CESifo WORKING PAPERS

9944
2022

September 2022

Let's Switch to the Cloud: Cloud Adoption and Its Effect on IT Investment and Productivity

Tomaso Duso, Alexander Schiersch

CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editor: Clemens Fuest
https://www.cesifo.org/en/wp
An electronic version of the paper may be downloaded
· from the SSRN website: www.SSRN.com
· from the RePEc website: www.RePEc.org
· from the CESifo website: https://www.cesifo.org/en/wp

CESifo *Working Paper No. 9944*

Let's Switch to the Cloud: Cloud Adoption and Its Effect on IT Investment and Productivity

Abstract

The advent of cloud computing promises to improve the way firms utilize IT solutions. Firms are expected to replace large and inflexible fixed-cost investments in IT with more targeted variable spending in cloud solutions. In addition, cloud usage is expected to increase the productivity of firms, as it allows them to quickly customize the IT they require to their specific needs. We assess these assertions using data on a representative sample of firms provided by the German statistical offices for the years 2014 and 2016, which allows to observe who are the cloud users. Our analysis explicitly accounts for the self-selection into cloud adoption within an endogenous treatment regression framework. Broadband availability at the municipality level is used as an exogenous shifter for cloud usage. We show that, while cloud adoption does not impact IT investment in any sectors, it does significantly improve labor productivity for firms in manufacturing and in information and communication services.

JEL-Codes: D240, D250, L600, L800, O140, O330.

Keywords: cloud computing, investment, productivity, IT, substitution, firm performance.

Tomaso Duso
German Institute for Economic Research
(DIW Berlin)
Mohrenstr. 58
Germany – 10117 Berlin
tduso@diw.de

Alexander Schiersch
German Institute for Economic Research
(DIW Berlin)
Mohrenstr. 58
Germany – 10117 Berlin
aschiersch@diw.de

September 8, 2022
The authors gratefully acknowledge funding provided by the German Federal Ministry for Economic Affairs and Climate Action as part of the project "Development and Measurement of the Digitalisation of the Economy in Germany." Special thanks goes to the staff of the RDC of the Berlin-Brandenburg Statistics Office for their help and continuous support.

1 Introduction

Investments in information technologies (IT)[1] can lead to more employment and innovation, higher productivity, and, thus, to higher economic growth (Inklaar et al., 2007; Bartel et al., 2007; Biagi, 2013; Cardona et al., 2013; Brynjolfsson and McAfee, 2014; Bertschek et al., 2015).

However, to take full advantage of IT, traditionally firms needed to make upfront investments, sometimes substantial. Such investments are generally easier to fund for larger firms than for smaller ones. Moreover, due to the scalability of IT, larger firms are also more likely to reap the full benefits of IT investments. This has changed fundamentally with the advent of cloud computing.

Cloud solutions function as a 'pay as you go' service, where firms pay for the IT capacities and the IT solutions they actually use. This enables firms to quickly up- and downscale the required IT resources. This is also referred to as 'scale without mass' (De Stefano et al., 2020; Brynjolfsson et al., 2008). In this context, Bloom and Pierri (2018) even argues that cloud computing has 'democratized' computing, as now any company can use (almost) any IT solution it needs, to any extent, and at any time without making (large) upfront investments. The elimination of the need to make IT investments is considered as one of the important consequences and a major benefit of cloud computing, especially for smaller firms (OECD, 2014; Jin and McElheran, 2019; Gal et al., 2019; De Stefano et al., 2020; Bloom and Pierri, 2018). Empirical evidence for this assertion, however, remains scarce. Thus, the first objective of this paper is to provide novel empirical evidence to support the hypothesis that firms which use the cloud invest significantly less in IT than firms that do not use cloud solutions.

In addition to saving on IT investments, it is also argued that firms using cloud solutions perform better for a multitude of reasons. For instance, cloud services allow firms to experiment and to learn about their optimal IT solution without prohibitively high costs, as in the past (Jin and McElheran, 2019). Another reason is technological change. Whereas in the past, firms always had to weigh whether the IT solutions already in place were still sufficient or whether new investments would once again be necessary, today they can access cutting edge IT solutions quickly and often more cost-effectively (Benlian and Hess, 2011; OECD, 2014).

Another advantage arises from the scalability of IT solutions and the resulting economies of scale that cloud providers have compared to individual, especially smaller, firms. To a certain extent, they pass on these economies of scale to their customers, who benefit from them in this way (Benlian and Hess, 2011; Jin and McElheran, 2019). We contribute to the ongoing discussion on the benefits of cloud computing by analyzing whether its use leads to higher productivity in firms. This is the second contribution of our paper.

We base our empirical analysis on the Jorgensonian model of firm behavior (Jorgenson, 1967). We assume that firms optimally choose their investments in tangible capital as well as IT capital to maximize their discounted profits given their production function. In turn, these investments

[1]We use information technologies (IT) information and communication technologies (ICT) synonymously throughout the paper.

determine firms' capital stocks, which affects their labor productivity. Following the existing literature, we then model that the use of cloud computing might be an important shifter of IT investment decisions and, thus, of firms' productivity.

When empirically assessing these linkages, however, one needs to account for the fact that the adoption of cloud solutions itself is not a random event but rather an active decision by the firm. Thus, our empirical strategy explicitly models the self-selection of firms into cloud adoption through a selection model of endogenous treatment (see Clougherty et al., 2016, for a discussion of the appropriate methodological approach). We use the availability of high-speed broadband in the municipality in which the focal firm operates as an instrument for cloud adoption. Indeed, high speed broadband is a necessary condition for the usage of cloud solutions and, therefore, it should be correlated with the adoption decision. Yet, the deployment of broadband networks should be uncorrelated with the firm-specific investment decisions.

To take this model to the data, we put together a rich firm-level database. The main component of our data are three databases provided by the German statistical offices on a wide range of firm characteristics, including value added, employees, costs, investments in tangible assets, investments in IT, and cloud adoption. This data covers the 2013 to 2016 period. We supplement this data with additional sources. Most importantly, we use granular data on broadband availability at the municipality level from the Federal Government's Broadband Atlas of the German Federal Ministry of Transport and Digital Infrastructure. The data at hand contains information on broadband availability at 16 Mbp/s transmission speed by municipality and year.

There are three main findings in our analysis. First, we show that the likelihood to adopt cloud solutions is higher for larger firms and firms that are more open to digital solutions. Moreover, the quality of the broadband infrastructure, as measured by broadband availability, is also an important driver of the choice to use the cloud, but only in manufacturing. Second, the use of the cloud does not affect firms' investment in IT. This is true for all sectors and also accounts for the endogenous selection into cloud adoption. Therefore, we provide new evidence showing that the substitutability between cloud services and IT investments supposed in the literature is not observed in a representative sample of German firms. Third, we show that using the cloud helps firms to improve their labor productivity both in manufacturing and in information and communications services. Thus, we add new evidence on the ability of cloud solutions to improve the efficiency of the adopting firms.

The reminder of this paper is organized as follows: section 2 presents a definition of cloud computing, discusses some stylized facts, and describes the main advantages that are attributed to the use of cloud computing. The following section discusses the literature and presents our derived research questions. Section 4 introduces the data and Section 5 describes the model and the empirical approach. The results are presented in section 6. The last section concludes.

2 Cloud computing: Definition and stylized facts

The two most recognized definitions of cloud computing come from the U.S. National Institute of Standards and Technology (NIST) (Armbrust et al., 2009) and the Berkeley RAD lab (Mell and Grance, 2011). Summarizing these sources, cloud computing is "a service model for computing services based on a set of computer resources that can be accessed in a flexible, elastic, on-demand way with low management effort" (OECD, 2014, p.4).

There are essentially three types of cloud services: First, Software as a Service (SaaS), where customers use software solutions that are made available by the provider (both own and foreign). The client only has access to the software but does not "manage or control the underlying cloud infrastructure... or even the individual application capabilities" (Mell and Grance, 2011, p.2). The second is Platform as a Service (PaaS). Here, the client uses the available infrastructure for self-created or bought software solutions. Again, the client has no control over the underlying infrastructure, but does have control over the software and must ensure that it works as desired. Finally, there is Infrastructure as a Service (IaaS). Here the cloud firm provides the main "computing resources such as processing, storage and networks" (OECD, 2014, p.10). Although the core of the underlying infrastructure is still not controlled by the clients, they control virtually all other aspects of the raw computing resources, which they can use as they see fit. In practice, of course, each of these services is available in different configurations and there is overlap between them.[2]

Cloud computing as a service really took off with the launch of Amazon Web Service (AWS) in 2006. Even at that early point in time, the price for an "instance," which is the price per hour for renting a virtual machine (EC2) in the cloud nomenclature, was at $0.10 (Jin and McElheran, 2019; Byrne et al., 2020). In the years that followed, the number of available IT solutions and their technical capabilities improved rapidly. At the same time, prices fell sharply, especially after 2009 and after 2014. A key driver of this development was the intensified competition in the cloud services market. Between 2009 and 2012, Microsoft, IBM, and Oracle deployed their cloud services. It was not only market entry that put pressure on the prices. Microsoft and Google also started to challenge the market leader (Amazon) by publishing their own prices online starting in 2014, which led to a drastic drop of prices in the subsequent years. By the end of 2016, the average prices for an instance of Amazon?s EC2 products was about 50% below the prices of 2009 and that of Amazons ADR products (database products) even 60% below the prices of 2010 (Byrne et al., 2020). Hence, by 2014 at the latest, firms therefore had access to a wide range of sophisticated IT solutions at low prices.

The use of the cloud has grown rapidly since its introduction as a commercial service. According to Bloom and Pierri (2018), the share of firms in the USA that make use of cloud solutions increased from 0.3% in 2010 to about 7% in 2016, which is equivalent to an annual growth rate of 50%. In the

[2] An example of an overlap or new layers is Function as a Service (FaaS), which is more than SaaS but less than PaaS. See Byrne et al. (2020) for more.

European Union (EU27), the number of firms in the business economy[3] using cloud solutions is also growing fast. By 2014, the first year comparable data was gathered, 18% of all firms in the EU27 business economy used a cloud service (Eurostat, 2021). This share increased to 24% by 2018. The corona pandemic worked as a booster for further diffusion, such that the share of users in the EU27 increased to 41% by 2021.

There is a large heterogeneity in cloud usage across countries, industries, and size classes. For instance, only 13% of firms in the Bulgarian business economy made use of the cloud by 2021, while this share was at 75% in Finland. In larger European economies, like Italy, Germany, Spain, and France, the shares in 2021 were 60%, 42%, 31%, and 29%, respectively. Considering the average at the EU27 level, the share of using firms in 2021 is lowest in construction (ISIC Rev.4 Code F) at 30%, while the highest share of 80% is found in information and ommunication services (ISIC Rev.4 Code J) (Eurostat, 2021).

