0.32 percent more German inventors. We learn from these results that, first, Polish immigrants patent and/or drive the innovativeness of incumbent Polish citizens. Second, Polish immigrants are complements to, not substitutes for German inventors, as reflected by the positive point estimate in Column 6. Third, the spillover effect on the innovativeness of German citizens is slightly higher than the effect on Polish inventors. This (small) difference suggests that the total innovation effect of immigrants comes more from complementary jobs pushing other workers' innovativeness than from immigrants' direct contribution.

[14] Indikatoren und Karten zur Raum- und Stadtentwicklung. Bundesinstitut für Bau-, Stadt- und Raumforschung (BBSR) im Bundesamt für Bauwesen und Raumordnung (BBR), Bonn 2016.

In absolute terms and at the mean, the direct effect of 0.28 percent corresponds to 1 Polish inventor and the indirect effect of 0.32 percent corresponds to 5 German inventors. As we employ population weights, our estimates are not simply representative of the German counties but of the German population, which means, that small counties contribute less to the estimated effect.

The coefficients on the settlement structure fixed effects are quite sizeable and highly significant for the specification with German inventors. They show that agglomeration characteristics such as population and population density are clearly a relevant factor for the distribution of German inventors across counties whereas the impact is smaller and more diffuse for Polish inventors.

Table 4.1: Main results: Reduced-form IV estimation

	No controls		With controls		Alternative set of controls	
	(1)	(2)	(3)	(4)	(5)	(6)
	ln(Pol inv)	ln(Ger inv)	ln(Pol inv)	ln(Ger inv)	ln(Pol inv)	ln(Ger inv)
ln(Emi) x Poles89	0.0231***	0.0232***	0.0286***	0.0307***	0.0281***	0.0315***
	(0.00269)	(0.00495)	(0.00298)	(0.00302)	(0.00322)	(0.00304)
Agglo: Urbanized	-0.182	0.163	-0.148	0.337***	-0.0542	0.396**
	(0.138)	(0.139)	(0.141)	(0.125)	(0.162)	(0.155)
Agglo: Mostly rural	-0.453***	-0.831***	-0.388***	-0.526***	-0.277	-0.426**
	(0.130)	(0.170)	(0.147)	(0.156)	(0.174)	(0.177)
Agglo: Rural	-0.467***	-1.369***	-0.412***	-1.034***	-0.293	-0.901***
	(0.137)	(0.181)	(0.157)	(0.165)	(0.187)	(0.184)
Constant	-0.240	5.623***	-4.424***	-0.687	-4.324***	0.105
	(0.410)	(0.754)	(1.353)	(1.586)	(1.538)	(1.843)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Pop. weights	Yes	Yes	Yes	Yes	Yes	Yes
N. of counties	326	326	326	326	326	326

Notes: This table reports linear IV estimations in reduced form at the county level. Dependent variables are the number of Polish inventors and the number of German inventors, aggregated across the 2001 to 2010 time period and in logs. The instrument applies the 1989 distribution of Poles across West Germany (normalized) to the emigration from Poland in 2001 to 2010 (in logs). Controls in Columns 3 and 4: Road distance to Polish border crossing, industry quota (share of industry employees), university location (dummy). Controls in Columns 5 and 6: Linear distance to Polish border, share of medium-skilled workers, number of students. All in logs. Fixed effects: federal states, settlement structure. The regressions are weighted by county population. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.2: Context: Comparing our results to Kerr and Lincoln (2010)

Impact of 10% more immigration on	Our analysis	Kerr & Lincoln (2010)	Comparison
Inventors of relevant immigrant group	Poles: 0.28%	Indian: 2.4% Chinese: 2.9%	Direct effects of non-selective vs. selective immigration
Native inventors	0.32%	0.14% insign.	Spillover effects are more pronounced in Germany than in the US

Notes: The results in the column "Our analysis" stem from Table 4.1.

Recall that we apply the methodology from Kerr and Lincoln (2010) to the German case, which is why we can directly compare our results to theirs in Table 4.2. Our coefficients of around 0.03 seem quite small. However, we find a direct effect of about one-tenth of the direct effect for the United States, even though in our analysis we consider all immigrants independent of their skill level, whereas the US effect is based on H1-B immigration only. Remember also that the largest group of first-generation Poles in Germany in the years 2000 is medium- and not high-skilled. In contrast to the US results, we find statistically significant indirect effects from Polish immigrants to German inventors, that is, locals. Our point estimate is twice the size of the US effect, suggesting much stronger spillovers in Germany.

What is the mechanism for spillover effects from new-arrivals to incumbents? New arrivals have a different background with respect to education, experience, market knowledge, and personal networks, all of which can lead to new topics of discussion, give rise to different, innovative ideas, open up new markets, and/or introduce new working processes. Note that we do not count patents but inventors. Thus our effect is not driven by higher productivity of inventors, but by workers joining innovating teams and becoming patentees. Furthermore, we count inventors on patent applications. By considering patent applications instead of patents we avoid taking into account only inventions (and therefore inventors) that are "good" enough to be granted a patent, this way limiting a certain quality bias. Besides, it takes time for a patent to be granted, which, in our 10-year period of analysis, could mean that, by measuring patents, we would not be capture the whole effect.

4.4.2 Assessing Instrument Validity

Our instrument is based on the argumentation that the distribution of our continuous treatment, the Polish political refugees in 1989, is exogenous to today's geographical locations of innovative industries. We discuss this in detail in Section 4.2. Furthermore, the different specifications in Table 4.1 show, that the migration effect is quite robust within the settlement structure groups and that other county characteristics have only a marginal impact. As a further assessment of the instrument's validity, we present a balance table of our covariates conditional on settlement type. To do this, we group the counties in the sample by quintiles of the distribution of Poles in 1989. Then, in six separate regressions, we regress the control variables of both sets on the agglomeration fixed effects and federal state fixed effects. We present the mean predicted residuals of these regressions in differences in a balance table (Table 4.3). The t-tests show that, except for a weak significant difference of the presence of a university in the higher percentiles, the sample is balanced within agglomeration groups. We therefore conclude that the fixed effects for the countys' settlement structure (city, urban, mostly rural, or rural) sufficiently control for structural differences between the counties.

