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ICT as an Enabler of Innovation
Evidence from German Microdata

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ICT as an Enabler of Innovation: Evidence from German Microdata*

Abstract

Using data from a survey of German manufacturing firms, this paper empirically tests the hypothesis that investment in ICT enables product innovation at the firm level. The empirical approach employs a value-added model, which controls for time-invariant firm characteristics. We instrument with exogenous impulses that affect firms' decision to invest in ICT to account for remaining endogeneity that arises due to the fact that firms may decide to innovate and invest in ICT simultaneously. In addition, we employ matching methods to corroborate the results. We find consistent evidence that ICT investment increases firms' product innovations.

JEL Code: O14, O31.
Keywords: Innovation, information and communication technology, manufacturing sector.

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1. Introduction

Investment in ICT is commonly believed to fundamentally have changed and to continue changing firms' business practices, thereby enabling innovations (Bresnahan and Trajtenberg, 1995; Spiezia, 2011). Various studies find that ICT enables innovation by capturing, organizing, and processing knowledge, all of which are important in the innovation process. Numerous efficiency gains can be realized from increased use of ICT, all of which may help in creating innovations. New forms of coordination, such as more efficient communication within firms and with customers, as well as networks among business partners, may occur. ICT applications allow for flatter hierarchies in firms, which result in the reorganization of responsibilities. Moreover, collecting information is facilitated as large amounts of data can be stored and processed. Better coordination in R&D, among business partners and customers may lead to the development of new products and processes. Geographic limitations are reduced as ICT allows reaching a bigger market and expands the universe of possible business partners (Forman et al., 2014; Koellinger, 2005). In addition, ICT makes firms more productive and therefore creates capacities that may be used for the development of innovations.

Investment in ICT capital has moreover economic implications beyond the single firm since it has been a crucial determinant of aggregate economic growth and productivity (e.g., van Ark et al., 2008). Given its importance to and impact on the economy, enhancing ICT investment is of strong political interest. The EU Digital Agenda lists as an explicit goal the promotion of longer-term strategic ICT innovation as well as enhanced investment in research and development of ICT (European Commission, 2010a). The EC's ICT Policy Support Program aimed at encouraging the use of ICT applications in small and medium-size enterprises to enhance their innovative capacity and competitiveness during the period 2007 to 2013.

To date, few studies tackle the endogeneity in the relationship between firms' investment in ICT and innovation. Disentangling the effect is not trivial since, in most cases, ICT investment and innovation occur together. Econometric challenges in measuring the benefits of ICT use stem from the fact that investment in ICT capital cannot be assumed to be exogenous to the innovation process, since ICT investment does not occur randomly across firms. On the contrary, in most cases, such investment serves certain organizational purposes that are unobservable by the researcher, causing an omitted variables bias. A large body of literature concludes that in order to fully profit from the adoption of ICT, a firm must engage in complementary co-innovation (see, e.g., Bresnahan et al., 2002; Brynjolfsson et al., 2002), which gives rise to a simultaneity bias. In addition, whether a firm successfully adopts ICT depends on its innovative history (Hempell et al., 2004), that is, already innovative firms find it easier to make use of new ICT, giving rise to reverse causality.

This provides provides empirical evidence on how investing in ICT impacts firm innovation. We use a cross-sectional sample of German manufacturing firms from the Ifo Innovation Survey. This survey annually gathers detailed information on firms' innovative activity as well as general firm characteristics. In 2011, it additionally asked about investment in ICT and the use of these technologies. We focus on product innovations in the empirical analysis, which allows us to exploit some exogenous variation. Controlling for lagged values of the dependent variable, we estimate a value added model that allows us to control for time-invariant firm characteristics.

Next, we further exploit the fact that the survey provides information on whether external IT consultants have provided an impetus to invest in ICT capital. Conditional on our control variables, we argue that IT consultants are exogenous to the companies' product innovation strategy, but are highly predictive of ICT investment, which allows us to additionally employ an instrumental variable approach.[1] We then provide alternative methods to get around endogeneity bias, we employ semi-parametric propensity score matching and direct matching. These methods allow us to check the assumptions on the underlying functional form, as well as to exclude selection on observable firm characteristics.

The empirical findings establish a positive relationship between ICT investment at the firm level and subsequent innovative activity. Results from propensity score and direct matching methods corroborate this relationship. According to the IV results, a manufacturing firm that made a major investment in ICT is roughly 11 percentage points more likely to introduce a product innovation within the next two years. This indicates that ICT is indeed an important enabler of product innovations.