The distribution across size classes is also important. As discussed above, several benefits associated with cloud use seem particularly attractive for smaller firms. This is partly confirmed by Bloom and Pierri (2018). They show that micro firms, i.e., firms with fewer than 9 employees, are among the most frequent users of cloud solutions. A higher proportion of cloud users is only found among large firms, i.e., those with more than 1,000 employees.However, if micro firms are ignored, a pretty clear pattern emerges: the share of firms using it increases across size classes. This is also what one finds in Europe. In 2021, the share of cloud users was 32% in firms with 10 to 49 employees, 53% in firms with 50-249 employees, and 72% in firms with 250 or more employees (Eurostat, 2021). Unfortunately, there is no data at the EU27 level on the share of using firms in companies with less than 9 employees. Apart from this shortcoming, these numbers confirm the pattern that is also found in the USA for companies with more than 9 employees: the proportion of users increases with the size of the firm.

3 Literature and research questions

3.1 Cloud adoption

A growing literature addresses the determinants of cloud adoption. The respective studies show that cloud computing adoption is positively related to firm size (Oliveira et al., 2014; Ohnemus and Niebel, 2016; Andres et al., 2020; De Stefano et al., 2020). In other words, the larger a firm is, the more likely it is to use the cloud. This is in line with the more general finding that the use of digital technologies, *per se*, increases with company size (see e.g. DeStefano et al., 2017; OECD, 2017; Zolas et al., 2021). It is also consistent with the data on cloud usage by size class reported in the previous section. However, this contradicts the presumption that small firms are more inclined to use the cloud

[3]The business economy entails all sectors from Mining (ISIC Rev.4 Code B) to Administrative Services (ISIC Rev.4 Code M) plus the 2-digit sector (ISIC Rev.4 Code S95). However, the actual ICT survey that contains the relevant questions regarding cloud computing does not cover the sectors of Financial Services (ISIC Rev.4 Code K) and Mining (ISIC Rev.4 Code B).

because, as described above, they should particularly benefit from its advantages.

In terms of firm capabilities, advanced management practices, top management support, the availability of sufficiently qualified staff, and the available IT-related capabilities in general increase the adoption rate (Benlian and Hess, 2011; Low et al., 2011; Yang and Tate, 2012; Garrison et al., 2014; Oliveira et al., 2014; Andres et al., 2020; Nicoletti et al., 2020). Importantly, Nicoletti et al. (2020) and De Stefano et al. (2020) also show that broadband availability is a necessary prerequisite and a strong predictor for adoption, which makes it a potentially good instrument in an instrumental variables (IV) estimation approach.

The literature is less unanimous regarding potential barriers or incentives that hamper or foster the take-up of cloud computing. Nicoletti et al. (2020) find administrative burdens and barriers to market entry in services hamper the adoption of cloud computing. They conclude that higher competitive pressure and less regulation increases adoption rates. In contrast, Oliveira et al. (2014) show that competitive pressure and regulatory support do not have a statistically significant effect on cloud computing adoption. This is partly in line with Garrison et al. (2014), who sees only short-term benefits but no lasting competitive advantages from cloud adoption and, thus, no effect from more competition on take-up rates. Finally, security concerns and complexity exert a negative impact on cloud adoption (Oliveira et al., 2014), a result in line with the general perception (OECD, 2014).

From this discussion, we expect the likelihood to adopt cloud computing solutions to be positively related to firm's size and technological capabilities as well as to the existence of a reliable broadband network.

3.2 The effects of cloud adoption

While there is already some evidence on the determinants of cloud computing adoption, very few studies address the two main issues of this paper, namely whether cloud computing leads to higher productivity and lower IT investments, even though the latter is continuously emphasized as one of the main benefits of cloud computing (e.g. OECD, 2014; van Ark, 2016; Bloom and Pierri, 2018; Gal et al., 2019; Jin and McElheran, 2019; Byrne et al., 2020; De Stefano et al., 2020).

Using a multi-sector growth model, Byrne and Corrado (2017) analyzes the contribution of ICT – in particular that of cloud computing – to labor productivity growth in the U.S. at the macro level. They conclude that the total contribution of IT is around 1.4 percent a year. However, they also find that any productivity-enhancing effect of cloud computing is hardly visible.

Gal et al. (2019) analyze how several digital technologies affect productivity growth at firm level, including the impact of cloud computing.[4] The authors find only a modest effect for cloud computing

[4]Estimates are obtained by OLS using combined firm- and industry-level data covering multiple countries and using an error correction model along the lines of Griffith et al. (2016) and others. Given the data constraints, adoption is measured as the average share of firms within a country and a two-digit industry that have reported the use of a specific digital technology across the entire 2010 to 2015 period. Hence, the variable of interest has no variation across time or firms. The main specification does not control for differences between firms in terms of the tangible capital stock or the software stock.

and no statistically significant effect for complex cloud computing in their main specification. A large number of robustness checks confirm this finding, namely that cloud computing has a comparatively low elasticity, it is often only weakly significant or not significant at all, and that complex cloud computing has no significant effect whatsoever. Two of these robustness checks are important for our analysis. In these, investments in tangible and intangible capital, which mainly include software investments, are included as additional control variables. In both specifications, when controlling for those factors, there is no statistically significant effect for cloud computing or complex cloud computing. Therefore, these must be included in any analysis on the impact of cloud usage, as they capture the productivity-enhancing effects of both types of capital that are otherwise attributed to cloud computing.

As part of a survey on cloud adoption decisions by UK firms to analyze lock-in effects, Opara-Martins et al. (2016) also asks about the reasons for cloud adoption. Of the 114 firms that completed the survey, about 40% cited potential cost savings as a reason for opting for cloud computing.[5] If asked for the actual benefits of cloud computing, the "majority of the respondents identified capacity and scalability (70.3%), increased collaboration, availability, geography and mobility as benefits for migration" (Opara-Martins et al., 2016, p.5). Cost savings as an actual benefit of cloud computing is mentioned less frequently and, if so, only by larger firms. Moreover, the specific question only refers to the costs for maintaining the IT infrastructure, which may include energy costs.[6] Whether the firms also save on investments in IT remains unclear.

The studies that are closest to our analysis are Jin and McElheran (2019) and De Stefano et al. (2020). Jin and McElheran (2019) analyze how cloud computing, which they approximate using purchased IT services, affects the survival and productivity of U.S. manufacturing firms, particularly young firms.[7] They find that cloud computing significantly increases the probability of survival. The results for IT services with regard to productivity are mixed. While there is no statistically significant effect when looking at all firms and applying OLS, IT services have a significant effect on output in the sub-sample of firms that are not older than 5 years. This result is confirmed by additional estimates that account for the endogeneity due to the simultaneity and selection issue inherent in all production function estimations. With regard to IT investments, two observations can be made. First, the elasticity of the IT capital stocks with respect to IT investments are significant across the board. This means that IT capital must be considered as a separate input in the estimation. Second, Jin and McElheran (2019) does not specifically analyze whether IT investments decline as a result of the use of IT services - their measure of cloud computing. However, they show that per capita investment in

[5] The other key reasons are: increased flexibility (37%), increased collaboration (41%), and the better scalability of IT resources (46%).

[6] Masanet et al. (2013) find that firms have significant potential for energy savings by shifting to cloud solutions.

[7] They use establishment-level data from the U.S. Census Bureau from 2006 to 2014. Estimations are performed for multiple subsamples, but always pooled across all industries. The underlying model is that of sales production function with the capital stock split into non-IT capital and IT capital. This standard production function is augmented with IT investments, IT services, a dummy for young firms, and interaction terms between these variables. Further controls are industry dummies as well as interaction terms between year and industries.

IT declines after 2008 in young and old firms, while spending on IT services increases. This could be interpreted as meaning that IT investments are decreasing as a result of more IT services.

De Stefano et al. (2020) analyze the impact of cloud computing on firm growth, as measured by employment and sales, on labor productivity, and on geographic dispersion in the United Kingdom. The analysis uses an instrumental variable approach that utilizes broadband availability to account for the endogenous nature of cloud's adoption.[8] The authors find that cloud computing stimulates firm growth for both young and established firms. However, no statistically significant effect is found for either group in terms of productivity. De Stefano et al. (2020) also provides a correlation analysis showing that IT investment per employee is negatively associated with the use of cloud computing.

From this discussion, we derive two conjectures on the impact of cloud computing on firms' performance. First, the most highlighted advantage of using the cloud is the shift from fixed to variable costs (OECD, 2014; van Ark, 2016; Bloom and Pierri, 2018; Gal et al., 2019; Jin and McElheran, 2019; Byrne et al., 2020; De Stefano et al., 2020). Hence, we expect that firms no longer need to build up and manage their own IT, but can outsource a large proportion of IT-related tasks and purchase them as required, turning IT into an intermediate input. Although the reduced need for IT investments is plausible and repeatedly emphasized in the literature, there is little empirical evidence as to whether the use of cloud solutions saves IT investments in individual firms. This study addresses this gap in the literature and provide empirical evidence on whether firms that use cloud computing invest significantly less in IT than firms that do not use cloud solutions.

Second, an issue with in-house IT capital is that it has to be oversized to cope with peak loads (Perry; OECD, 2014). In turn, this means that higher IT investments are required than what would actually be optimal. It also means higher costs due to maintenance requirements and energy consumption. These costs are eliminated when cloud computing is used (Masanet et al., 2013). Cloud users further benefit from the fact that cloud providers can fully utilize economies of scale, which means that they have significantly lower operating costs in turn (Benlian and Hess, 2011). Even if cloud providers do not pass this on to their customers in full, as they themselves also need to make a profit, operating costs for cloud users are still lower than what they "would have if they ran their own IT infrastructure" (OECD, 2014, p.4). In addition, the use of the cloud provides firms with constant and easy access to cutting edge technologies and services. This is expected to support growth and productivity. Cloud providers have also begun not only to buy and assemble IT equipment to expand capacity, but also to develop devices and software solutions that are optimally tailored to the needs of cloud computing (Byrne et al., 2020). Thus, they have become innovators, with cloud users benefiting from this technological progress without having to invest in new technologies themselves. Finally, the cloud enables firms

[8] While the analysis overcomes the potential endogeneity due to cloud adoption by using an instrumental variable approach, it suffers from a lack of control variables, such as IT capital, physical capital, etc. The actual estimation equation uses dummies that captures cloud computing, firm age, foreign ownership, the number of establishments of a firm, and fixed effects. However, no information on tangible capital, IT capital, or other firm characteristics could be used to due data constraints.

to experiment with different IT solutions and flexibly adapt their use to their own changing needs.[9] Due to this multitude of potential benefits, we empirically assess whether cloud computing users are indeed more productive than firms that do not use cloud services.