In the 1980s, West Germany also took in refugees from East Germany and their geographic location might be correlated with the location of Polish refugees. We therefore need to make sure that we are not measuring the Eastern Germans' impact on locals' innovativeness, which is likely to be stronger than the impact of Poles. To this end, we conduct a placebo test replacing the distribution of Poles across Germany in 1989 with the distribution of refugees from Eastern Germany in 1961, which we obtain from Burchardi and Hassan (2013). This share covers about 50 percent of the refugees from the East in the period from 1949 to 1961 because Burchardi and Hassan (2013) were only interested in expellees of German ethnicity who had lived in the Eastern territories before the war. This group of people (2.8 million) was first allocated to Eastern Germany after the war and relocated to West Germany until the construction of the Berlin Wall in 1961. We do not expect a significant difference between their distribution across Germany and the distribution of the other 50 percent coming from

Table 4.3: Balance table of covariates

	T-tests Difference bn. quintiles of *Poles1989*			
Covariate	(2) - (1)	(3) - (2)	(4) - (3)	(5) - (4)
Road distance to Poland	0.010	-0.003	-0.014	-0.015
	(0.032)	(0.033)	(0.028)	(0.030)
Industry quota	-0.014	0.039	0.007	-0.041
	(0.061)	(0.053)	(0.060)	(0.065)
University location	0.049	0.073	-0.070	0.159
	(0.077)	(0.085)	(0.088)	(0.076)**
Linear distance to Poland	0.001	0.012	-0.030	-0.009
	(0.032)	(0.031)	(0.027)	(0.030)
Share of medium qualified	0.029	0.041	-0.045	0.009
	(0.052)	(0.044)	(0.041)	(0.038)
Num of students	0.068	0.180	-0.216	0.515
	(0.253)	(0.255)	(0.273)	(0.264)*
Agglo FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	132	132	132	128

Notes: This table reports the differences of mean residuals of covariates conditional on settlement type. It shows that the different quintiles of the distribution of Poles in 1989 across counties are not significantly different from each other once we control for agglomeration types (with the exception of university locations in the higher quintiles). The sample is highly balanced conditional on settlement type. Descriptive statistics for the variables can be found in Table 4.A.2 in the Appendix.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Eastern Germany as both groups immigrated with the same background and the same goals. If we construct our instrument with the distribution of expellees from 1961, we do not find any statistically significant effect on the number of Polish inventors (see Table 4.4, Column 1). This is a strong indication that our chosen distribution using social security statistics is not accidentally measuring refugees from Eastern Germany but is indeed only capturing the intended Polish political refugee group.

Table 4.4: Robustness checks: Placebo test, inventors of other nationalities

	Placebo test	Non-Polish inv	Other nationalities
	(1)	(2)	(3)
	ln(Pol inv)	ln(Non-Pol inv)	ln(Other inv)
ln(Emi) x Expellees67	0.00740		
	(0.00772)		
ln(Emi) x Poles89		0.0356***	0.0505***
		(0.00346)	(0.00505)
Constant	-2.994	-1.192	-12.43***
	(2.323)	(1.881)	(2.359)
State FE	Yes	Yes	Yes
Agglo type FE	Yes	Yes	Yes
Pop. weights	Yes	Yes	Yes
N. of counties	319	326	326

Notes: This table reports reduced-form IV estimations. See notes for Table 4.1 for instrument, controls, fixed effects, and time period. Column 1 shows a Placebo test for German refugees from Eastern Germany. Column 2 gives the effect for all Non-Polish incumbent inventors, that is, inventors of German or other (non-Polish) nationality. Column 3 also excludes Polish inventors, which is a test whether naturalization of Poles in Germany is driving the spillover effects. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Naturalization could be another factor interfering with the causal interpretation of our results. Although it is quite difficult to gain German citizenship, it is still likely that there are some inventors in our sample who did manage to change their nationality during the period of our analysis and would therefore be counted as new German inventors. As a test we therefore estimate the effect of our instrument on the number of (incumbent) inventors of nationalities other than Polish and German. In the absence of naturalizations, we expect this effect to be similar in size to the effect on German inventors because the same mechanisms apply:

Polish immigrants push locals of another nationality then themselves to become patentees. If our test does not yield any significant effect, we can conclude that there are no spillovers from Polish immigrants to non-Polish local inventors and therefore probably also none to German inventors. In this case our baseline spillover effect would be likely to be generated by Poles becoming German citizens. Column 3 of Table 4.4 shows that, compared to our baseline results, we have a slightly higher, but very similar, coefficient. Hence we are confident that a change of nationality is not essentially driving our effect.

4.4.3 Effect Heterogeneity and Alternative Model Specification

The different sets of covariates we use in Table 4.1 are a first test of the robustness of our results and have been discussed above. We also estimate all specifications without the population weights and find no significant changes in the results (see Table 4.5, Columns 1 and 2). This means that our sample does not seem to include some, in relative terms, particularly innovative but weakly populated counties acting as the main contributors to the estimated innovativeness effect of immigrants. Interestingly, the point estimates almost double when we exclude the five biggest cities in Germany, namely, Berlin, Hamburg, Munich, Cologne, and Frankfurt (see Table 4.5, Columns 3 and 4). It could have been expected that the biggest agglomeration (compared to other cities) were allocated many refugees in the 1980s, consequently also received many immigrants in the 2000s, and are, at the same time, particularly innovative. This does not seem to be the case and we conclude that the effects are not driven by the biggest German agglomerations either, but, on the contrary, by smaller counties than these.

As our measure of inventor counts is strongly skewed to the right, OLS regressions might be inappropriate. Count data often follow a Poisson distribution. However, a Poisson distribution requires that mean and variance of the dependent variable are equal, which is not the case either for Polish inventors or for inventors of German or other nationalities. We therefore test for overdispersion with a likelihood-ratio test and conclude that a negative binomial model

Table 4.5: Robustness checks: Population

	No pop. weights		w/o B, HH, MUC, K, FFM	
	(1)	(2)	(3)	(4)
	ln(Pol inv)	ln(Ger inv)	ln(Pol inv)	ln(Ger inv)
ln(Emi) x Poles89	0.0297***	0.0438***	0.0490***	0.0831***
	(0.00356)	(0.00867)	(0.0103)	(0.00701)
Constant	-2.741**	5.076**	-2.984*	8.074***
	(1.090)	(2.249)	(1.592)	(2.003)
State FE	Yes	Yes	Yes	Yes
Agglo type FE	Yes	Yes	Yes	Yes
Pop. weights	No	No	No	Yes
N. of counties	326	326	321	321

Notes: This table reports reduced-form IV estimations. See notes for Table 4.1 for dependent variables, instrument, controls, fixed effects, and time period. The effects in Columns 1 and 2 are not weighted by county population. Columns 3 and 4 exclude the five biggest cities in Germany, namely, Berlin, Hamburg, Munich, Cologne and Frankfurt Main. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

best fits our data. Furthermore, even though our Polish inventor variable includes many zeros, we can reject a zero-inflated regression model. Zero inflation requires that the excess zeros can be modeled independently, for example, in our case, by considering the total absence of inventors or innovative industries in a county. When looking at total patent counts, there does not seem to be such a zero-generating process with respect to industry structure for the number of Polish inventors. We therefore estimate a negative binomial model without zero-inflation. The coefficients we report in Table 4.6 are directly comparable to the former results and we find very similar and significant effects.

Following the example of Hunt and Gauthier-Loiselle (2010), we also run our baseline reduced-form specification with granted patents as the dependent variable. There is evidence in the literature that, in recent years, research teams had a tendency to increase in terms of number of members. Column 2 of Table 4.7 shows the effects on patents, which we can directly relate to the total number of inventors in Column 1. As the estimates are of the same magnitude, we conclude that it does not matter whether we measure inventors or patents: Polish immigrants had a positive effect on total patent production in Germany. We then also compute patents per capita and find an effect that is much smaller than what Hunt and

Table 4.6: Negative binomial regression

	(1) Pol inv	(2) Ger inv
ln(Emi) x Poles89	0.0379***	0.0302***
	(0.00674)	(0.00267)
Constant	-10.31**	-0.0600
	(4.054)	(1.704)
State FE	Yes	Yes
Agglo type FE	Yes	Yes
Population weights	Yes	Yes
N. of counties	326	326

Notes: The table reports a negative binomial estimation. See notes of Table 4.1, Columns 5 and 6 for time period, dependent variables, instrument, controls, and fixed effects. The effects are weighted by county population. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Gauthier-Loiselle (2010) find for the United States. Their main result is that a 1 percentage point higher share of skilled immigrants in the population leads to an increase of 12 to 15 percent in the number of patents per capita. However, our results are not directly comparable. First, Hunt and Gauthier-Loiselle (2010) measure high-skilled migrants. Second, they include immigrants of all nationalities. Third, the mean share of skilled immigrants in their sample is 1.5 percent and a one percentage point increase in the share corresponds to an increase of about 60 percent. Hence, our positive and significant estimate rather reinforces our earlier results.