The paper proceeds as follows. Section 2 introduces previous studies on the relationship between ICT investment and firm performance. Sections 3 and 4 introduce the data and the identification strategy, respectively. Section 5 presents and discusses the results from OLS, the value added model, matching, and IV approaches. Section 6 concludes.

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1 IT consultants cannot be regarded exogenous to the innovation of new processes. We therefore concentrate on product innovation in this analysis.

2. Previous Evidence on ICT Investment and Firm Performance

Numerous empirical studies show the importance of ICT for firm performance, measured as innovation or productivity. The causal, positive link between ICT infrastructure and economic performance has been established at the aggregate level (Czernich et al., 2011; Röller and Waverman, 2001). In particular, the lower ICT intensity of the European economy has been identified as one explanation for the lower growth in productivity in European firms relative to U.S. establishments during the second half of the 1990s (van Ark et al., 2008).

At the firm level, various studies find that ICT enables innovation by capturing, organizing, and processing knowledge, all of which are important in the innovation process. Early studies on ICT investment focus on the role of ICT in organizational innovation and conclude that the successful implementation of ICT is tied to organizational changes. That is, firms need to engage in certain organizational "co-innovation" to fully capture the benefits of ICT (see, e.g., Brynjolfsson and Hitt, 2000). Examples of organizational change include flatter hierarchies in firms due to improved communication channels, resulting in the reorganization of responsibilities.

Moreover, collecting information is facilitated by ICT capital, as large amounts of data can be stored and processed. In addition, geographic limitations are reduced (Koellinger, 2005), which may open the door to new markets and new ways of conducting business. Gretton et al. (2004) argue that ICT allows for new forms of coordination, such as more efficient communication within firms and with customers, and has the potential to create networks among business partners. Better coordination in R&D, among business partners and customers may lead to the development of new products and processes.

All these changes may plausibly facilitate the development of new ideas and products in that they make firms more productive and therefore create additional capacities that may be used for the development of innovations. Findings are heterogeneous with regard to which sector of the economy benefits most from ICT, but the weight of the evidence to date points to the service sector. For example, using panel data, Hempell et al. (2004) find that ICT capital increased productivity in German and Dutch firms in the service sector. Polder et al. (2009) stress the importance of ICT in all sectors of the economy, but nevertheless find that ICT investment plays a rather limited role in manufacturing and is, moreover, only marginally significant for organizational innovation. A survey among firms in the Madrid metropolitan area finds that benefits of ICT are most prevalent in the IT and services sector (Gago and Rubalcaba, 2007). By contrast, a study among German firms by Bertschek et al. (2013) finds that local broadband infrastructure positively affects innovations of firm in manufacturing and service sectors.

The studies mentioned so far have confirmed a strong association between ICT and business innovation. However, they do not take into account the pronounced endogeneity between firm performance and ICT. ICT use, organizational change, and product innovation can be complementary (Bresnahan et al., 2002). Moreover, whether a firm successfully adopts ICT depends on its innovative history (Hempell et al., 2004), that is, already innovative firms find it easier to make use of new ICT. One study that directly addresses the endogenous nature of ICT use in firms is Spiezia (2011). Using a comprehensive dataset on firms in OECD countries, the author employs an instrumental variables approach in which he instruments ICT use with lagged values of ICT (which addresses a bias from simultaneity, but not from omitted variables). He also uses an indicator for whether a firm made use of e-government – i.e., whether it interacted with authorities online – as instrument. Spiezia finds that ICT enables innovation, particularly product and marketing innovation, in the manufacturing as well as the services sector. He finds no evidence that ICT use increases the capability of a firm to cooperate, develop innovation in house, or introduce new products to the market. Hall et al. (2012) also try to model the endogeneity of ICT. Rather than treating it as a mere input to the production function, they investigate ICT in parallel with R&D as an input to innovation. They thus take into account the possible complementarities among different types of innovation activities. Using Italian firm-level data, they find that R&D and ICT are both strongly associated with innovation and productivity, with R&D being more important for innovation and ICT for productivity.

3. Data from the Ifo Innovation Survey

The data we use in this analysis are from the Ifo Innovation Survey, which aims at mapping innovative activity in Germany. The paper based survey has been conducted annually since 1979 among German manufacturing firms (for a detailed description, see e.g. Penzkofer, 2004; Lachenmaier, 2007). In 2012, the paper based questionnaire on activity in 2011 was sent out to 2,124 firms, out of which 744 replied. The response rate is therefore 35 percent. Information on ICT investment and use was obtained only for the year 2011 as a special feature. Our data are thus of cross-sectional nature regarding ICT investment, while innovative activity and other firm characteristics are available as a panel.