4 Data

4.1 Data source

Three different firm-level datasets provided by the German statistical offices and covering the period 2013 to 2016 are used for the analysis: the 'Survey on ICT usage and Ecommerce in Enterprises,' the 'AFiD-Panel Manufacturing Firms,' and the 'AFiD-Panel Service Firms' (FDZ der Statistischen Ämter des Bundes und der Länder, 2021, 2020, 2019).

The firm-level data are supplemented by external data. These are, in particular, data on broadband availability, the price deflators published by the Federal Statistical Office at the two-digit industry level for value added, for IT investment, as well as for investments in property, plant, and equipment. The depreciation rates for the two types of capital are also provided by the Federal Statistical Office at the two-digit industry level. The capital stocks are constructed such that they include the (deflated) contemporaneous investments, i.e. $K_{jt} = (1 - \rho)K_{jt-1} + i_{jt}$.[10]

The two AFiD-Panels are the main source of firm-specific variables, as they contain a wide range of firm characteristics, including value added as an output variable and various inputs such as the number of employees. They cover 50 two-digit industries (divisions) from most economic section of the business economy.[11] These datasets are used in previous studies and are presented in detail there, which is why we do not discuss them in depth here but refer to these studies (e.g. Richter and Schiersch, 2017; Le Mouel and Schiersch, 2020; Duso et al., 2021). Instead, we focus on those questions in the underlying surveys that provide information on cloud computing and investment.

In the surveys on which the two AFiD panels are based, firms are asked to report the investment sum in 'property, plant, and equipment'.[12] In addition, the firms are asked about their IT investments

[9] There are also several potentially negative effects of cloud computing, *inter alia*: lock in effects that do not allow to easily switch between cloud providers, privacy issues and the partial loss of data sovereignty, contractual issues, firms are at risks to lose firm specific knowledge if the business model relies on IT solutions (OECD, 2014; Opara-Martins et al., 2016).

[10] The use of deflated investment data to calculate the capital stock by means of the perpetual inventory method (PIM) approach is standard and is also used in Doraszelski and Jaumandreu (2013), on whose model our estimation approach is based. The PIM is widely used in major papers that rely on the control function procedure. See for an overview Ackerberg et al. (2007); Van Beveren (2012); De Loecker and Syverson (2021).

[11] Specifically, the 'AFiD-Panel Manufacturing Firms covers mining (B) and the manufacturing (C) industries. Observations belonging to the mining industry are dropped from the analysis to comply with the privacy policy requirements of the German Statistical Offices. The 'AFiD-Panel Service Firms' covers the following economic sectors: transport and warehousing (H), information and communication services (J), real estate (L), business services (M), administrative activities (N), and repair services (S).

[12] It should be noted that only investments in capital goods that are intended for permanent use in the unit and that are included in the balance sheet in accordance with German accounting law (service life of at least one year) are reported here. Investments with a write-off period of less than one year are classified as 'Other operating expenses and

in a separate question.[13] This question provides the data for IT investments by firm and year. The volume of spending on cloud computing is not explicitly surveyed by the German statistical offices. The respective expenditures are buried into two rather broad variables. According to the metadata of the AFiD panels, firms mainly report them under 'Other operating expenses and purchased services.' In case leasing contracts are involved, they can also be reported in the category 'Expenses for rentals, leases and leasing.' Since both variables capture a wide range of expenses – from expenditures for electricity, gas, and water to rental costs for buildings and machines – they do not allow any conclusions to be drawn about the volume of cloud computing expenditures. While this forces us to rely on the ICT survey for all information on cloud usage, it also ensures that our IT investment variable is not confounded by spending on cloud computing.

The ICT survey is the German section of Eurostat's 'community survey on ICT usage and e-commerce in enterprises.' Almost all questions are designed as yes/no questions, so that the corresponding variables are dichotomous. With regard to cloud computing, the survey includes a general question about whether or not cloud computing is used. Questions about cloud computing were part of the survey in 2014 and 2016. Two further variables from the ICT survey are used in the analysis. First, the share of sales over the internet. This variable ranges from 0 to 100 and indicates how much of the turnover is derived by selling products over the internet. The second variable is IT staff. Firms are asked whether they employ IT personal, but unfortunately not how many. Thus, it is only a dichotomous variable.

The timing of data collection differs between the ICT survey and the surveys on which the AFiD panel are based. The surveys underlying the AFiD panels for a given year are conducted over the course of the following year(s). In other words, and in simple terms, the questionnaire on investments for the year t reaches the firms in $t+1$. Thus, the values reported in the AFiD panels are based on the actual observed investments etc., after completion of each year. In contrast, the ICT survey takes place in the first weeks of each year for the respective year. In other words, the firms are asked at the beginning of each year whether they use cloud computing or not. The consequences of the different survey dates are obvious and must be accounted for in the econometric analysis: The cloud computing variable in the dataset captures whether a firm used cloud computing at the beginning of each year, while the investment variable includes all expenditures until the end of that very same year. For the econometric analysis, the ICT survey is merged with the AFiD panels using a unique firm identifier in order to combine the information on cloud usage with the data on investment, output, capital stocks, and other firm characteristics.

The firm level data are enriched by adding information on broadband availability at the municipality level. This variable serves as an instrument in the estimations (see Section 5). This data comes from the Broadband Atlas of the German Federal Ministry of Transport and Digital Infrastructure.[14]

purchased services' and entailed in the respective variable.

[13] The focus of the specific question is on investments in software and databases according to the survey meta data.

[14] See https://www.bmvi.de/DE/Themen/Digitales/Breitbandausbau/Breitbandatlas-Karte/start.html.

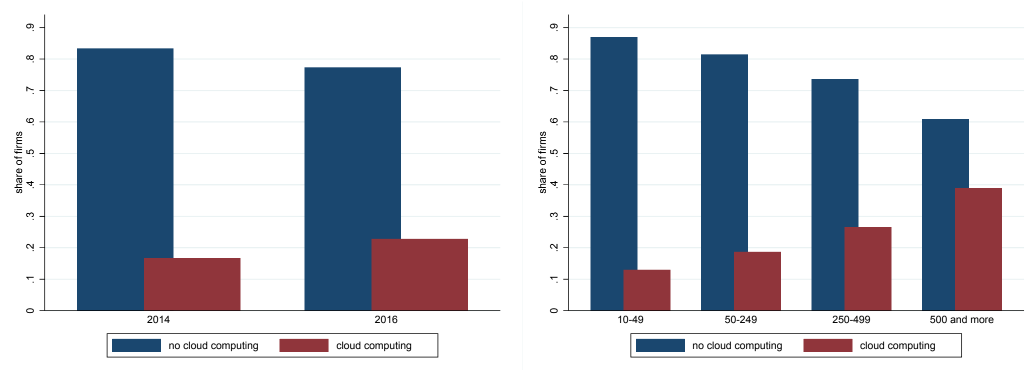
The data at hand contains information on broadband availability at 16 Mbps transmission speed by municipality and year. Although the data does not cover all German municipalities, it covers most of the West German municipalities, which together produced about 80 percent of the German GDP in the observation period. Furthermore, we add deflators and other sector-level measures at the two-digit industry level.

Because of the various merging procedures, the final dataset for the estimations contains 2,937 firms and 3,218 observations in total. As these two figures suggest, there are only few firms, 281 in total, with observations in both 2014 and 2016. This prevents the use of panel data models, even if 2015 is ignored. The descriptive statistics for the final dataset are presented in detail in Section 6, after the model is developed, which defines the relevant variables.

4.2 Descriptive evidence

At this point, we provide an overview of the usage of cloud computing. Figure 1a reveals that the percentage of firms using cloud computing increased from about 18% to about 22% between 2014 and 2016. This is in line with the general trend observed in other countries (Eurostat, 2021). Figure 1b reveals the distribution across size classes. The fraction of firms using the cloud increases with size and the differences between the classes are large. While the share is just over 10% for firms with 10 to 49 employees, the share of users among firms with 500 or more employees is around 40%. This is consistent with findings in the literature regarding adoption of advanced digital technologies. However, it contradicts the expectation that smaller firms are particularly strong adopters of cloud computing. The differences between the size classes also indicate that firm size and the likelihood of cloud adoption are positively related.

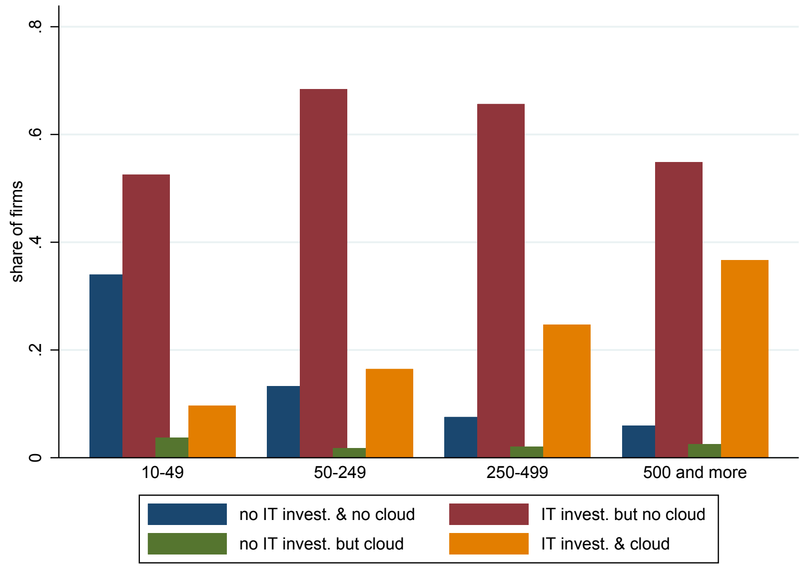
Figure 1: Share of firms using cloud computing per size and year



(a) size classes (b) period

Figure 2 provides first insights on differences between cloud users and non-users in terms of IT investment. It contains the percentage of firms in each size class that (a) neither use the cloud nor report IT investments; (b) have made IT investments but do not use the cloud; (c) have not made IT investments but use the cloud; and (d) make IT investments and, at the same time, use the cloud. The figure reveals that only a tiny fraction of firms that do make use of cloud computing but do not invest in IT. This proportion is highest among small firms. Hence, these firms seem to substitute IT investments with the use of cloud services, which is somewhat consistent with the presumption discussed in the literature. The fraction of these firms, however, is very small. Second, as expected, the largest share of firms that neither invest in IT nor use the cloud is also found among small businesses.[15] Third, the majority of firms invest in IT but do not use cloud computing solutions. This holds for all classes, although the relative share of these firms is highest in the middle size categories. Fourth, there is a group of firms that invest in IT and use cloud computing at the same time. Although the share of these firms is lower than that of firms that only invest in IT, it is considerably higher than the share of firms that do nothing or only use cloud computing. The chart also shows that the percentage of firms doing both increases with firm size. In other words, the larger a firm is, the more likely it is to both use cloud computing and invest in IT. It remains to be seen whether the level of investment is lower than for firms that do not use the cloud.