To estimate the local average treatment effect (LATE), we implement a two-stage least-squares specification. Like Kerr and Lincoln (2010), we do not have information on immigration at the regional level. We therefore compute the differences in the number of Polish inhabitants in each county between two successive years and aggregate these differences to our 10-year period of analysis, thus measuring Polish net migration at the county level, which we use as endogenous variable. Twenty-one out of the 326 West German counties in our sample have negative net migration, which is most likely a result of migration between counties. Internal migration is particularly selective as, once an immigrant gets to know local labor market conditions and opportunities, she might readjust her location choice (if she

Table 4.7: Patents

	(1)	(2)	(3)
	ln(all inv)	ln(Patents)	ln(Patents p.c.)
ln(Emi) x Poles89	0.0321***	0.0308***	0.00456**
	(0.00309)	(0.00310)	(0.00225)
Constant	-0.150	-0.0977	2.556*
	(1.847)	(1.873)	(1.368)
State FE	Yes	Yes	Yes
Agglo type FE	Yes	Yes	Yes
Pop. weights	Yes	Yes	Yes
N. of counties	326	326	326

Notes: This table reports reduced-form IV estimations with alternative dependent variables: Number of total inventors, Number of patents, Patents per capita (per 10,000 inhabitants of the county). All variables are in logs. See notes for Table 4.1, Columns 5 and 6 for instrument, controls, fixed effects and time period. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

has the right to work and to move). For our analysis, we set the counties with negative net migration to 1 in order to be able to take the logs. Columns 1 and 2 of Table 4.8 report the OLS with the endogenous immigration variable. Columns 3 and 4 show the 2SLS estimation where we instrument the immigration measure by our predicted migration. The F-statistic of the first stage amounts to 9.86, which is not particularly high but still very close to the rule-of-thumb limit for weak instruments.

The 2SLS results are clearly higher than the OLS for both dependent variables, possibly due to the fact that OLS estimates an average treatment effect across the whole population while the 2SLS identifies a particular subgroup (local average treatment effect). In our case, the latter effect is associated with the Poles who settled across German counties following existing networks of Polish citizens. The Solidarnosc migrants were rather high-skilled and/or intellectual individuals and, according to our results, they attracted inventors or, at least, innovation-boosting immigrants. In their study on immigrant shares and patents in the United States, Hunt and Gauthier-Loiselle (2010) also find a LATE that is larger than the average treatment effect, and they, too, argue that this effect is due to innovative individuals being particularly affected by historical geographic considerations.

Table 4.8: Two-stage least-squares

	OLS		2SLS	
	(1)	(2)	(3)	(4)
	ln(Pol inv)	ln(Ger inv)	ln(Pol inv)	ln(Ger inv)
ln(Pol immi)	0.127***	0.160***	0.642***	0.720***
	(0.0301)	(0.0505)	(0.175)	(0.211)
Constant	5.593***	10.88***	-4.739	-0.361
	(1.277)	(2.035)	(3.921)	(5.112)
First stage			0.0437***	0.0437***
F			9.866	9.866
State FE	Yes	Yes	Yes	Yes
Agglo type FE	Yes	Yes	Yes	Yes
Pop. weights	Yes	Yes	Yes	Yes
N. of counties	326	326	326	326

Notes: This table reports two-stage least-squares estimations. See notes of Table 4.1, Columns 5 and 6 for dependent variables, instrument, controls, fixed effects, and time period. The instrumented variable "Immigration" at the county level is computed as the difference of Polish citizens of the respective county between two years. Negative figures are set to 1 in order to allow for logs. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.5 Conclusion

Accounting for migrants' potentially endogenous location choices, we discover a positive causal effect of Polish migration on county-level innovativeness in West Germany in the years around the EU enlargement in 2004. Greater innovativeness is largely due to indirect spillover mechanisms: Polish migration helps leverage the innovativeness of native (German) inventors, rather than solely consisting of bringing additional Polish inventors into German counties. Hence, Polish inventors are complements, allowing more non-Polish specialists to become inventors. They do not substitute incumbent inventors.

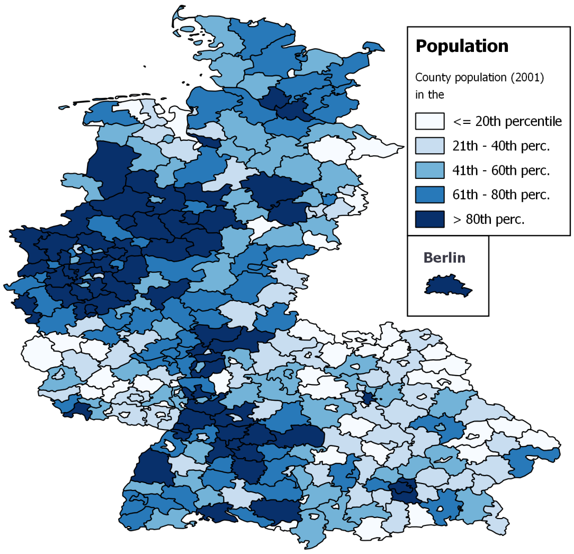
Note that, during the period of our analysis, there had been no skill-selective immigration policy in Germany, which distinguishes the German case from the US-one where H1-B immigrants are chosen because of their skills, special knowledge, and potential. Our analysis underlines that entry of both low- *and* high-skilled migrants can lead to positive contributions in the innovation context. Our example of Polish immigrants' impact on German patenting demonstrates that positive spillovers from migrants to residents do occur. These insights contribute to ongoing public debates over the costs and benefits of migration.

For the spillover effects to unfold, interaction and communication between new arrivals and incumbents is crucial. Poles in Germany are known for their high willingness and capacity to integrate into the society (Loew, 2017), so we can assume a high degree of interaction and communication with their German co-workers. This is not necessarily the case for the Chinese and Indian high-skilled workers in the United States subject of Kerr and Lincoln (2010)'s analysis. This difference in integration motivation might explain the higher spillover effects in the German case of our analysis compared to the results of the U.S. study. It is also intuitive that integration is crucial for immigration to be beneficial for the host country. Interestingly, immigrants' home countries can also experience positive complementarities. Fackler et al. (2016) find positive spillovers from immigrants in Germany coming from new EU member states on patenting activities in their home countries.

However, it must be highlighted that we look at an (Eastern) European immigrant group that is relatively skilled compared to recent refugee groups in Germany. Our results are therefore not necessarily transferable to this latest group of immigrants.