The unit of observation is a single firm or, respectively, a product range in the case of multi-product firms. Throughout the paper, we refer to the observations as "firms" for ease of exposition. In 2012, 744 firms participated in the survey, and it is from these that we obtain information for the year 2011. The actual wording of the questions relevant for this study can be found in Figure A-1 in the Appendix.

The centerpiece of the questionnaire is information on innovative activity in the preceding year. Innovations are defined as "the implementation of a new or significantly improved product (or process), as well as production and process techniques including the information technique in office and administration." Specifically, firms are asked annually whether they started or completed a product innovation during the preceding year. Table 1 reveals that 42 percent of the firms completed, and 44 percent started, a product innovation. Combining the information, we find that 59 percent of the firms engaged in innovative activity in 2011, defined as an indicator variable that takes the value 1 if a firm either started or completed a product innovation, and zero otherwise. We use a dummy variable for completed product innovations as the main measure of innovative activity. This variable captures an informal and direct measure of innovative output at the firm level, and thus reflects an actual benefit to the economy as opposed to started innovations that have not yet been introduced to the market. Our innovation holds certain advantages over alternative measures such as patent counts or R&D expenditure: patents capture only a fraction of all innovations; R&D may not necessarily lead to innovations (for an overview of different innovation measures and their characteristics, see Hagedoorn and Cloodt, 2003).

Our measure is a more direct indicator of innovative activity, and yet has certain disadvantages. In general, the indicator variable we observe is a crude measure of innovative activity that does not allow for further differentiation. The Ifo Innovation Survey captures major technological breakthroughs and minor inventions alike; changes in an existing product receive the same weight as completely new products. We thus cannot draw conclusions as to the size or importance of the innovations enabled by ICT investment. Neither does the dummy information on innovative activity provide a count of the number of product innovations realized in the previous year.

In addition to product innovations, firms are asked about their process-innovation behavior. The question is worded identically to that about product innovations, that is, firms are asked whether they introduced, started, or aborted a process innovation during the previous year. In 2011, 49 percent of firms introduced at least one process innovation.

Table 1: Descriptive Statistics for 2011, Firms Participating in the Ifo Innovation Survey

	Obs.	Mean	Std. Dev.	Min	Max
Product innovation					
Started	744	0.44	0.50	0	1
Realized	744	0.42	0.49	0	1
Started or realized	744	0.59	0.49	0	1
Process innovation started	744	0.49	0.50	0	1
ICT investment and use					
ICT investment	744	0.59	0.49	0	1
IT equipment	744	0.53	0.50	0	1
Communications equipment	744	0.26	0.44	0	1
Software	744	0.50	0.50	0	1
Investment impulse from IT consultancy	744	0.15	0.35	0	1
Share of employees using computer	744	0.52	0.27	0	1
General firm characteristics					
Share academics	744	0.11	0.13	0	1
No. employees	744	539.58	3,810.80	1	83,156
Total sales (in million €)	744	357.93	3,049.69	38	57,400
Firm exports	744	0.75	0.43	0	1
Previous innovations and panel survival					
Product innovation realized in t-1	744	0.44	0.42	0	1
Product innovation realized in t-2	744	0.43	0.40	0	1
Non-response in t-1	744	0.33	0.47	0	1
Non-response in t-2	744	0.41	0.49	0	1

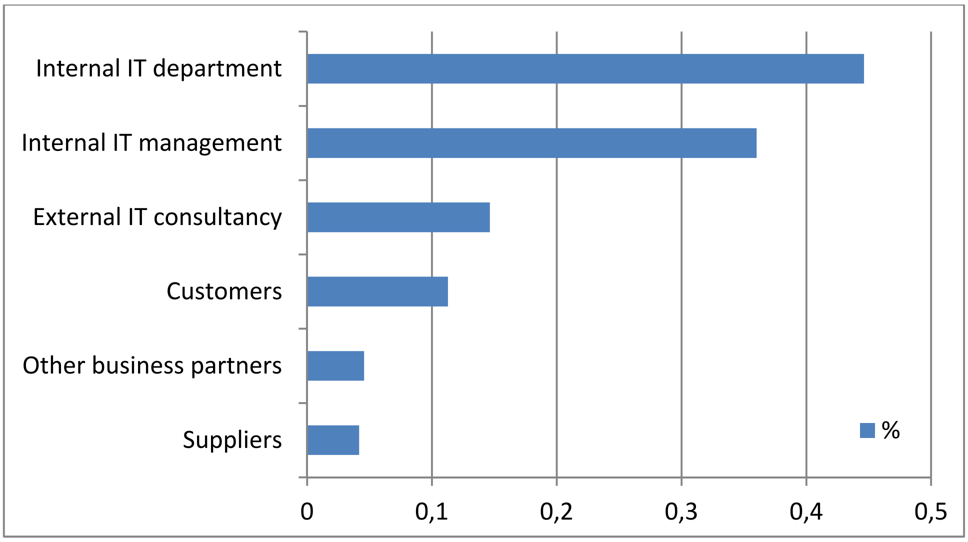
Notes: Data Source: Ifo Innovation Survey (Ifo Institute, 2012). The number of employees variable contains 39 missing values; total sales contains 102 missing values. Previous innovations in t-1 are imputed for 242 observations and for 308 in t-2. Variables are imputed with the annual average of their respective NACE code at the two-digit level.