Figure 2: Share of firms conducting IT investments and use cloud computing



[15]One might wonder how a firm is able to operate without IT investments when it is not using an alternative, such as cloud computing. It should be noted that the IT investments reported in the investment survey only include IT investments that are taken up in the balance sheets. Expenditures for small IT goods that are immediately and completely written off – e.g. a new monitor, an office package for an PC – are included as low-value assets under current expenses in the income statement, not as IT investments. It follows that these firms may spend some very small amounts on IT, but these are negligible. They have no impact on the classification of the firms concerned as non-investors.

5 Model and estimation strategy

5.1 IT investment

The estimation approach to assess the relation between cloud usage and IT investment builds on the Jorgensonian model of firm behavior and investment (Jorgenson, 1967). We closely follow the approach proposed by Doraszelski and Jaumandreu (2013), which allows investments in two capital types – tangible capital and knowledge capital in their specific context – and modify it for the present research question. Thus, we assume that production can be described by a value-added Cobb-Douglas production function with tangible capital and IT capital:

$$Y_{jt} = f(L_{jt}, K_{jt}^{TC}, K_{jt}^{IT}) \tag{1}$$

where Y_{jt} is value-added, L_{jt} the labor input, K_{jt}^{TC} the tangible capital input and K_{jt}^{IT} the IT capital input of firm j at time t.

Like Doraszelski and Jaumandreu (2013), we assume that capital is accumulated over time through a deterministic investment process.[16] The single period profit is $\pi(\boldsymbol{s_{jt}}) - c(i_{jt}^{TC}) - c(i_{jt}^{IT})$, where i_{jt}^{TC} and i_{jt}^{IT} are the respective investments in tangible capital and IT (TC, IT) and $\boldsymbol{s_{jt}}$ is a vector of state variables. These state variables describe the information set of a firm at the beginning of each period. Importantly, it contains the capital stocks at the beginning of each period and Δ_t, which captures the economic environment to which firms are exposed, such as market conditions, industry characteristics, and so on (Ackerberg et al., 2007; Doraszelski and Jaumandreu, 2013).[17]

We follow the bulk of the literature in production function estimation and assume that labor is a fully flexible and non-dynamic input in the production process, which is why it is not part of the profit function (e.g. Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2007; Doraszelski and Jaumandreu, 2013).[18] The Bellman equation describing the maximization problem a firm faces at the beginning of each period is:[19]

$$V(\boldsymbol{s_{jt}}) = \underset{i_{jt}^{TC}, i_{jt}^{IT}}{max} \left(\pi(\boldsymbol{s_{jt}}) - c(i_{jt}^{TC}) - c(i_{jt}^{IT}) + \gamma E\left[V(s_{jt+1}|\boldsymbol{s_{jt}}, i_{jt}^{TC}, i_{jt}^{IT})\right]\right) \tag{2}$$

Firms solve this maximization problem with respect to investment, leading to two policy functions $i_{jt}^{TC} = i(\boldsymbol{s_{jt}})$ and $i_{jt}^{IT} = r(\boldsymbol{s_{jt}})$ for investments in tangible capital and in IT, respectively. Put differently, investment in IT is a function of the tangible capital stock, the IT capital stock, the productivity of the firm, and the economic environment.

[16] This corresponds to the PIM method used in the present study. See also Section 4.

[17] Note that we include the IT capital in the vector $\boldsymbol{s_{jt}}$ since it is a dynamic input in our context. Thus, we follow the procedure that Doraszelski and Jaumandreu (2013, p.1380f) discuss in Appendix C for the case of a second dynamic input besides tangible capital.

[18] Similarly, we will also assume that cloud usage is a fully flexible and non-dynamic input in the production process and, therefore, it is excluded from the profit function as well.

[19] See for example Ackerberg et al. (2007, p.4213) or Doraszelski and Jaumandreu (2013, p.1341f).

Doraszelski and Jaumandreu (2013) do not specify the functional form of the investment functions, but discuss whether $r(\cdot)$ can be inverted in order to back out tangible capital, which would cause a problem if $r(\cdot)$ is to be estimated. They argue that "if a cost shifter x_{jt} [exists and] is added to the cost functions... to capture variations in investment opportunities," then the investment functions also vary in this shifter (Doraszelski and Jaumandreu, 2013, p.1348). In other words, i_{jt}^{IT} becomes a function of $\boldsymbol{s_{jt}}$ and the shifter x_{jt}. From that it follows the functional relationship between $K_{jt}^{TC} = (1-\delta)K_{jt-1}^{TC} + E(i(\cdot))$ and $r(\cdot)$ is broken.[20]

We assume that cloud computing CC_{jt} is one such cost shifter, as it affects firms' willingness to invest in IT and their price expectations. Therefore, the IT investment function becomes $i_{jt}^{IT} = r(\boldsymbol{s_{jt}}, CC_{jt}, \boldsymbol{x_{jt}})$, where $\boldsymbol{x_{jt}}$ is a vector containing additional control variables.

For further specifying this function and for its estimation, the following three elements are crucial: i) the timing assumption on the firms' input choices; ii) the timing of data collection; and iii) the way the capital stocks are constructed. On the first issue, the literature assumes that firms know about their capital stocks and the market conditions at the beginning of each period and *before* they observe their (total factor) productivity (TFP) or decide on investment. Hence, it is the capital stock that has been built up until the beginning of period t. Given the construction of capital stock in the data at hand (see Section 4), this means that $\boldsymbol{s_{jt}}$ contains k_{jt-1}^{TC} and k_{jt-1}^{IT}. Moreover, firms know about the overall economic environment. We capture this using a set of dummy variables that control for the location of the firm, its two-digit, and the years. Finally, throughout the literature, it is assumed that firms observe a shock to productivity and, thus, know (at least partly) about their TFP (ω_{jt}) *after* observing all state variables but *before* they solve the optimization problem above. In other words, *after* they observed the shock to productivity, they have all the relevant information and will *then* solve the maximization problem and decide on the IT investment (Olley and Pakes, 1996; Ackerberg et al., 2007, 2015; De Loecker and Syverson, 2021). The fact that TFP is part of $\boldsymbol{s_{jt}}$ has to be kept in mind and will be addressed below as it complicates the estimation. Assuming that $r(\cdot)$ is a linear function, the estimation equation for IT investment is thus:

$$i_{jt}^{IT} = \beta_0 + \beta_{IT}k_{jt-1}^{IT} + \beta_{TC}k_{jt-1}^{TC} + \beta_{cc}CC_{jt} + \boldsymbol{x_{jt}\gamma} + \underbrace{\omega_{jt} + \nu_{jt}}_{\varepsilon_{jt}} \tag{3}$$

where CC_{jt} is a dummy variable taking the value of one when firms report using cloud computing,[21] $\boldsymbol{x_{jt}}$ contains the set of control variables, and ν_{jt} is an heteroscedastic error term. Note that the TFP (ω_{jt}) is an unobservable variable in firm-level data. Therefore, when estimating equation 3, it enters a composite error term $\varepsilon_{jt} = \omega_{jt} + \nu_{jt}$. As the decisions about any of the inputs in equation 3,

[20] For the full discussion see Doraszelski and Jaumandreu (2008, p.13f) and Doraszelski and Jaumandreu (2013, p.1348f).

[21] Clearly, it would be better to have more precise information on the amount spent on cloud computing rather than only having the dichotomous information on the adoption of cloud services. Unfortunately, this is not available in our data.

including the adoption of cloud solutions, might be correlated with the unobserved TFP, this creates an endogeneity problem that needs to be accounted for.

5.2 Endogeneity and selection

One way to at least partially address the endogeneity issue identified above is to relay on the timing assumptions about the firm's decisions and the timing of data collection. This is particularly relevant for the input choices k_{jt-1}^{IT} and k_{jt-1}^{TC}. First, given the fact that firms observe k_{jt-1}^{TC} and k_{jt-1}^{IT} before they observe ω_{jt}, the lagged capital stock variables are uncorrelated with contemporaneous TFP and, thus, are predetermined. As described in Section 4, all information in the ICT survey are gathered at the very beginning of each year. Therefore, it is reasonable to assume that the firms decided about the relevant items already in $t-1$ or at the very beginning of t. It follows that CC_{jt} might also be predetermined and, consequently, not correlated with the error term.

Second, in equation 3 we control for time, industry and regional dummies, which are generally not determined by the TFP of a firm and account for other potential omitted factors that might correlate with the various input choices. We also add population density as another important control variables to $\boldsymbol{x_{jt}}$. This choice is motivated by the literature on regional economy, which shows that firms benefit from agglomeration economies in terms of higher productivity (Melo et al., 2009; Martin et al., 2011; Cainelli et al., 2015; Melo et al., 2017; Ahrend et al., 2017; Cainelli and Ganau, 2018; Gornig and Schiersch, 2019). In other words, productivity is positively correlated with population density. Thus, we use this variable as a (very rough) proxy to additionally control for the unobserved productivity. All these steps at least help to partially to address the problem of not observing ω_{jt} and reducing the potential omitted variable bias.

A second source of endogeneity stems from selection. The decision to adopt cloud solutions is not a random event but an endogenous choice by firms. This selection-based endogeneity can be accounted for empirically through an endogenous dummy variable (or endogenous treatment) model, which is appropriate in situations where a binary-treatment variable – in our case the adoption of cloud computing – partitions the sample into two sub-groups – cloud users or not– and this partitioning might be endogenous.[22] This is a linear potential-outcome model that assumes a specific correlation structure between the unobservables that affect the adoption of cloud services (the selection into treatment) and the unobservables that affect the investment decisions (potential outcomes).

The model is composed by the outcome equation (3) and an equation for the endogenous treatment (CC_{jt}). Since CC_{jt} is a dichotomous variable, we estimate the following probit model:

$$CC_{jt} = \alpha_0 + \alpha_L l_{jt-1} + \alpha_{IT} k_{jt-1}^{IT} + \alpha_{TC} k_{jt-1}^{TC} + \alpha_{bb} BB_{jt} + \boldsymbol{x_{jt}} \boldsymbol{\gamma} + u_{jt}. \tag{4}$$

We assume that the same (predetermined) variables that we use in equation 3 – lagged stocks of

[22] See A discussion of this model is found in Clougherty et al. (2016) and an application to RJV participation in Banal-Estañol et al. (2022).