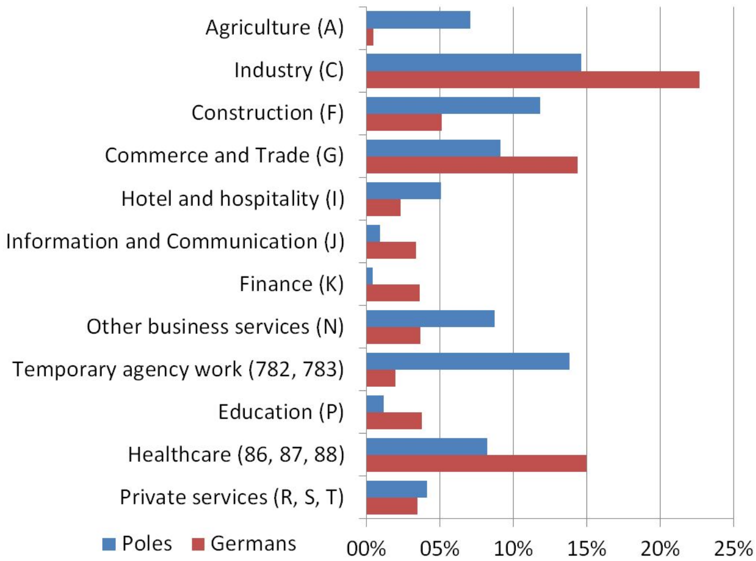
Appendix 4.A Appendix

Figure 4.A.1: Geographic distribution of population in 2001 across Germany in percentiles of counties



Source: Own presentation based on data from Regional Statistics provided by the German Statistical Office.

Figure 4.A.2: Sectors of activity of Polish and German employees in Germany



Source: Own presentation based on data from the Migrationsmonitor Arbeitsmarkt, Beschäftigte nach Staatsangehörigkeiten Stand 30.9.2017, provided by the German Employment Office.
Notes: The blue bars show the number of employees with Polish nationality in the respective sector as a share of the total number of Polish employees in Germany. The red bars show the number of employees with German nationality in the respective sector as a share of the total number of German employees in Germany. The data are from 2017, information for earlier years cannot be accessed.

Table 4.A.1: Asylum seekers in Germany 1980–1990 by country of origin

Country of Nationality	1980	1983	1984	1985	1986	1987	1988	1989	1990
Europe	86,809	6,589	11,553	18,174	25,164	36,629	71,416	73,387	101,631
including:									
Yugoslavia					1,242	4,713	20,812	19,423	22,114
Poland	2,090	1,949	4,240	6672	10,981	15,194	29,023	26,092	9,155
Romania	777	587	644	887	1,512	1,964	2,634	3,121	35,345
Czechoslovakia	2,385	1,400	1,475	1,411	1,394	1,516	1,686	2,388	781
Turkey	57,913	1,548	4,180	7,526	8,683	11,426	14,873	20,020	22,082
Hungary	1,466	587	485	736	1,116	1,585	1,996	1,583	439
Africa	8,339	3,484	5868	8,083	9,486	3,568	6,548	12,479	24,210
Asia	31,996	5,152	16,849	44,296	56,575	15,961	23,006	32,718	60,900

Data: Bundesamt für die Anerkennung ausländischer Flüchtlinge, Zirndorf. Found in: Statistisches Jahrbuch 1991.

Table 4.A.2: Summary statistics controls

Variable	Obs	Mean	Std. Dev.	Min	Max	P50
Road distance to Poland	326	538.94	120.76	102	840	556
Industry quota	326	17.67	8.61	6.4	76	15.95
University location	326	.5	.5	0	1	0
Linear distance to Poland	326	434.49	104.38	77	660	444
Share of medium qualified	326	35.45	11.64	15.2	100.4	32.7
Num of students	326	21	42.05	0	233.94	.99
ln(Road distance to Poland)	326	6.26	.25	4.62	6.73	6.32
ln(Industry quota)	326	2.85	.38	2	4.34	2.83
ln(Linear distance to Poland)	326	6.04	.27	4.34	6.49	6.1
ln(Share of medium qualified)	326	3.52	.29	2.72	4.61	3.49
ln (Num of students)	326	1.53	1.76	0	5.46	.69

Data: Own calculations based on data from INKAR database provided by the Bundesamt für Bauwesen und Raumordnung.
Notes: This table reports summary statistics for the different county-specific control variables added to the baseline specification in Table 4.1 and discussed in Table 4.3.

Table 4.A.3: Panel summary statistics: Immigrants and net migration

Variable	Obs	Mean	Std. Dev.	Min	Max	P50
Polish residents (county-year)	3257	1022.2	2350.74	43	36660	469
Polish net migration (county-year)	3257	35.64	309.53	-12289	3137	18

Data: Own calculations based on data from Regional Statistics provided by the German Statistical Office.
Notes: This table reports summary statistics on immigration variables before aggregation to the 10-year period of analysis (2001–2010). Polish residents are the stock per county and year. Polish net migration are first differences of the stock variable. Aggregated to the 10-year period, it is used in the 2SLS specification.

Bibliography

Abadie, A. (2018). Statistical Non-Significance in Empirical Economics. *NBER Working Paper No. 24403*.

Acemoglu, D., P. Aghion, L. Bursztyn, and D. Hemous (2012). The Environment and Directed Technical Change. *American Economic Review 102*(1), 131–166.

Acemoglu, D., D. Autor, D. Dorn, G. H. Hanson, and B. Price (2014). Return of the Solow Paradox? IT, Productivity, and Employment in US Manufacturing. *American Economic Review: Papers & Proceedings 104*(5), 394–399.

Acemoglu, D., D. Autor, D. Dorn, G. H. Hanson, and B. Price (2016). Import Competition and the Great US Employment Sag of the 2000s. *Journal of Labor Economics 34*(S1), S141–S198.

Acemoglu, D. and P. Restrepo (2017). Robots and Jobs: Evidence from US Labor Markets. *NBER Working Paper No. 23285*.

Aghion, P., A. Dechezlepretre, D. Hemous, R. Martin, and J. van Reenen (2016). Carbon Taxes, Path Dependency, and Directed Technical Change: Evidence from the Auto Industry. *Journal of Political Economy 124*(1), 1—-51.

Aghion, P. and P. Howitt (1992). A Model of Growth Through Creative Destruction. *Econometrica 60*(2), 323—-351.

Akerman, A., I. Gaarder, and M. Mogstad (2015). The Skill Complementarity of Broadband Internet. *Quarterly Journal of Economics 130*(4), 1781–1824.

Aljabre, A. (2012). Cloud Computing for Increased Business Value. *Journal of Business and Social Science 3*(1), 315–345.

Alshamaila, Y., S. Papagiannidis, and F. Li (2013). Cloud Computing Adoption by SMEs in the North East of England: A Multi-Perspective Framework. *Journal of Enterprise Information Management 26*(3), 250–275.

Armbrust, M., A. Fox, R. Griffith, A. D. Joseph, R. H. Katz, A. Konwinski, G. Lee, D. A. Patterson, A. Rabkin, I. Stoica, and M. Zahari (2009). *Above the Clouds: A Berkeley View of Cloud Computing.* Technical Report UCB/EECS-2009-28, University of California at Berkeley.

Arrow, K. J. (1962). The economic implications of learning by doing. *Review of Economic Studies 29*(3), 155—-73.