In 2012, the survey collects data on firms' ICT investment and usage in the years 2011 and 2010 as a special feature. First, and most importantly, firms are asked whether they invested in new ICT equipment during the preceding two years. This was the case for 58 percent of the responding firms. This dummy information is a measure of ICT at the firm level in that it captures any notable changes in a firm's ICT capital stock. We prefer this measure over, for instance, the level of capital stock. The latter will not be readily known to most respondents, and even if they do know, they may be reluctant to disclose it, a problem that also plagues other financial measures in the Ifo Innovation Survey. In this way, we capture some information with the investment dummy and all respondents reply to this question. As Table 1 reveals, in our sample, 59 percent of firms made considerable investment in ICT innovations during the previous two years.

Investment in ICT capital is then divided into three categories, in accordance with the classification of the OECD (2010a).[2] Firms are asked to indicate the type of ICT capital in which they predominantly invested: *information technology equipment* (computers and related hardware), *communications equipment* (infrastructure to make the hardware interconnect), or any type of *software*. Table 1 reveals that about 53 percent of all firms (90 percent of the investing firms) invested in IT equipment, followed by software at 50 percent (84 percent of investing firms) and communications equipment at 26 percent (48 percent of investing firms).

To glean some understanding of firms' investment behavior, they are asked what motivated them to invest in ICT. All firms are asked this question, irrespective of whether they undertook major investment in ICT. Figure 1 displays the results: most ICT investments are initiated by internal sources, namely, internal IT management or the IT department in general (at 44 and 36 percent, respectively). About 15 percent of firms invest in ICT based on advice from external IT-consultancies; another 13 percent are inspired by customer suggestions. Suppliers and other business partners play a minor role in the decision to acquire new ICT equipment, at 4 and 5 percent, respectively. The survey also inquired about the number of employees who use a computer. On average, just over half the employees (53 percent) use a computer as part of the job on a daily basis. Moreover, as of 2011, 12 percent of the employees are academics in our sample of manufacturing firms, defined as employees who have a university degree.

Figure 1: Catalysts for investing in ICT



2 According to the OECD (2010a), investment in ICT is defined as "the acquisition of equipment and computer software that is used in production for more than one year. ICT has three components: information technology equipment (computers and related hardware); communications equipment; and software. Software includes acquisition of pre-packaged software, customized software and software developed in-house".

Data Source: Ifo Innovation Survey (Ifo Institute, 2012).

The firms participating in the Ifo Innovation Survey are a subset of the firms that take part in the Ifo Business Survey, a monthly survey that measures the business climate in Germany (for a detailed description, see Becker and Wohlrabe, 2008). We therefore obtain more general firm characteristics, such as size and general performance, from the Ifo Business Survey. The average firm in our sample has around 540 employees and annual sales of 368 million euros. 75 percent of responding firms report that they engage it export activity. We also have information on firms' locations from the Ifo Business Survey but, due to privacy concerns, a firm's location can be identified only at the level of German Federal States.