IT and tangible capital – are determinant of the cloud adoption choice. We also add lagged labor as a regressor, as the literature and descriptive findings suggest that cloud adoption rates increase with firm size. We then add two additional instruments, which are assumed to capture the firm's propensity to using advanced digital technology – thus to adopting the cloud – such as IT staff and share of sales over the internet. We also control for some exogenous factors ($\boldsymbol{x}_{jt}$) such as population density, as well as year, state, and industry fixed-effects.

For the sake of identification, we need an exogenous shifter that affects the choice to adopt cloud computing but does not affect the investment. We follow the existing literature and propose to use broadband availability as an instrument for the adoption of cloud computing (e.g. De Stefano et al., 2020; Fabling and Grimes, 2016). Indeed, the existence of high-speed broadband is a fundamental prerequisite for using cloud solutions, which often requires large flows of data between the using firm and the service providers. Therefore, we add to our regression the variable BB_{jt}, which represents the level of broadband availability in the municipality where firm j is located. The error term u_{jt} is assumed to be heteroscedastic.

The error terms of the two equations that compose the endogenous treatment model, ε_{jt} and u_{jt}, are assumed to be distributed as a bivariate normal with mean zero and a given unknown covariance matrix, which is jointly estimated.[23] We estimate the model by a two-step maximum likelihood estimator.[24]

5.3 Labor productivity

For estimating the effect of cloud computing on labor productivity, the value-added Cobb-Douglas production function from equation 1 is also used. We rearrange it such that labor productivity is the dependent variable.[25] In addition, we include cloud computing in the function as an additional regressor. This follows the established literature on the effects of ICT assets on productivity, such

[23] While the variance of the error term ε_{jt}, which is denoted (σ), as well as the correlation between the two error terms (ρ), are jointly estimated in the model, the variance of the error term u_{jt} is normalized to one for identification.

[24] We use the `etregress` command in Stata and implement a consistent two-step estimator, which is more robust and shows fewer problems with convergence if compared to the full-information maximum likelihood estimator as well as the one-step control-function estimator using the generalized method of moments with stacked moments (e.g. Wooldridge, 2010). We also estimate robust standard errors to account for heteroscedasticity. The two-step procedure consists of the following steps: first, we estimate equation 4 by maximum likelihood and recover the hazard rate – or inverse Mill's ratio (λ). This is defined as the ratio of the probability density function and the complementary cumulative distribution function. In the second step, we augment the regression equation (3) with this hazard rate. The coefficient estimates for the λ can be interpreted as the product of ρ – the relevant statistic to assess the potential endogeneity – and the variance of the error term in the outcome equation (σ). Finally, consistent standard errors are also computed, which account for the fact that λ is an estimated variable.

[25] We assume variable returns to scale (VRS) instead of constant returns to scale (CRS), since the latter is very restrictive and hardly justifiable. Importantly, while $1 = \beta_l + \beta_k$ holds under CRS, VRS is characterized by $1 \neq \beta_l + \beta_k$. The scale assumption directly affects the estimation equation. When dividing equation 1 by labor (L), we obtain labor productivity ($\frac{Y}{L}$) defined as: $\frac{Y}{L} = AL^{\beta_l - 1}K^{\beta_k}$. In case of CRS, $1 = \beta_l + \beta_k$ can be rearranged to $\beta_l = 1 - \beta_k$ and plugged into $\frac{Y}{L} = ...$, leading to $\frac{Y}{L} = AL^{1-\beta_k-1}K^{\beta_k}$ or $\frac{Y}{L} = A\left(\frac{K}{L}\right)$. Hence, labor is (almost) disappearing and only remains on the right side as part of capital intensity ($\frac{K}{L}$). In contrast, if $1 \neq \beta_l + \beta_k$ due to VRS, L cannot drop from the right side of $\frac{Y}{L} = ...$ and any estimation of the labor productivity function needs to estimate the coefficient ($\beta_l - 1$).

as in Bugamelli and Pagano (2004), Bertschek and Niebel (2016), Bartelsman et al. (2019), Jin and McElheran (2019), Bertschek et al. (2019), and as discussed in the overview study by Biagi (2013). Thus, in log terms, the production function to be estimated is:

$$lp_{jt} = \beta_0 + (\beta_l - 1)l_{jt} + \beta_{TC}k_{jt}^{TC} + \beta_{IT}k_{jt}^{IT} + \beta_{CC}CC_{jt} + \epsilon_{jt} \tag{5}$$

where ϵ_{jt} is an heteroscedastic error term.[26]

Estimating equation 5 is complicated by the same kind of endogeneity issues discussed in section 5.2. Firms decide on their variable production inputs, the adoption of cloud computing, as well as investments in various assets at the beginning of each period *after* they observed the shock to productivity. However, because TFP is not observed by the econometrician, it is part of the error term and all variable inputs are no longer exogenous. The same is true for contemporaneous capital stocks in the present dataset, since they include the investments undertaken at period t.

Unfortunately, the typical control function approach for estimating the production function cannot be applied here because the data lack the necessary panel structure (see Section 4).[27] Thus, we address these endogeneity issues in a similar fashion as we do for the investment function. First, we use the behavioral model described in section 5.1, its timing assumptions, and the timing of data collection to address the simultaneity issue between unobserved productivity and input choices. Once-lagged capital stocks are observed before TFP at period t and are, therefore, predetermined. Hence, we make use of these variables in the estimations instead of the contemporaneous capital stock. Firms choice on labor input in period t is clearly affected by the productivity shock in that same period, which is why l_{jt} cannot be considered as an exogenous variable. Consequently, once-lagged labor is used instead of contemporaneous labor when estimating equation 5, as firms have already decided upon it before they observed TFP at time t. Therefore, once-lagged labor is not affected by TFP at time t by definition. As described in Section 4, the ICT survey is conducted at the very beginning of each year. Hence, firms had already made their decision on cloud computing in $t-1$ and before they observed the productivity shock in period t; thus the cloud computing variable is not subject to the simultaneity problem. We also add population density as an additional control, as well as the dummies for time, region, and industry. In sum, by using lagged variables and utilizing the specific timing of data collection, we aim to overcome the potential bias that steams from the simultaneity issue.

[26] Note that cloud computing is included as an input in the production function and not in the law of motion for TFP, as it is the case, for example, in studies of broadband and productivity (see Duso et al., 2021, among others). The reason for this modeling choice is the main characteristic of cloud computing: it can (or should) replace internal IT as an input in production.

[27] For an overview of the so-called simultaneity problem created by the unobservability of productivity and its potential solutions, in particular by means of the control function approaches, see Ackerberg et al. (2007), Van Beveren (2012), and De Loecker and Syverson (2021). Note that other methods proposed to overcome the simultaneity problem, such as fixed effects regressions or gmm (Ackerberg et al., 2007; De Loecker and Syverson, 2021), also cannot be used here due to the lack of panel structure.

Further, in this model, the adoption of cloud computing is endogenous in the sense that firms self-select themselves into the usage of this technology. Again, to address this issues, we estimate an endogenous dummy variable model composed by the new outcome equation 5 and the equation for the endogenous treatment 4. We use the exact same specification for the probit as discussed above, here using internal (predetermined) instruments (i.e. lagged investments in IT and tangible assets as well as IT staff and share of sales over the internet), some exogenous factors (population density and fixed-effects), and broadband availability as external instrument: .

6 Results

6.1 Descriptive results

Table 1 presents the descriptive statistics for all the main variables, distinguishing by industry and whether or not firms use cloud computing. Starting with the manufacturing companies, it can be seen that about 23 percent of them used cloud computing during the observation period. Tests of the comparison of the means show large differences between the two groups of cloud users and not-users. Cloud using firms in manufacturing are much larger in terms of value added and employment. They also use more tangible capital and more IT capital. These descriptive differences are consistent with what is observed in the literature, which states that use of digital technologies increases with firm size. There are also considerable differences in the two main variables of interest, labor productivity and IT investment. Firms that use cloud computing are significantly more productive, but they also invest more than firms that do not use cloud computing. These mean differences between the two groups are statistically significant.

These simple comparisons might however be misleading. As already shown in Section 4, the share of firms using the cloud is considerably larger among large firms in comparison to small firms. Thus, the substantial differences between cloud users and the rest might simply be the result of a bigger share of large firms in the group of cloud users. This will be controlled for in the econometric analysis. With regard to manufacturing, it remains to be noted that cloud users are significantly more likely to employ IT personal. Although revenue generated via the internet accounts for only 3.4 percent of total sales on average, this share is still more than twice as high as for firms that do not use cloud computing. Both variables thus seem well suited for predicting cloud usage.

Table 1: Descriptive statistics

Industries		(1) value adde#	(2) tang. capitale#	(3) IT capitale#	(4) labor	(5) labor prod.	(6) IT investm.$	(7) share web sales§	(8) IT staffΨ	(9) broadband§
manufacturing										
cloud user	mean	201.09	348.17	6.22	1754.83	86.21	933.53	3.44	.88	72.47
	sd	(1350.39)	(2302.97)	(31.54)	(10428.99)	(62.98)	(4776.14)	(10.89)	(.32)	(28.38)
	N	446	446	446	446	446	446	446	446	446
non-user	mean	39.67	71.19	1.19	417.42	69.42	173.99	1.49	.67	65.29
	sd	(328.23)	(485.24)	(7.62)	(1717.3)	(34.85)	(1342.56)	(5.79)	(.47)	(29.78)
	N	1414	1414	1414	1414	1414	1414	1414	1414	1414
	p-value t-test	.000	.000	.000	.000	.000	.000	.000	.000	.000
inform.&com. serv.										
cloud user	mean	81.63	50.84	5.18	464.63	100.1	902.2	8.01	.92	85.36
	sd	(457.92)	(177.57)	(20.64)	(1467.99)	(67.77)	(3996.1)	(17.86)	(.27)	(20.88)
	N	216	216	216	216	216	216	216	216	216
non-user	mean	30.04	46.74	5.04	251.96	101.44	1502.49	5.88	.81	82.79
	sd	(89.49)	(270.03)	(39.81)	(649.82)	(170.64)	(11751.9)	(15.7)	(.39)	(23.57)
	N	284	284	284	284	284	284	284	284	284
	p-value t-test	.06	.85	.96	.03	.91	.47	.16	.000	.2
business serv.										
cloud user	mean	18.42	50.43	1.3	359.32	65.89	155.43	11.61	.71	84.26
	sd	(36.38)	(227.02)	(4.91)	(834.63)	(38.21)	(592.36)	(26.78)	(.46)	(21.84)
	N	111	111	111	111	111	111	111	111	111
non-user	mean	15.48	36.01	.43	293.82	65.12	80.89	2.45	.46	80.09
	sd	(34.23)	(206.84)	(2.01)	(512.24)	(74.58)	(608.91)	(8.8)	(.5)	(24.98)
	N	365	365	365	365	365	365	365	365	365
	p-value t-test	.43	.53	.01	.32	.92	.26	.000	.000	.11
other serv.										
cloud user	mean	122.45	2899.54	2.72	1269.24	128.35	636.48	5.04	.73	83.25
	sd	(456.02)	(13190.2)	(14.42)	(4585.24)	(132.36)	(3292.97)	(17.97)	(.45)	(22.14)
	N	107	107	107	107	107	107	107	107	107
non-user	mean	25.4	404.01	.37	358.56	134.79	43.21	2.55	.48	76.98
	sd	(75.09)	(805.91)	(1.24)	(1325.04)	(373.13)	(130.79)	(9.63)	(.5)	(26.64)
	N	275	275	275	275	275	275	275	275	275
	p-value t-test	.000	.000	.01	.000	.86	.000	.08	.000	.03

in million euros, $ in thousand euros, § share in percentage ranging from 0 to 100, Ψ 0/1-dummy