Atasoy, H. (2013). The Effects of Broadband Internet Expansion on Labor Market Outcomes. *Industrial and Labor Relations Review 66*(2), 315–345.

Autor, D. H., D. Dorn, and G. H. Hanson (2013). The China Syndrom: Local Labor Market Effects of Import Competition in the United States. *American Economic Review 103*(6), 2121–2168.

Autor, D. H., D. Dorn, and G. H. Hanson (2016). The China Shock: Learning from Labor-Market Adjustment to Large Changes in Trade. *Annual Review of Economics 8*, 205–240.

Autor, D. H., F. Levy, and R. J. Murnane (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. *Quarterly Journal of Economics 118*(4), 1279–1333.

Bartel, A., C. Ichniowski, and K. Shaw (2007). How Does Information Technology Affect Productivity? Plant-Level Comparisons of Product Innovation, Process Improvement, and Worker Skills. *Quarterly Journal of Economics 122*(4), 1721–1758.

Bartik, T. J. (1991). *Who Benefits from State and Local Economic Development Policies?* Kalamazoo, MI: W.E. Upjohn Institute for Employment Research.

Bauner, C. and C. L. Crago (2015). Adoption of Residential Solar Power under Uncertainty: Implications for Renewable Energy Incentives. *Energy Policy 86*, 27–35.

Bayrak, E., J. P. Conley, and S. Wilkie (2011). The Economics of Cloud Computing. *The Korean Economic Review 27*(2), 203–230.

Beaudry, P., M. Doms, and E. Lewis (2010). Should the Personal Computer Be Considered a Technological Revolution? Evidence from U.S. Metropolitan Areas. *Journal of Political Economy 118*(5), 988—-1036.

Beise, M. and K. Rennings (2005). Lead markets and regulation: a framework for analyzing the international diffusion of environmental innovations. *Ecological Economics 52*, 5–17.

Benlian, A. and T. Hess (2009). Welche Treiber lassen SaaS auch in Großunternehmen zum Erfolg werden? Eine empirische Analyse des SaaS-Adoption auf Basis der Transaktionskostentheorie. In H. R. Hansen, D. Karagiannis, and H.-G. Fill (Eds.), *Business Services: Konzepte, Technologien, Anwendungen*, pp. 567–576. Vienna: Österreichische Computer Gesellschaft.

Bertschek, I., D. Cerquera, and G. J. Klein (2013). More Bits - more Bucks? Measuring the Impact of Broadband Internet on Firm Performance. *Information Economics and Policy 25*(3), 190–203.

Black, S. E. and L. M. Lynch (2004). What's driving the new economy?: The benefits of workplace innovation. *The Economic Journal 114*(February), F97—-F116.

Bloom, N., M. Draca, and J. van Reenen (2012). Americans Do IT Better: US Multinationals and the Productivity Miracle. *American Economic Review 102*(1), 167–201.

Bloom, N., M. Draca, and J. van Reenen (2016). Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity. *Review of Economic Studies 83*(1), 87–117.

Bloom, N., L. Garicano, R. Sadun, and J. Van Reenen (2014). The Distinct Effects of Information Technology and Communication Technology on Firm Organization. *Management Science 60*(12), 2859–2885.

Borjas, G. J. (1994). The Economics of Immigration. *Journal of Economic Literature XXXII*, 1667–1717.

Bosetti, V., C. Cattaneo, and E. Verdolini (2015). Migration of Skilled Workers and Innovation: A European Perspective. *Journal of International Economics 96*, 311–322.

Braconier, H., G. Nicoletti, and B. Westmore (2014). Policy Challenges for the Next 50 Years. *OECD Economic Policy Paper No. 9*.

Bratti, M. and C. Conti (2018). The Effect of Immigration on Innovation in Italy. *Regional Studies 52*(7), 934–947.

Bräuninger, M., J. Haucap, K. Stepping, and T. Stühmeier (2012). Cloud Computing als Instrument für effiziente IT-Lösungen. *HWWI Policy Paper No. 71*.

Bresnahan, T. F., E. Brynjolfsson, and L. M. Hitt (2002). Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence. *The Quarterly Journal of Economics 17*(1), 339–376.

Bresnahan, T. F. and S. Greenstein (1996). Technical Progress and Co-invention in Computing and in the Use of Computers. *Brookings Papers 1996: Microeconomics*.

Brumec, S. and N. Vrček (2013). Cost effectiveness of commercial computing clouds. *Information Systems 38*(4), 495–508.

Brynjolfsson, E. and L. M. Hitt (1995). Information Technology as as Factor of Production: the Role of Differences between among firms. *Economics of Innovation and New Technology 3*(3), 183–200.

Brynjolfsson, E. and L. M. Hitt (1996). Paradox Lost? Firm level Evidence on the Returns to Information System Spending. *Management Science 42*(4), 541–558.

Brynjolfsson, E. and L. M. Hitt (2003). Computing Productivity: Firm-level Evidence. *The Review of Economics and Statistics 85*(4), 793–808.

Brynjolfsson, E., T. W. Malone, and A. Kambil (1994). Does Information Technology Lead to Smaller Firms? *Management Science 40*(12), 1628–1644.

Brynjolfsson, E., D. Rock, and C. Syverson (2018). Artificial Intelligence and the Modern Productivity Paradox: A Clash of Expectations and Statistics. *NBER Working Paper No. 24001.*

Bundesamt für Migration und Flüchtlinge (2006). *Migrationsbericht 2005.* Berlin.

Burchardi, K. B. and T. A. Hassan (2013). The Economic Impact of Social Ties: Evidence from German Reunification. *Quarterly Journal of Economics 128*(3), 1219–1271.

Cachon, G. P. and M. Fisher (2000). Supply Chain Inventory Management and the Value of Shared Information. *Management Science 46*(8), 1032–1048.

Candel-Haug, K., T. Kretschmer, and T. Strobel (2016). Cloud adaptiveness within industry sectors – Measurement and observations. *Telecommunications Policy 40*(4), 291–306.

Canzian, G., S. Poy, and S. Schüller (2015). Broadband diffusion and Firm Performance in Rural Areas: Quasi-Experimental Evidence. *IZA Discussion Paper No. 9429.*

Carcary, M., E. Doherty, and G. Conway (2013). The Adoption of Cloud Computing by Irish SMEs - an Exploratory Study. *The Electronic Journal Information Systems Evaluation 16*(4), 258–269.

Card, D. (1990). The Impact of the Mariel Boatlift on the Miami Labor Market. *Industrial and Labor Relations Review 43*(2), 245–257.

Card, D. (2001). Immigrant Inflows, Native Outflows, and the Local Labor Market Impacts of Higher Immigration. *Journal of Labor Economics 19*(1), 22–64.

Cardona, M., T. Kretschmer, and T. Strobel (2013). ICT and productivity: conclusions from the empirical literature. *Information Economics and Policy 25*(3), 109–125.

Catalini, C. and C. Tucker (2016). Seeding the S-Curve? The Role of Early Adopters in Diffusion. *NBER Working Paper No. 22596*.

Center for Economics and Business Research (2010). *The economic benefits of cloud computing to business and the wider EMEA economy*. Report for EMC. London.

Colombo, M. G., A. Croce, and L. Grilli (2013). ICT services and small businesses' productivity gains: An analysis of the adoption of broadband Internet technology. *Information Economics and Policy 25*, 171–189.