The analysis relies in part on information about innovative activity in previous periods for product innovation. We thus use information from previous waves. On average, the sample's product innovation behavior is relatively stable over time, with 44 percent of firms having realized a product innovation in 2010 and 43 percent in 2009. Over time, the number of observations decreases, which is due to firms dropping out of the panel. Kipar (2012) calculated an average annual dropout rate of 20 percent and a survival of 4.6 years in each wave since 1981. The number of firms whose innovative behavior can be followed over time is considerably smaller compared to the cross-section in 2011. Out of the 744 respondents in 2011, 502 firms are contained in the 2010 survey and 361 can be observed in 2009. To retain the remaining information for the firms that cannot be observed in previous periods, we impute the missing values of innovative activity in each year with the annual average of each two-digit NACE code for product and process innovations, respectively.[3]

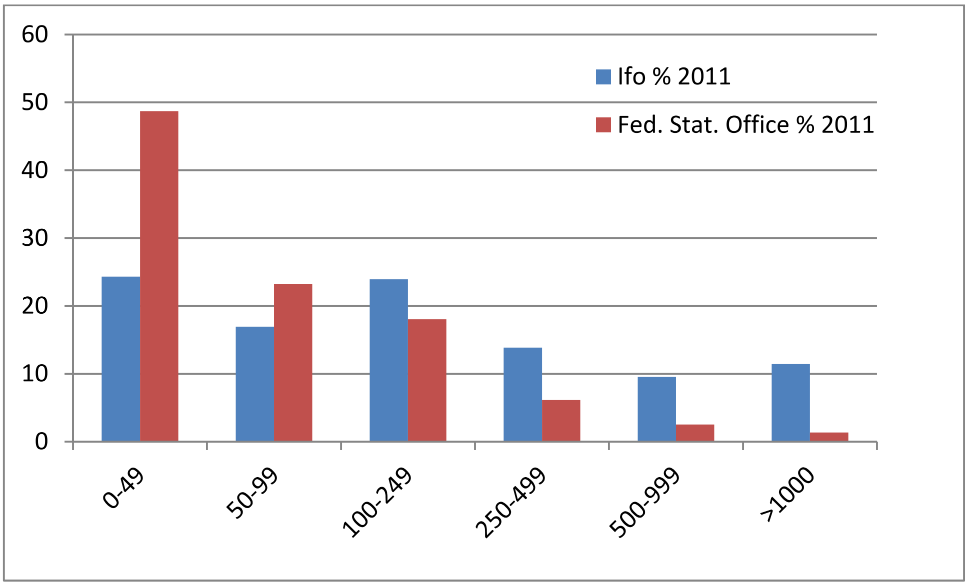
The Ifo Innovation Survey is paper based and participation is voluntary, both aspects that may raise concern as to its representativeness. This section compares the firms in the Ifo Innovation Survey with official statistics on German establishments in the manufacturing business from the Federal Statistical Office. Our sample of 744 firms captures about 2.5 percent of all employees in the manufacturing sector in Germany.[4] But large firms are overrepresented in this sample with an average of about 540 employees. The average firm in the German manufacturing sector employs 130 people in 2011 (Federal Statistical Office, 2014). Figure 2 highlights the relative distribution of firm sizes. Compared to the distribution of all manufacturing businesses in Germany (as of

3 We test for the robustness of the results with respect to the imputation when we present the results.

4 The sum of employees captured by the survey is 401,448. According to the Federal Statistical Office (2014), in 2011 15,867,580 people were employed in the German manufacturing sector.

2011), firms up to 100 employees are under- and firms with 100 or more employees are oversampled relative to the full population of manufacturing firms. This selection bias of the Ifo Innovation Survey toward larger firms stems from the fact that the survey is intended to capture as much of the workforce in the manufacturing business as possible (Kipar, 2012). Comparisons between the 2011 sample of the Ifo Innovation Survey and the official statistics by industry branch and location are presented in the Appendix. Figures A-4 and A-5 reveal that overall, the distribution of the Ifo survey follows the distribution of German manufacturing firms quite well. Regarding the three largest sectors, one can see in Figure A-5 that the Survey over-represents machinery and equipment and firms in fabricated metal products and food products and beverages are underrepresented by about 9 and 8 percentage points, respectively. Also if plotted by Federal State, the two distributions are largely congruent, merely Bavaria is notably over-represented in our sample.

Figure 2: Representativeness of the Ifo Innovation Survey by number of employees



Data Source: Ifo Innovation Survey (2012) and Federal Statistical Office (2014).

4. Identification Strategy

4.1. Value Added Model

We want to determine the extent to which ICT capital enables product innovation. Since many firm characteristics remain unobserved, we use the fact that we can follow the firms' innovation behavior over time and employ a value-added model.[5] In this setup, lagged values of the dependent variable are included on the right hand side of the estimation equation to account for time-persistent firm characteristics. The basic equation we estimate thus takes the following form:

$$Y_{i,2011} = \alpha + \beta_1 ICT_{i,2011/2010} + \beta_2 Y_{i,2010} + \beta_3 Y_{i,2009} + X'_{i,2011}\gamma + \varepsilon_i \qquad (2.1)$$

where the dependent variable Y is a dummy variable that takes the value 1 if firm i introduced a product innovation to the market during 2011. *ICT* is a binary indicator for whether the firm made substantial investments in ICT during the period 2010 to 2011. We control for lagged values of product innovation activity in the previous two periods.[6] This is intended to account for the fact that, overall, generally more innovative firms are likely to persist in innovation over time. They may also exhibit a different ICT investment pattern than generally less innovative firms.