While the differences between cloud users and other firms in the manufacturing sector are significant, the picture is less clear in services. Within the information and communication services, about 40 percent of the firms in the dataset are cloud users.[28] This larger share is to be expected, as these firms

[28]This is perfectly in line with the share that is published by Eurostat (2021) for the years 2014 and 2016 for the

are usually very open to new IT-technologies.[29] Even in information and communication services, the cloud using firms are larger in terms of value-added and labor. The difference of the means for both variables are statistically significant. Notably, cloud using firms invest an average of about 900,000 Euro in IT, while the non-users invest an average of about 1.5 million Euros in the observation period. While this is a large difference, it is not statistically significant. There are also no differences between the two groups when considering physical capital and IT capital. The same holds for labor productivity, despite the fact that cloud using firms are larger. This is different than in manufacturing and in contrast to expectations.

In business services, the share of firms using cloud in the dataset is about 23 percent. While cloud users in this sector are again larger in terms of value added and number of employees, just as in manufacturing and information and communication services, these differences are not statistically significant. Although they have a significantly larger IT capital stock, cloud users neither invest larger sums in IT nor are they more productive during the observation period. The main differences between firms that use cloud computing and the other firms are in the proportion of sales made over the internet, which is 4.5 times greater for cloud users, and in the use of IT staff. Of the firms that use cloud computing, 71% reported having IT staff, while this percentage is 46% for the firms that do not use cloud computing. This underscores the point that both variables are good predictors of cloud usage. However, apart from these differences, the descriptive statistics provide little evidence that there are differences between cloud users and non-users in business services, especially in terms of IT investment and labor productivity.

Considering the other service firms in the dataset, there are significant differences between the cloud users and the other firms for almost all variables. However, the firms summarized here come from a wide variety of service industries. They include real estate firms as well as shipping firms. The aggregation is necessary because otherwise the number of cases would not be sufficient for an econometric analysis. The regression analyses will show whether these differences are retained when controlling for industry affiliation.

A final point concerns broadband availability. Cloud using firms have, on average, greater broadband availability than non-using firms in all sectors we consider. Yet, these differences are significant only for firms operating in manufacturing and other services, while they are not for firms operating in information and communications services and business services. To further understand these differences, we breakdown broadband availability by industry and region, distinguishing between urban and rural areas.[30] As shown in Table A.1, there are few firms in information and communication services located in rural regions. In other words, almost all firms in this service sector are located in urban centers. For this reason, cloud using firms and non-users in this sector have about the same quality

German information and communication section.

[29] We can also rule out that this higher share in comparison to manufacturing and other sectors is driven by the data preparation process. Eurostat statistics show similar shares for this service industry Eurostat (2021).

[30] The number of observations in the 'rural' and 'partially urban' categories is too small, so the two categories must be combined into one to meet confidentiality requirements. The combined category is referred to as 'rural' in the table.

for broadband infrastructure. The same holds for business services, which explains why the means in broadband availability between cloud users and the rest of the firms are not statistically significant in Table 1.

Overall, the descriptive statistics provide four findings. First, there are significant differences in key characteristics between cloud users and non-users in the manufacturing sector, but less so in the service sectors. Second, there is only little evidence that cloud users are investing less in IT. On the contrary, it seems that the IT investments of cloud users are sometimes even greater than those of non-users. The further analysis will show whether this is only due to the composition of the group of users in terms of firm size. The descriptive results, however, at least partially support the claim that cloud users are more productive. Third, the share of online sales and IT staff seem to be good indicators for predicting cloud usage. Finally, broadband availability also appears to be a good instrument for cloud adoption, yet it probably works better for manufacturing than for services.

6.2 Cloud adoption

The first step of our econometric analysis consists of estimating a probit model for cloud adoption. This has two reasons. First, we want to better understand what observable characteristics help explain the choice of cloud solutions. This should help improve the descriptive analysis provided in the previous sections. Second, and perhaps more importantly, this probit constitutes the first step of the endogenous dummy variable model discussed in section 5.2.

The relevant explanatory variables used in this estimation are derived from the discussion of the method and the model in Section 5.3 as well as from the literature discussion and the descriptive results. Thus, in addition to the capital stocks, IT staff and the share of sales over the web are also included as explanatory variables. As discussed above, firm size and cloud computing seem to be positively correlated, which is why labor is also included in the estimation to control for firm size. We also control for year, industry affiliation, and federal states. Finally, broadband availability is used as the main exogenous instrument.

The first four columns in Table 2 show the estimation results for manufacturing adding different variables. As expected, we find that increasing broadband availability is a good predictor for cloud usage, regardless of which variable is added to the regression. Moreover, the size of the firms, captured by the labor variable, is also an important determinant, at least in manufacturing, which conforms to the descriptive findings and the literature. IT capital seems not to be a crucial driver of cloud adoption. Although significant in the first estimations, it loses significance once IT staff is added to the regression. Finally, the share of sales over the internet seems also to be a good predictor for whether or not firms make use of cloud computing.

While the results for manufacturing are pretty much what one might expect, the same is not true for services. For one thing, firm size has no relevance to explain cloud adoption. This shows that the size differences between cloud users and non-users found for services in Table 1 disappear once we

Table 2: Probit regression: The determinants of cloud adoption

Variable	(1)	(2)	(3)	(4)	(5)	(7) inform. &com. serv.	(8) business serv.	(9) other serv.
	manufacturing							
Broadband$_t$	0.00318**	0.00316**	0.00317**	0.00321**	0.00334**	–0.00185	–0.00498	0.00168
	(0.00153)	(0.00154)	(0.00153)	(0.00154)	(0.00155)	(0.00342)	(0.00418)	(0.00435)
Labor$_{t-1}$	0.412***	0.343***	0.301***	0.271***	0.262***	0.0500	–0.0907	0.0659
	(0.0327)	(0.0438)	(0.0836)	(0.0844)	(0.0850)	(0.0892)	(0.0875)	(0.121)
IT Capital$_{t-1}$		0.0533**	0.0505**	0.0399	0.0378	0.0465	0.0805**	0.0461
		(0.0234)	(0.0238)	(0.0245)	(0.0246)	(0.0314)	(0.0359)	(0.0436)
Tang.Capital$_{t-1}$			0.0417	0.0423	0.0454	–0.0634	–0.0565	0.0880
			(0.0694)	(0.0697)	(0.0701)	(0.0793)	(0.0631)	(0.0751)
IT Staff$_t$				0.278***	0.280***	0.634***	0.400**	0.357**
				(0.0991)	(0.0995)	(0.206)	(0.157)	(0.179)
Perc. Web Sales$_t$					0.0151***	0.00611*	0.0199***	0.00393
					(0.00416)	(0.00361)	(0.00482)	(0.00545)
Constant	–2.573***	–2.801***	–3.192***	–3.093***	–3.017***	–0.777	–0.279	–2.083**
	(0.420)	(0.430)	(0.766)	(0.772)	(0.776)	(1.118)	(1.011)	(1.027)
N	1,860	1,860	1,860	1,860	1,860	500	476	368

All estimations contain dummies for federal states, two-digit industries and years as well as population density as additional control variables. The dependent variable *cloud computing* is an indicator which takes value 1 if a firm uses cloud computing. Robust standard errors in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

control for other firm characteristics. The broadband variable is also no longer significant. However, this is only partly surprising, since the descriptive comparison in Table 1 already found hardly any significant differences in this variable between users and non-users in services. Noteworthy, the IT staff and the share of sales generated via the internet remain significant. The latter, however, not in other services.

Overall, the results of the probit estimations support the view established in the previous section that there are notable differences between cloud users and non-users in the manufacturing sector, but less so in the services sector.

6.3 IT investments and cloud computing

In this section, we present the estimation of equation 3 by OLS as well as by using the endogenous treatment model that accounts for the self-selection into cloud adoption. Table 3 shows the results of the former. All regressions show that, once accounting for lagged tangible and intangible capital, cloud computing usage is unrelated to investment.

Table 3: IT-investment, OLS

variables	(1)	(2)	(3)	(4)	(5) inform. &com. services	(6) business services	(7) other services
	manufacturing						
Cloud Comp.$_t$	2.183***	0.667**	0.395	0.313	0.434	0.478	0.441
	(0.282)	(0.273)	(0.246)	(0.246)	(0.427)	(0.506)	(0.557)
Tang.Capital$_{t-1}$		1.595***		0.195*	–0.112	0.216	–0.137
		(0.0810)		(0.106)	(0.183)	(0.156)	(0.226)
IT-Capital$_{t-1}$			1.408***	1.326***	1.350***	0.914***	1.085***
			(0.0475)	(0.0677)	(0.103)	(0.0942)	(0.127)
Constant	4.717***	–20.87***	–11.09***	–13.30***	–6.296*	–12.14***	–1.060
	(1.766)	(2.053)	(1.505)	(1.892)	(3.694)	(3.046)	(3.987)
R^2	0.076	0.220	0.357	0.358	0.398	0.374	0.312
N	1,860	1,860	1,860	1,860	500	476	382

All estimations contain dummies for federal states, two-digit industries and years as well as population density as additional control variables. Robust standard errors in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Focusing on manufacturing, the IT investment of manufacturing and service firms is correlated with the IT capital stock that has been built up until the beginning of each year and the tangible capital stock. Thus, the raw correlation between CC and investment in IT observed in manufacturing is spurious. The pattern for manufacturing, shown in detail in Table 3, is also found in the regressions for each of the service sectors. Cloud computing is also positively and significantly correlated with IT investment when controlling only for the time-invariant effects. However, the coefficient of the cloud variable always becomes insignificant once lagged IT capital is taken into account. In contrast to manufacturing, tangible capital has no significant correlation with IT investment in any of the service sectors. Thus, the positive correlation of cloud computing and IT investment that is found in the descriptive comparison vanishes once we control for the variables that drive IT investment according to the IT investment model derived in Section 5.1. There is, however, also no support for the claim that the use of cloud computing goes hand in hand with lower IT investments.