Costa, P. M., N. Bento, and V. Marques (2017). The Impact of Regulation on a Firm's Incentives to Invest in Emergent Smart Grid Technologies. *The Energy Journal 38*(2), 149–174.

Coyle, D., G. von Graevenitz, S. Bowles, and W. Carlin (2017). *Innovation, Information, and the Networked Economy*. CORE. `http://www.core-econ.org` Last accessed 11 September 2018.

Cusumano, M. (2010). Cloud computing and SaaS as new computing platforms. *Communications of the ACM 53*(4), 27–29.

Czernich, N., O. Falck, T. Kretschmer, and L. Woessmann (2011). Broadband Infrastructure and Economic Growth. *The Economic Journal 121*(552), 505–532.

Damm, A. P. (2009). Ethnic Enclaves and Immigrant Labor Market Outcomes: Quasi–Experimental Evidence. *Journal of Labor Economics 27*(2), 281–314.

Dauth, W., S. Findeisen, and J. Sudekum (2014). The Rise of the East and the Far East: German Labor Markets and Trade Integration. *Journal of the European Economic Association 12*(6), 1643–1675.

De Stefano, T., R. Kneller, and J. Timmis (2014). The (Fuzzy) Digital Divide: The Effect of Broadband Internet Use on UK Firm Performance. *Discussion Paper in Economics No. 14/06, The University of Nottingham.*

Deloitte (2011). The digital workplace: Think, share, do. *White Paper, Deloitte Canada.*

Dery, K., I. M. Sebastian, and N. van der Meulen (2017). The Digital Workplace is Key to Digital Innovation. *MIS Quarterly Executive 16*(2), 135–152.

Deutscher Akademischer Austauschdienst (DAAD) and Institut für Hochschulforschung (HIS) (2012). *Wissenschaft weltoffen 2012.* Bielefeld.

Dietz, B. (2005). Europäische Integration von unten? Mittel- und osteuropäische Migranten in Deutschland und die Rolle transnationaler Netzwerke im EU-Erweiterungsprozess. *Forschungsverbund Ost- und Südosteuropa (forost) Arbeitspapier Nr. 34.*

Draca, M., R. Sadun, and J. V. Reenen (2006). Productivity and ICTs: A Review of the Evidence. *CEP Discussion Paper No. 749.*

Dustmann, C., F. Fabbri, and I. Preston (2005). The Impact of Immigration on the British Labour Market. *The Economic Journal 115*, F324—-F341.

Dustmann, C., T. Frattini, and A. Rosso (2012). The Effect of Emigration from Poland on Polish Wages. *CReAM Discussion Paper 29/12.*

Edin, P.-A., P. Fredriksson, and O. Aslund (2003). Ethnic Enclaves and the Economic Success of Immigrants – Evidence from a Natural Experiment. *Quarterly Journal of Economics 118*(1), 329–357.

ESPAS (2015). *Global Trends to 2030: Can the EU meet the challenges ahead?* European Strategy and Policy Analysis System by the EU institutions.

Etro, F. (2009). The Economic Impact of Cloud Computing on Business Creation, Employment and Output in Europe. *Review of Business and Economics Katholieke Universiteit Leuven 02/2009.*

Etro, F. (2011). The Economics of Cloud Computing. *IUP Journal of Managerial Economics 9*(2), 7–22.

European Commission (2012). *Evaluation of the EU initiative on Stimulation innovation for European enterprises through smart use of ICT.* DG Enterprise and Industry.

Fabling, R. and A. Grimes (2016). Picking up speed: Does ultrafast broadband increase firm productivity? *Motu Working Paper No. 16-22.* Wellington, New Zealand.

Fabritz, N. (2015). Investment in ICT: Determinants and Economic Implications. In H.-W. S. Sinn and C. W. Nam (Eds.), *ifo Beiträge zur Wirtschaftsforschung No. 60.* Munich: ifo Institut.

Fackler, T., Y. Giesing, and N. Laurentsyeva (2016). Knowledge Remittances: Does Emigration Foster Innovation? *Mimeo.*

Falck, O., R. Gold, and S. Heblich (2014). E-lections: Voting Behavior and the Internet. *Journal of the European Economic Association 104*(7), 2238–2265.

Falck, O., J. Haucap, and J. Kühling (2013). *Wachstumsorientierte Telekommunikationspolitik - Handlungsbedarf und -optionen: Studie im Auftrag des Bundesministeriums für Wirtschaft und Technologie.* Baden-Baden: Nomos.

Forman, C., A. Goldfarb, and S. Greenstein (2012). The Internet and Local Wages: A Puzzle. *American Economic Review 102*(1), 556–575.

Forman, C., A. Goldfarb, and S. Greenstein (2016). Invention and Agglomeration in the Bay Area: Not Just ICT. *American Economic Review: Papers and Proceedings 106*(5), 146—-151.

Gaggl, P. and G. Wright (2015). A Short-Run View of What Computers Do: Evidence from a UK Tax Incentive. *American Economic Journal: Applied Economics 9*(3), 262–294.

Galasso, A. and M. Schankerman (2015). Patents and Cumulative Innovation: Causal Evidence from the Courts. *The Quarterly Journal of Economics 130*(1), 317–369.

Galbraith, J. R. (1974). Organization Design: An Information Processing View. *Interfaces 4*(3), 28–36.

Gansky, L. (2010). *The Mesh: Why the Future of Business Is Sharing.* New York: Penguin Group.

Geroski, P. (2000). Models of technology diffusion. *Research Policy 29*(4-5), 603–625.

Gerpott, T. and S. May (2014). Anbietergruppen im Cloud Computing-Markt. *WiSt* (4), 172–178.

Giannakouris, K. and M. Smihily (2014). *Cloud computing – Statistics on the use by enterprises.* Eurostat, European Commission.

Goldsmith-Pinkham, P., I. Sorkin, and H. Swift (2018). Bartik Instruments: What, When, Why, and How. *NBER Working Paper No. 24408*.

Grance, T., J. Hash, S. Peck, J. Smith, and K. Korow-Diks (2002). *Security Guide for Interconnecting Information Technology Systems.* National Institute of Standards and Technology. U.S. Department of Commerce.

Griliches, Z. (1957). Hybrid Corn: An Exploration in the Economics of Technological Change. *Econometrica 25*(4), 501–522.

Grimes, A., C. Ren, and P. Stevens (2012). The Need for Speed: Impacts of Internet Connectivity on Firm Productivity. *Journal of Productivity Analysis 37*, 187–201.

Grossman, R. L. (2009). The Case for Cloud Computing. *IT professional 11*(2), 23–27.

Hall, B. H. and J. Lerner (2010). The Financing of R&D and Innovation. In B. H. Hall and N. Rosenberg (Eds.), *Handbook of the Economics of Innovation*, pp. 609–639. North Holland: Elsevier.

Haller, S. A. and S. Lyons (2015). Broadband Adoption and Firm Productivity: Evidence from Irish Manufacturing Firms. *Telecommunications Policy 39*, 1–13.

Hecker, A. and T. Kretschmer (2010). Outsourcing decisions: the effect of scale economies and market structure. *Strategic Organization 8*(2), 155–175.