X contains several characteristics at the firm level. We control for differences in scale by including turnover and number of employees, both scaled as logarithms. Firms with a high share of skilled labor are likely to adopt new ICT more quickly and are likely to innovate more. To reflect the skill level as well as IT intensity in the firm, the share of employees using a computer, as well as the share of employees with an academic degree, are included. A dummy for whether a firm exports is included, since exports have been established as a cause of innovation by the literature on endogenous innovation and economic growth (cf. Grossman and Helpman, 1991). Moreover, we include industry fixed effects, at the NACE two-digit level, to capture sector-specific differences in innovative activity, and regional fixed effects to capture influences such as innovation policy and subsidy programs that may occur at the Federal State level.

Ordinary least squares (OLS) is likely to yield biased estimates due to a selection bias that arises from the fact that firms do not randomly invest in ICT, but instead choose to invest in a certain technology at a certain point in time. For a causal interpretation of OLS we would have to make the assumption that ICT investment occurred randomly conditional on the control variables. But despite the fact that we control for pre-treatment innovations, the treatment and comparison groups may systematically differ from each other, leading to a biased estimation of the effect of ICT. We generally expect the ICT coefficient to be upward biased due to endogeneity concerns that arise from the fact that firms may simultaneously decide to engage in innovative activity and

5 This estimation strategy has found predominant use in education economics to evaluate teacher effectiveness. See Kim and Lalancette (2013) for a detailed description and a review of the studies using value-added models.

6 We furthermore provide robustness tests for including one and three lags when we present the results.

invest in the needed ICT equipment. Furthermore, there may be an omitted variables bias if more innovative firms simply invest a larger share of their total sales in capital – and therefore in ICT equipment – as part of the general management strategy or for other reasons we cannot observe. In principle, including the lagged dependent variable should account for a large part of this effect. Nevertheless, there may still be unobserved heterogeneity that is unaccounted for by including previous innovations in the analysis. We refrain from including lagged innovations that exceed the second lag, since the number of firms that can be continually observed over three years already dropped by around 41 percent.

A bias in the opposite direction is also possible. Consider the case where generally non-innovative firms purposely invest in ICT capital in order to improve their innovation record. If the time lag between ICT investment and product innovations is longer than the two years we assume, we might actually underestimate the effect of ICT.

Also, the data may suffer from measurement error due to questionnaire design, which might lead to a downward bias under certain circumstances. As the survey is paper based and filled out by one representative (the position held by which may vary across firms), answering the questions on completed innovations as well as on ICT investment both involves subjective assessments. It is up to the respondent to decide whether the introduction of a new product or the "substantial improvement" of an already existing product occurred. Similarly, the regressor is unity when "considerable investments" in new ICT equipment were made. It is thus up to the respondent to decide on the importance of the innovation or the size of the investment. Since the values of both variables are generated by the same person, the measurement errors of the dependent variable and the regressor are most likely correlated. In the case of correlated measurement errors – provided they are correlated with the error term in Equation (2.1) – it is not possible to determine the direction of the bias of the coefficient of ICT in Equation (2.1) (see, e.g., Hyslop and Imbens, 2001).

4.2. Instrumental Variables

To test whether ICT investment does in fact lead to an increase in innovations, we need an empirical strategy that identifies variation in ICT investment that is exogenous to product innovation. To address remaining endogeneity concerns, as well as the potential measurement error, and to isolate the effect of ICT as much as possible, we use an instrumental variable approach to identify the effect of ICT investment on product innovation. To qualify as a valid instrument in this context, a variable must fulfill two crucial prerequisites: first, it must be highly predictive of ICT investment (relevance) and, second, it must have no other relation with innovation activity than through ICT investment (exogeneity) conditional on the other covariates. We propose the information on a catalyst for ICT investment as an instrument, specifically whether a firm received an impulse to invest in ICT from external IT consultancies.[7] We therefore estimate:

$$Y_{i,2011} = \alpha + \delta_1 I\hat{C}T_{i,2011/2010} + \delta_2 Y_{i,2010} + \delta_3 Y_{i,2009} + X'_{i,2011}\upsilon + \varepsilon_i \qquad (2.2)$$

with

$$I\hat{C}T_{i,2011/2010} = \mu + \xi_1 IT\_Consult_{i,2011/2010} + \xi_2 Y_{i,2010} + \xi_3 Y_{i,2009} + X'_{i,2011}\rho + \nu_i \qquad (2.3)$$