These results in Table 3 might, however, be biased due to self-selection of firms into cloud usage. This issue is addressed by using the endogenous treatment approach outlined in section 5.2. The first stage results for this model are shown in Table 2 and are not presented again here. The result of the endogenous treatment approach are presented in Table 4 and are in line with those obtained when using OLS (Table 3). In all sectors, there is no effect of the adoption of cloud computing on investment. Moreover, IT capital is significant at the one percent level and the magnitude of coefficients is close to those shown in Table 3. Note that coefficient estimate for the inverse Mill's ratio (lambda) is never significant.[31] This suggests that there is no endogeneity issue in the way firms with a specific

[31] The inverse Mill's ratio is the hazard-rate variable that captures the likelihood of observing the outcome, i.e. being a

investment behavior self select into cloud usage. It also explains why the estimated coefficients are very close to those obtained with OLS.

Table 4: IT-investment regression, endogenous treatment approach

variables	(1) manufac turing	(2) inform. &com. services	(3) business services	(4) other services
Cloud Comp.$_t$	–1.407	1.425	2.639	0.436
	(1.312)	(2.637)	(1.707)	(3.324)
IT-Capital$_{t-1}$	1.358***	1.328***	0.850***	1.086***
	(0.0713)	(0.124)	(0.106)	(0.134)
Tang.Capital$_{t-1}$	0.322**	–0.106	0.244	–0.136
	(0.142)	(0.191)	(0.156)	(0.240)
Constant	–13.71***	–6.017*	–11.71***	–2.975
	(2.171)	(3.479)	(3.012)	(3.272)
Lambda$_t$	1.029	–0.623	–1.339	0.00337
	(0.769)	(1.635)	(1.012)	(1.987)
Chi2	1076	354.3	311.9	194.7
N	1,860	500	476	382

All estimations contain dummies for federal states, two-digit industries and years as well as population density as additional control variables. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Both the results of the OLS as well as of the endogenous treatment approach confirm that cloud computing is not a significant driver of IT investment, once controlling for once-lagged IT capital, regardless of the considered sector. Thus, we clearly reject the claim that firms using the cloud invest significantly less in IT.

6.4 Cloud computing and productivity

We now turn to the last step of our analysis: the impact of cloud computing on firm's labor productivity. Table 5 presents the findings of both the OLS estimates of equation 5 as well as the estimates from the endogenous treatment model.

Panel A shows the OLS results. The coefficients of labor, tangible capital, and intangible capital have the expected signs and magnitude as found in other studies (e.g. Le Mouel and Schiersch, 2020). Recall that variable returns to scale (VRS) are assumed and, therefore, labor must remain in the production function and its estimated coefficient must be negative, of course, since $\beta_l - 1$ is estimated instead of β_l due to the VRS assumption and the use of labor productivity as the dependent variable.[32]

cloud user, and is estimated in the first stage probit model. This variable – which captures and corrects for the selection process – is missing in the OLS regression discussed above, creating an omitted variable bias.

[32] A detailed discussion on why labor remains in the production function under VRS and why $(\beta_l - 1)$ is estimated instead of just β_l is provided in section 5.3 (see footnote 25). For interpretation, the closer the estimated value of $(\beta_l - 1)$ is to zero, the larger is the actual β_l.

In the OLS regression, the coefficient of cloud computing is significant only for manufacturing.

Table 5: Production function estimation

Method	Variables	manufac turing	inform. &com. services	business services	other services
Panel A: OLS					
	Cloud Comp.$_t$	0.0575***	0.0394	0.0875	–0.0448
		(0.0221)	(0.0502)	(0.0595)	(0.0752)
	Labor$_{t-1}$	–0.212***	–0.165***	–0.288***	–0.346***
		(0.0277)	(0.0509)	(0.0358)	(0.0559)
	Tang.Capital$_{t-1}$	0.232***	0.182***	0.148***	0.221***
		(0.0227)	(0.0412)	(0.0275)	(0.0407)
	IT-Capital$_{t-1}$	0.0481***	0.0207	0.0599***	0.0845***
		(0.00619)	(0.0145)	(0.0123)	(0.0201)
	Constant	7.433***	8.728***	8.779***	7.670***
		(0.298)	(0.532)	(0.516)	(0.583)
	R-squared	0.345	0.257	0.511	0.576
	N	1,860	500	476	382
Panel B: Endogenous treatment regression (2nd stage)					
	Cloud Comp.$_t$	0.381***	0.796**	0.00395	0.0828
		(0.139)	(0.383)	(0.223)	(0.494)
	Labor$_{t-1}$	–0.242***	–0.176***	–0.288***	–0.351***
		(0.0256)	(0.0457)	(0.0308)	(0.0546)
	Tang.Capital$_{t-1}$	0.230***	0.194***	0.148***	0.217***
		(0.0184)	(0.0404)	(0.0241)	(0.0374)
	IT-Capital$_{t-1}$	0.0436***	0.00422	0.0624***	0.0825***
		(0.00658)	(0.0180)	(0.0140)	(0.0190)
	Constant	7.660***	8.004***	8.509***	8.250***
		(0.222)	(0.573)	(0.405)	(0.477)
	Lambda$_t$	–0.191**	–0.475**	0.0518	–0.0770
		(0.0808)	(0.237)	(0.132)	(0.295)
	Chi2	1029	156.1	532.2	539.3
	N	1,860	500	476	382

All estimations contain dummies for federal states, two-digit industries and years as well as population density as additional control variables. Robust standard errors in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Panel B of Table 5 reports the results of the endogenous treatment model where we account for the endogeneity of cloud adoption. The findings are somewhat in line with those in Panel A. First, the standard production function coefficients are close to those obtained with OLS in all sectors. Second, cloud computing is again significant in manufacturing, but now also in information and communications services. However, cloud usage remains irrelevant for productivity in the remaining two service industries. In this model, self-selection of more productive firms into cloud usage is relevant as shown by the fact that the lambda is negative and significant. This coefficient is the product between the correlation between the error terms in both the main and selection equations and the standard deviation of the error term in the selection equation. The fact that it is negative means that the unobservables that increase labor productivity simultaneously lower the probability of cloud adoption.

For firms active in manufacturing and in information and communication services, we find strong evidence that firms that use cloud computing are more productive than firms that do not use this new digital technology. Yet, this is not the case for companies in business services or other service firms.

7 Concluding remarks

The advent of cloud computing is expected to revolutionize firms' usage of IT technologies. Cloud solutions allow firms to flexibly adapt their IT capacities and the IT solutions to their current needs, thus quickly up- and downscaling their IT resources. The elimination of the fixed-costs connected with large in-house IT investments and their substitution with variable costs related to cloud usage is seen as the major benefit of this technological revolution. Particularly for small firms, it could represent a true game changer that enables productivity growth.

The empirical evidence on who uses the cloud, especially with respect to its impact on firms' IT investment behavior and productivity, is still scarce. Our paper aims to add three pieces of evidence to the existing discussion. First, it provides some novel empirical evidence on the determinants of cloud adoption. While this is interesting *per se*, it is also an important step to model the selection process into cloud adoption, which is a fundamental ingredient for the next steps. Second, accounting for the endogenous nature of cloud adoption, we assess how the use of the cloud affects investment in IT. Third, we present evidence on whether and how the use of the cloud affects labor productivity.

We focus on a sample of German firms drawn from the ICT Survey of the German statistical offices and matched to the AFiD panels on manufacturing and services. While, due to the merging procedure, the sample is unfortunately small, it is representative and covers different sectors of the economy. Moreover, for the firms in the sample we have accurate information about their investment behavior and characteristics. The sample covers 3,218 observations for the years 2014 and 2016.

Our first result is that cloud adoption is positively related to the firm's size, the amount of IT staff, and the share of sales over the internet, although the former is only true for manufacturing. Moreover, we show that manufacturing firms are more likely to adopt cloud solutions as the quality of their local broadband infrastructure increases. We do not find the same correlation for service firms. Yet, this is likely driven by the fact that these firms are mainly located in urban areas where the quality of the broadband infrastructure is generally good.

We then assess the impact of cloud adoption on IT investment and labor productivity. We use a simple OLS approach with industry, year, and region fixed effects, but we also implement an endogenous treatment regression model to account for the potential endogenous selection into cloud usage.

When assessing IT investment, there appears to be a significant positive correlation with the usage of the cloud; but this disappears once we control for the firm's IT capital stock from the previous year. Therefore, we do not find evidence that the use of the cloud is a substitute for in-house investment in IT technologies as hypothesized by the literature. To the best of our knowledge, this is the very first empirical evidence on this linkage. We instead estimate a positive and significant impact of cloud usage on firms' labor productivity, yet only for firms in manufacturing and, when accounting for the cloud's adoption endogeneity, also for firms in information and communication services.

Our study provide a coherent and overarching framework to assess the motives and the implications of the usage of cloud computing solutions in a representative sample of German firms. Our findings yield a comprehensive view of the role of cloud computing for firms behavior, which significantly contributes to the current discussion. Not only do we provide new evidence on the lack of an impact of cloud solutions on investment behavior, but we also provide more compelling evidence that this is the "true" causal impact since we explicitly model the endogenous nature of the cloud adoption and we address selection by using a plausibly exogenous instrument: broadband availability.

Nonetheless, our study suffers of some limitations. First, and foremost, the available data, although better than in other studies, is still not ideal. Unfortunately, we lack a large panel tracking more firms over time. This latter limitation is particularly severe as it does not allow us to use state-of-the-art methodologies to better assess the impact of the cloud on productivity. Second, we only observe whether a firm adopts cloud solutions at a given point in time, but we do not observe how much the firm invests in these solutions. This has implication for the empirical approach we take and does not allow us to fully assess firms' investment behavior and usage of the cloud.

References

Ackerberg, D., Benkard, C., Berry, S., Pakes, A., 2007. Econometric tools for analyzing market outcomes, in: Heckman, J.J., Leamer, E.E. (Eds.), Handbook of Econometrics. Amsterdam: North-Holland. volume 6A. chapter 63, pp. 4171–4276.

Ackerberg, D.A., Caves, K., Frazer, G., 2015. Identification properties of recent production function estimators. Econometrica 83, 2411–2451. doi:10.3982/ECTA13408.

Ahrend, R., Farchy, E., Kaplanis, I., Lembcke, A.C., 2017. What makes cities more productive? Agglomeration economies and the role of urban governance: Evidence from 5 OECD countries. OECD Productivity Working Papers, No. 6 .

Andres, R., DeStefano, T., Niebel, T., Viete, S., 2020. Capital incentive policies in the age of cloud computing: an empirical case study. ZEW Discussion Paper 20-036.

van Ark, B., 2016. The productivity paradox of the new digital economy. International Productivity Monitor 31.