Helpman, E. and M. Trajtenberg (1998). A Time to Sow and a Time to Reap: Growth Based on General Purpose Technologies. In E. Helpman (Ed.), *General Purpose Technologies and Economic Growth*, pp. 85–119. Cambridge, MA: The MIT Press.

Henderson, R. and K. B. Clark (1990). Architectural Innovation: The Reconfiguration of Existing Product Technologies and the Failure of Established Firms. *Administrative Science Quarterly 35*(1), 9–30.

Heng, S. and S. Neitzel (2012). *Cloud Computing. Freundliche Aussichten für die Wolke.* Deutsche Bank DB Resarch, E-conomics, Frankfurt am Main.

Hermann, M., T. Pentek, and B. Otto (2015). Design Principles for Industrie 4.0 Scenarios: A Literature Review. *Working Paper No. 01/2015.* TU Dortmund.

Hitt, L. M. (1999). Information Technology and Firm Boundaries: Evidence from Panel Data. *Information Systems Research Vol. 10*(No. 2), 134–149.

Hitt, L. M., D. J. Wu, and X. Zhou (2002). Investment in Enterprise Resource Planning: Business Impact and Productivity Measures. *Journal of Management Information Systems 19*(1), 71–91.

Hoisl, K., D. Harhoff, M. Dorner, T. Hinz, and S. Bender (2016). Social Ties or Patent Quality Signals – Evidence from East German Inventor Migration. *Academy of Management Proceedings 2016/1*(13594).

Hunt, J. and M. Gauthier-Loiselle (2010). How Much Does Immigration Boost Innovation. *American Economic Journal: Macroeconomics 2*(2), 31–56.

IDC (2014). IDC Forecasts Public IT Cloud Services Spending.

Im, K. S., V. Grover, and J. T. Teng (2012). Do Large Firms Become Smaller by Using Information Technology? *Information Systems Research 24*(2), 470–491.

Jaffe, A., M. Trajtenberg, and R. Henderson (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Econometrics 108*, 577–598.

Jahn, V. and M. F. Steinhardt (2016). Innovation and Immigration – Insights from a Placement Policy. *Economics Letters 146*, 116–119.

Janssen, S. and J. Mohrenweiser (2018). The Shelf Life of Incumbent Workers during Accelerating Technological Change: Evidence from a Training Regulation Reform. *IZA Discussion Paper Series No. 11312*.

Jorgenson, D. W. (1966). The embodiment hypothesis. *Journal of Political Economy 74*(1), 1–17.

Jorgenson, D. W. (2001). Information Technology and the U.S. Economy. *American Economic Review 91*(1), 1–32.

Jorgenson, D. W. (2005). Accounting for growth in the information age. In P. Aghion and S. Durlauf (Eds.), *Handbook of Economic Growth*, pp. 743–815. Amsterdam: Elsevier B.V.

Jorgenson, D. W. (2007). Industry origins of the american productivity resurgence. *Economic Systems Research 19*, 229–252.

Jorgenson, D. W. and K. J. S. M. S. Ho (2005). *Productivity – Information technology and the American growth resurgence.* Cambridge, MA: MIT Press.

Kaluza, A. (2002). Zuwanderer aus Polen in Deutschland. *UTOPIE kreativ 141/142*, 699–709.

Kern, T., J. Kreijger, and L. Willcocks (2002). Exploring ASP as sourcing strategy: theoretical perspectives, propositions for practice. *Journal of Strategic Information Systems 11*(2), 153–177.

Kerr, W. R. and W. F. Lincoln (2010). The Supply Side of Innovation: H-1b Visa Reforms and the U.S. Ethnic Invention. *Journal of Labor Economics 28*(3), 473–508.

Klems, M., J. Nimis, and S. Tai (2009). Do Clouds Compute? A Framework for Estimating the Value of Cloud Computing. In C. Weinhardt, S. Luckner, and J. Stößer (Eds.), *Designing E-Business Systems. Markets, Services, and Networks*, pp. 110–123. Berlin: Springer.

KPMG AG (2013). *Cloud-Monitor 2013: Cloud-Computing in Deutschland - Status quo und Perspektiven.* Düsseldorf.

Kretschmer, T. (2004). Upgrading and niche usage of PC operating systems. *International Journal of Industrial Organization 22*(8-9), 1155–1182.

Kretschmer, T., E. J. Miravete, and J. C. Pernías (2012). Competitive Pressure and the Adoption of Complementary Innovations. *American Economic Review 102*(4), 1540–1570.

Kshetri, N. (2013). Privacy and security issues in cloud computing: The role of institutions and institutional evolution. *Telecommunications Policy 37*(4-5), 372–386.

Lam, W. (2013). Cloud Computing: Investment, Competition and Demand Correlation. *Mimeo. IIIrd ICT Conference Munich.*

Leavitt, N. (2009). Is Cloud Computing Really Ready for Prime Time? *Computer 42*(1), 15–20.

Levinsohn, J. and P. Amil (2003). Estimating Production Functions Using Inputs To Control For Unobservables. *70*(2), 317–341.

Lewis, E. (2011). Immigration, Skill Mix, and Capital Skill Complementarity. *Quarterly Journal of Economics 126*, 1029–1069.

Lin, A. and N.-C. Chen (2012). Cloud computing as an innovation: Perception, attitude, and adoption. *International Journal of Information Management 32*, 533–540.

Lissoni, F. (2018). International Migration and Innovation Diffusion: An Eclectic Survey. *Regional Studies 52*(5), 702–714.

Lodovici, M. S. and M. Patrizio (2013). *How can Regional and Cohesion Policies Tackle Demographic Challenges?* European Union, Directorate-General for Internal Policies.

Loebbecke, C., B. Thomas, and T. Ullrich (2012). Assessing Cloud Readiness at Continental AG. *MIS Quarterly Executive 11*(11-23).

Loew, P. O. (2017). Unsichtbar? Polinnen und Polen in Deutschland — die zweitgrößte Zuwanderergruppe. Bundeszentrale für Politische Bildung. `http://www.bpb.de/gesellschaft/migration/kurzdossiers/256398/polnische-diaspora` Last accessed 13 June 2018.

Luthra, R., L. Platt, and J. Salamonska (2014). Migrant Diversity, Migration Motivations and Early Integration: The Case of Poles in Germany, the Netherlands, London and Dublin. *LEQS Paper No. 74*.

Mack, E. A. and S. J. Rey (2014). An econometric approach for evaluation the linkages between broadband and knowsledge intensive firms. *Telecommunications Policy 38*(1), 105–118.

Mahr, F. and T. Kretschmer (2010). Complementarities between IT and Organizational Structure: The Role of Corporate Exploration and Exploitation. *Münchener Wirtschaftswissenschaftliche Beiträge (BWL) 2010–3*.

Maraut, S., D. Helene, C. Webb, V. Spiezia, and D. Guellec (2008). The OECD REGPAT Database: A Presentation. *STI Working Paper 2/2008*.

Marston, S., Z. Li, S. Bandyopadhyay, J. Zhang, and A. Ghalsasi (2011). Cloud computing – The business perspective. *Decision Support Systems 51*, 176–189.

McAfee, A. and E. Brynjolfsson (2008). Investing in the IT That Makes a Competitives Difference. *Harvard Business Review July-August 2008*.