The first prerequisite – the instrument's relevance – will be tested in the following analysis; however, the second cannot be tested. For the instrumental variable to be valid, we have to assume that external IT consultants do not directly affect product innovations. We defend the validity of the instrument with the argument that, typically, IT consultancies are not involved in the firms' business strategies and do not directly make decisions concerning the product range. There is one way, however, in which IT consultancies may have a connection to product innovations. Process innovations are considered complementarities to new products (Bresnahan et al., 2002). If a firm engages an IT consultant as part of implementing a new strategy, for example, following a change in the management, and at the same time changes the product portfolio and the internal organization of processes, our assumption of strict exogeneity would be violated. To reduce the likelihood, that our instrument affects the outcome through this channel, we control for a firm's current activity in process innovations. We thus argue that conditional on the covariates (including the process innovation channel), our instrument likely fulfills conditional exogeneity.

In interpreting the instrumental variable results, it must be kept in mind that the variation in ICT investment caused by external IT consultants is not the same for the entire population of firms.

7 An IV approach that is similar in spirit to ours and that uses the Ifo Innovation Survey can be found in (Lachenmaier and Woessmann, 2006) where exogenous impulses to firms' innovative activities are used as instruments in order to analyze the impact of innovation on exports.

We expect to identify a local average treatment effect (LATE) from the instrumental variables estimation (Angrist and Pischke, 2009). Our instrument identifies the average treatment effect for that subgroup of firms that change their ICT investment behavior because they engaged an external IT consultant. In the spirit of Angrist and Pischke, we call these "compliers", i.e. the firms that change their treatment status due to the instrument. That is, these firms will not invest in ICT unless induced by a consultant and likewise, if induced, they will follow the advice and invest. Such firms may well differ from others in the quantity as well as the quality of ICT investments. If our assumption that external IT consultants are not directly linked to product innovations holds, the IV estimation will identify the causal effect of ICT investment on product innovation for the complier group. Normally, we would expect to overestimate the population effect of ICT in OLS. However, due to the LATE interpretation of our instrument it seems plausible that firms that undergo the effort and incur the expense of consulting external IT experts will invest in different types of ICT, or in larger amounts of ICT capital as part of a general reorganization campaign. Firms that do not need an IT consultant to accompany the ICT investment may on average replace already existing equipment rather than buying disruptive new technology. The local average treatment effect we estimate therefore might well be above the expected population effect.

4.3. Matching

We moreover propose matching (Rosenbaum and Rubin, 1983) as an alternative way to get around certain estimation biases. Matching methods eliminate that part of the selection problem that stems from selection on observable characteristics. As a non-parametric method, matching allows for a more careful comparison of treated and control group. We propose two kinds of matching methods, propensity score matching (see, e.g., Heckman et al., 1998) and direct matching (e.g., Abadie and Imbens, 2002). Both methods have the distinct advantage that they do not rely on linearity in the relationship between ICT investment and innovation, an assumption that may be especially hazardous in our case where the outcome variable as well as the main explanatory variable of interest is a dummy indicator. The estimation strategy of propensity score matching generates in a first step the predicted probability of investing in ICT for every firm based on past innovative activity as well as the other covariates. Common matching algorithms are nearest neighbor, radius caliper, or kernel (e.g., Epanechnikov) matching. In a second step, only firms with positive probabilities of both investing and not investing in ICT are compared to each other with respect to their innovations in order to ensure common support.

A slightly different approach to the propensity score – direct matching – is proposed as an alternative method that is considered superior to propensity score matching, at least in some aspects (Stuart, 2010). Direct matching relies on pairs of observations that are not only similar, but identical in all the required dimensions, that is, the method results in closer matches than does propensity score matching. We therefore chose to use exact matching as a supplementary tool for analysis. Unfortunately, the high comparability of treatment and control group comes at the cost of losing many observations – a problem that is aggravated as the number of covariates, for which identical characteristics are required, increases. Nonetheless, this method allows us to impose identical histories of innovative behavior on firms that invested in ICT and those that did not. Many of the covariates, such as innovation in previous periods, are binary. The small number of values that the covariates can take enables us to directly match on several characteristics without losing too many observations. The continuous variables "share of employees using a computer" and "share academics" are recoded into categories by quartiles, thus allowing exact matching. We create groups that are identical with respect to the size range of academics and range of computer use, whether the firm exports, the industry branch at the NACE one-digit level, and their history of product and process innovation, as well as non-response in the two previous periods. In addition, a propensity score for firm size, measured as the number of employees and annual turnover is generated and included in the matching process. The number of employees as a continuous variable contains valuable information that would be unused if this variable was converted into a categorical variable.