Armbrust, M., Fox, A., Griffith, R., Joseph, A.D., Katz, R.H., Konwinski, A., Lee, G., Patterson, D.A., Rabkin, A., Stoica, I., Zaharia, M., 2009. Above the Clouds: A Berkeley View of Cloud Computing. Technical Report No. UCB/EECS-2009-28 URL: www.eecs.berkeley.edu/Pubs/TechRpts/2009/EECS-2009-28.pdf.

Banal-Estañol, A., Duso, T., Seldeslachts, J., Szücs, F., 2022. R&d spillovers through rjv cooperation. Research Policy 51, 104465.

Bartel, A., Ichniowski, C., Shaw, K., 2007. How does information technology affect productivity? plant-level comparisons of product innovation, process improvement, and worker skills. The Quarterly Journal of Economics 112, 1721–1758.

Bartelsman, E., Falk, M., Hagsten, E., Polder, M., 2019. Productivity, technological innovations and broadband connectivity: firm-level evidence for ten European countries. Eurasian Business Review 9, 25–48. doi:https://doi.org/10.1007/s40821-018-0113-0.

Benlian, A., Hess, T., 2011. Opportunities and risks of software-as-a-service: Findings from a survey of it executives. Decision Support Systems 51, 232–246.

Bertschek, I., Briglauer, W., Hüschelrath, K., Kauf, B., Niebel, T., 2015. The economic impacts of telecommunications networks and broadband internet: A survey. Review of Network Economics 14, 201–227.

Bertschek, I., Niebel, T., 2016. Mobile and more productive? firm-level evidence on the productivity effects of mobile internet use. Telecommunications Policy 40, 888–898.

Bertschek, I., Polder, M., Schulte, P., 2019. Ict and resilience in times of crisis: evidence from cross-country micro moments data. Economics of Innovation and New Technology 28, 759–774. doi:10.1080/10438599.2018.1557417.

Biagi, F., 2013. ICT and Productivity: A Review of the Literature. JRC Working Papers on Digital Economy 2013-09 .

Bloom, N., Pierri, N., 2018. Cloud Computing Is Helping Smaller, Newer firms Compete. Harvard Business Review .

Brynjolfsson, E., McAfee, A., 2014. The Second Machine Age: Work, Progress and Properity in a Time of Brilliant Technologies. W.W. Norton & Company.

Brynjolfsson, E., McAfee, A., Sorell, M., Zhu, F., 2008. Scale without mass: Business process replication and industry dynamics. Harvard Business School Technology & Operations Mgt. Unit Research Paper 07-16.

Bugamelli, M., Pagano, P., 2004. Barriers to investment in ict. Applied Economics 36, 2275–2286.

Byrne, D., Corrado, C., 2017. Ict services and their prices: What do they tell us about productivity and technology? International Productivity Monitor 33, 150–181.

Byrne, D.M., Corrado, C., Sichel, D., 2020. The Rise of Cloud Computing: Minding your P's, Q's and K's. Mimeo .

Cainelli, G., Fracasso, A., Marzetti, G.V., 2015. Spatial agglomeration and productivity in Italy: A panel smooth transition regression approach. Papers in Regional Science 94, S40–S67.

Cainelli, G., Ganau, R., 2018. Distance-based agglomeration externalities and neighbouring firms' characteristics. Regional Studies 52, 922–933.

Cardona, M., Kretschmer, T., Strobel, T., 2013. ICT and Productivity: Conclusions from the Empirical Literature. Information Economics and Policy 25, 109–125. doi:10.1016/j.infoecopol.2012.12.002.

Clougherty, J.A., Duso, T., Muck, J., 2016. Correcting for self-selection based endogeneity in management research: Review, recommendations and simulations. Organizational Research Methods 19, 286–347.

De Loecker, J., Syverson, C., 2021. An industrial organization perspective on productivity. CEPR Discussion Paper 16513.

De Stefano, T., Kneller, R., Timmis, J., 2020. Cloud computing and firm growth. Research Paper 2020/02, University of Nottingham .

DeStefano, T., Backer, K.D., Moussiegt, L., 2017. Determinantes of digital technology use by companies. OECD Science, Technology and Innnovation Policy Papers 40.

Doraszelski, U., Jaumandreu, J., 2008. R&D and productivity: Estimating production functions when productivity is endogenous. CEPR Discussion Papers 6636.

Doraszelski, U., Jaumandreu, J., 2013. R&D and productivity: Estimating endogenous productivity. Review of Economic Studies 80, 1338–1383.

Duso, T., Nardotto, M., Schiersch, A., 2021. Broadband and productivity: Structural estimates for germany. DIW Discussion Paper 1988.

Eurostat, 2021. Cloud computing - statistics on the use by enterprises. URL: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Cloud_computing_-_statistics_on_the_use_by_enterprises#Enterprises_using_cloud_computing.

Fabling, R., Grimes, A., 2016. Picking up speed: Does ultrafast broadband increase firm productivity? Motu Working Paper 16-22 .

FDZ der Statistischen Ämter des Bundes und der Länder, 2019. AFiD-Panel Industrieunternehmen 2001-2016, Metadatenreport. doi:10.21242/42221.2016.00.01.1.1.0.

FDZ der Statistischen Ämter des Bundes und der Länder, 2020. AFiD-Panel Strukturerhebung im Dienstleistungsbereich 2008-2018, Metadatenreport. doi:10.21242/47415.2018.00.01.1.1.0.

FDZ der Statistischen Ämter des Bundes und der Länder, 2021. Erhebung zur Nutzung von Informations- und Kommunikationstechnologien in Unternehmen 2019. doi:10.21242/52911.2019.00.00.1.1.0.

Gal, P., Nicoletti, G., Renault, T., Sorbe, S., Timiliotis, C., 2019. Digitalisation and productivity: In search of the holy grail - firm-level empirical evidence from eu countries. OECD Economics Working Papers No.1533 .

Garrison, G., Wakefield, R.L., Kim, S., 2014. The effects of it capabilities and delivery model on cloud computing success and firm performance for cloud supported processes and operations. International Journal of Information Management 35, 377–393.

Gornig, M., Schiersch, A., 2019. Agglomeration economies and firm tfp: different effects across industries. DIW Discussion Paper 1788.

Griffith, R., Huergo, E., Peters, B., Mairesse, J., 2016. Innovation and productivity across four European countries. Oxford Review of Economic Policy 22, 483–498.

Inklaar, R., Timmer, M.P., van Ark, B., 2007. Mind the Gap! international Comparisons of Productivity in Services and Goods Production. German Economic Review 8, 281–307.

Jin, W., McElheran, K., 2019. Economies before scale: Learning, survival, and performance of young plants in the age of cloud computing. Rotman School of Management Working Paper 3112901.

Jorgenson, D., 1967. The Theory of Investment Behavior. URL: http://www.nber.org/books/ferb67-1.

Le Mouel, M., Schiersch, A., 2020. Knowledge-based capital and productivity divergence. DIW Discussion Paper 1868.

Levinsohn, J., Petrin, A., 2003. Estimating production functions using inputs to control for unobservables. Review of Economic Studies 70, 317–341.

Low, C., Chen, Y., Wu, M., 2011. Understanding the determinants of cloud computing adoption. Industrial Management & Data Systems 111, 1006–1023.

Martin, P., Mayer, T., Mayneris, F., 2011. Spatial concentration and plant-level productivity in France. Journal of Urban Economics 69, 182–195.

Masanet, E., Shehabi, A., Liang, J., Ramakrishnan, L., Ma, X., Hendrix, V., Walker, B., Mantha, P., 2013. The Energy Efficiency Potential of Cloud-?Based Software: A U.S. Case Study. Technical Report. Lawrence Berkeley National Laboratory.

Mell, P., Grance, T., 2011. The NIST Definition of Cloud Computing. NIST Special Publication 800-145 URL: https://csrc.nist.gov/publications/detail/sp/800-145/final.

Melo, P.C., graham, D.J., Levinson, D., Aarabi, S., 2017. Agglomeration, accessibility and productivity: Evidence for large metropolitan areas in the US. Urban Studies 54, 179–195.

Melo, P.C., Graham, D.J., Noland, R.B., 2009. A meta-analysis of estimates of urban agglomeration economies. Regional Science and Urban Economics 39, 332–342.

Nicoletti, G., von Rueden, C., Andrews, D., 2020. Digital technology diffusion: A matter of capabilities, incentives or both? European Economic Review 128, 103513. URL: https://www.sciencedirect.com/science/article/pii/S0014292120301446, doi:https://doi.org/10.1016/j.euroecorev.2020.103513.

OECD, 2014. Cloud Computing: The Concept, Impacts and the Role of Government Policy. OECD Digital Economy Papers 240.

OECD, 2017. Oecd digital economy outlook doi:https://doi.org/10.1787/9789264276284-en.

Ohnemus, J., Niebel, T., 2016. On the determinants of cloud computing adoption. 27th European Regional Conference of the International Telecommunications Society (ITS) .

Oliveira, T., Thomas, M., Espadana, M., 2014. Assessing the determinants of cloud computing adoption: An analysis of the manufacturing and services sectors. Information & Management 51, 497–510. doi:10.1016/j.im.2014.03.006.

Olley, S., Pakes, A., 1996. The dynamics of productivity in the telecommunications equipment industry. Econometrica 64, 1263–1297.

Opara-Martins, J., Sahandi, R., Tian, F., 2016. Critical analysis of vendor lock-in and its impact on cloud computing migration: a business perspective. Journal of Cloud Computing: Advances, Systems and Applications 5, 1–18. doi:10.1186/s13677-016-0054-z.

Perry, G., . How cloud & utility computing are different. URL: https://gigaom.com/2008/02/28/how-cloud-utility-computing-are-different/.

Richter, P.M., Schiersch, A., 2017. CO_2 emission intensity and exporting: Evidence from firm-level data. European Economic Review 98, 373–391.

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

Wooldridge, J.M., 2010. Econometric analysis of cross section and panel data. MIT press.

Yang, H., Tate, M., 2012. A descriptive literature review and classification of cloud computing research. Communications of the Association for Information Systems 31, 35–60.

Zolas, N., Kroff, Z., Brynjolfsson, E., McElheran, K., Beede, D.N., Buffington, C., Goldschlag, N., Foster, L., Dinlersoz, E., 2021. Advanced technologies adoption and use by U.S. firms: Evidence from the annual business survey. NBER Working Paper 28290.

A Tables

Table A.1: Cloud user and non-user by region and industry

	rural		urban	
	cloud user	non-user	cloud user	non-user
manufacturing	128	464	318	950
inform.&com. serv.	12	26	204	258
business serv.	7	37	104	328
other serv.	15	42	92	233