Meister, H.-P. (1992). Polen in der Bundesrepublik Deutschland. In *Ethnische Minderheiten in Deutschland - Arbeitsmigranten, Asylbewerber, Ausländer, Flüchtlinge, regionale und religiöse Minderheiten, Vertriebene, Zwangsarbeiter*, Berliner Institut für Vergleichende Sozialforschung. Berlin: Edition Parabolis.

Mell, P. and T. Grance (2011). *The NIST Definition of Cloud Computing*. Recommendations of the National Institute of Standards and Technology, U.S. Department of Commerce, Gaithersburg and MD.

Miguelez, E. and C. Fink (2013). Measuring the International Mobility of Inventors: A New Dataset. *WIPO Economic Research Working Paper No. 8*.

Moser, P. and A. Voena (2012). Compulsory Licensing: Evidence from the Trading with the Enemy Act. *American Economic Review 102*(1), 396–427.

Moser, P., A. Voena, and F. Waldinger (2014). German Jewish Émigrés and US Invention. *American Economic Review 104*(10), 3222–3255.

Musolesi, A. and J.-P. Huiban (2010). Innovation and productivity in knowledge intensive business services. *Journal of Productivity Analysis 34*(1), 63–81.

National Institute of Standards and Technology (2013). *NIST Cloud Computing Standards Roadmap*. Special Publication 500-291 V2.

Nguyen, T. H. (2009). Information technology adoption in SMEs: an integrated framework. *International Journal of Entrepreneurial Behaviour & Research 15*(2), 162–186.

Nordhaus, W. D. (2007). A Review of the Stern Review on the Economict of Climate Change. *Journal of Economic Literature XLV*, 686–702.

OECD (2009). *Guide to Measuring the Information Society*. `http://www.oecd.org/science/sci-tech/43281062.pdf` Last accessed 27 January 2014.

Ozgen, C., P. Nijkamp, and J. Poot (2013). The Impact of Cultural Diversity on Firm Innovation: Evidence from Dutch Micro-Data. *IZA Journal of Migration 18*(2).

Pallis, G. (2010). Cloud Computing: The New Frontier of Internet Computing. *IEEE Internet Computing 14*(5).

Peri, G., K. Shih, and C. Sparber (2015). STEM workers, visas and productivity in US cities. *Journal of Labor Economics 33*(S1), S225–S255.

Peri, G. and C. Sparber (2009). Task Specialization, Immigration, and Wages. *American Economic Journal: Applied Economics 1*(3), 135—-169.

Porter, M. E. (1985). *Competitive advantage: Creating and sustaining superior performance*. New York: Simon and Schuster.

Prajogo, D. and J. Olhager (2012). Supply chain integration and performance: The effects of long-term relationships, information technology and sharing, and logistics integration. *International Journal of Production Economics 135*(1), 514–522.

Prasad, A., P. Green, and J. Heales (2014). On cloud computing service considerations for the small and medium enterprises. *Americas Conference on Information Systems, Association of Information Systems.*

Raffo, J. and S. Lhuillery (2009). How to Play the “Names Game": Patent Retrieval Comparing Different Heuristics. *Research Policy 38*, 1617—-1627.

Riordan, M. H. and O. E. Williamson (1985). Asset specificity and economic organization. *International Journal of Industrial Organization 3*(4), 365–378.

Rogers, E. M. (1962). *Diffusion of innovations.* New York: Free Press of Glencoe.

Romer, P. M. (1986). Increasing Returns and Long-Run Growth. *Journal of Polical Economy 94*(5), 1002–37.

Salentin, K. (2007). Die Aussiedler-Stichprobenziehung. *Gesis: Methods – Data – Analyses 1*(1), 25–44.

Schubert, P. and F. Adisa (2011). Cloud Computing for Standard ERP Systems: Reference Framework and Research Agenda. *Arbeitsberichte aus dem Fachbereich Information. Universität Koblenz-Landau 16/2011.*

Schumpeter, J. (1942). *Capitalism, Socialism and Democracy.* New York City, US: Harper & Brothers.

SearchCloudComputing (2013). Cloud computing experts forecast the market climate in 2014. `http://searchcloudcomputing.techtarget.com/feature/Cloud-computing-experts-forecast-the-market-climate-in-2014` Last accessed 24 July 2017.

Shy, O. (1996). Technology revolutions in the presence of network externalities. *International Journal of Industrial Organization 14*(6), 785–800.

Solow, R. (1957). Technical change and the aggregate production function. *Review of Economics and Statistics 39*(3), 312—-320.

Staehr, L. (2010). Understanding the role of managerial agency in achieving business benefits from ERP systems. *Information Systems Journal 20*(3), 213–238.

Stern, N. (2007). *The Economics of Climate Change: The Stern Review.* Cambridge and New York: Cambridge University Press.

Stieninger, M. and D. Nedbal (2014). Diffusion and Acceptance of Cloud Computing in SMEs: Towards a Valence Model of Relevant Factors. *47th Hawaii International Conference on System Science.*

Stiroh, K. (2002). Information Technology and the US Productivity Revival: What Do The Industry Data Say? *American Economic Review 92*(5), 1559–76.

Suciu, G., S. Halunga, A. Apostu, A. Vulpe, and G. Todoran (2013). Cloud Computing as Evolution of Distributed Computing - A Case Study for SlapOS Distributed Cloud Computing Platform. *Informatica Economica 17*(4), 109–122.

Sultan, N. (2011). Reaching for the cloud: How SMEs can manage. *International Journal of Information Management 31*, 272–278.

Tambe, P. and L. M. Hitt (2012). Now IT's Personal: Offshoring and the Shifting Skill Composition of the U.S. Information Technology Workforce. *Management Science 58*(4), 678–695.

TechTaget Glossary (2011). Dropbox. `http://searchconsumerization.techtarget.com/definition/Dropbox`. Last accessed 20 March 2015.

Telekom AG (2010). *Life 2 - Vernetztes Arbeiten in Wirtschaft und Gesellschaft.* LIFE-Studien der Telekom AG, Bonn.

Tornatzky, L. G. and M. Fleischer (1990). *The process of technology innovation.* Lexington, MA: Lexington Books.

Trigueros-Preciado, S., D. Pérez-González, and P. Solana-González (2013). Cloud computing in industrial SMEs: identification of the barriers to its adoption and effects of its application. *Electronic Markets 23*(2), 105–114.

van Ark, B., M. O'Mahony, and M. P. Timmer (2008). The Productivity Gap between Europe and the United States: Trends and Causes. *Journal of Economic Perspectives 22*(1), 25—-44.

Van Beveren, I. (2012). Total factor productivity estimation: A practical review. *Journal of Economic Surveys 26*(1), 98–128.

Varian, H. R. (2010). Computer Mediated Transactions. *American Economic Review 100*(2), 1–10.

Williams, H. and B. Sampat (2018). How Do Patents Affect Follow-On Innovation? Evidence from the Human Genome. *NBER Working Paper No. 21666*.

Yang, S. and E. Brynjolfsson (2001). The Productivity Gap between Europe and Unites States: Trends and Causes. *Center for eBusiness at MIT, Paper No. 136*. Cambridge, MA.

Yoo, C. S. (2011). Cloud Computing: Architectural and Policy Implications. *Review of Industrial Organization* (38), 405–421.