Post-matching, we apply the baseline regression in both methods to control for any differences that may remain in the matched sample. This procedure allows us to impose common support in the sample and it provides a convincing way to select observations on which the analysis is based. Moreover, the estimated ICT effect from the matching approaches may be interpreted as the average treatment effect under the assumption of conditional independence (or unconfoundedness), that is, if we observe everything that influences product innovations as well as ICT investment. Nonetheless, a positive association can – again – not necessarily be interpreted as a causal effect. In the presence of unobservable influences, however, neither ordinary least squares nor the matching approaches will isolate the causal effect of ICT investments.

Finally, we combine the instrumental variable and matching approaches and apply IV estimates to the matched samples.

5. ICT Investment and Innovation – Empirical Results

This section presents results from our empirical models. The basic results from the value-added model are introduced first as a benchmark, followed by the instrumental variables approach. Results from propensity score and exact matching methods and the combined approach of IV and matching are then presented to verify the plausibility of our findings.

5.1. Baseline Results from Value Added Model

Results from OLS (Columns (1) to (3)) and the value added regression (Column (4)) are reported in Table 2. ICT has a positive, statistically significant impact on innovative activity. If a firm made substantial investments in ICT within the previous two years, it is 19.5 percentage points more likely to have completed a product innovation, according to Column (1) of the table, in which we include only few firm controls. All control variables exhibit the expected signs. Firm size – measured by the number of employees (in logs) – , the share of highly educated employees, the share of employees that uses a computer on a daily basis as well as export activity are all positively related to and significant predictors of product innovation. We consecutively introduce the industry branch fixed effects (at the NACE two-digit level, Column (2)) and the Federal State fixed effects (Column (3)) in the regression. Controlling for these does not considerably change the estimated ICT coefficient.

This pattern changes considerably when we control for the lagged dependent variables, defined as product innovations in *t-1* and in *t-2*. The size of the ICT coefficient decreases by about 30 percent to 13.4 percentage points in Column (4).[8] In this estimation, the share of academics and the share of employees using the computer lose much of their predictive power, whereas past product innovations are highly indicative of contemporaneous activity. The coefficients of the number of employees and export activity considerably decrease in magnitude. This finding is in line with our expectations, and it supports the hypothesis that innovative behavior is highly persistent over time. We choose the specification in Column (4) as our baseline specification. The R-squared is 47.4 percent, indicating that the set of covariates explains much of the variation in the dependent variable.[9]

8 The two coefficients are statistically different from each other on a 1 percent level.

9 We test the robustness of our general specification by 1) restricting the first lagged dependent variable to 1, and 2) by restricting the average value of the two lags to 1. The ICT coefficients remain in the same order of magnitude (around 11 percentage points) and are statistically significant at the 99 percent level. Results are not shown and can be provided on request.

There is substantial fluctuation with regard to the firms responding in the survey. This situation necessitates a large number of imputed values, which might raise concern despite the fact that we control for imputed values in all specifications. Columns (5) and (6) in Table 3 therefore report results from a sample that consists of a panel of firms that can be observed in the survey between 2011 and 2009. Only firms that did not respond in 2010 (but are observed before and after) are imputed with the average value of product innovations of 2011 and 2009. Albeit the number of observations decreases by roughly 22 percent in the two-year panel in Column (5), and by about 41 percent in the three-year panel in Column (6), the effect of ICT investment is persistently positive and statistically significant. In addition, Columns (7) and (8) show results for the samples without any imputation for lagged innovation. The number of observations decreases further to 502, respectively 361. The estimates remain statistically significant and within the same order of magnitude as the previous specifications.

Table 3 reports some robustness checks of the presented results. In the first column, we introduce a third lag to the information on previous product innovations. The coefficient remains positive; it decreases slightly in magnitude and is statistically significant at 5 percent. The number of observations is only 265. The share of responding firms is already reduced considerably when two lags are included. We therefore refrain from making further use of information prior to two lagged time periods.

The way in which we define ICT investment does not capture innovations that take longer than two years to complete. To test whether ICT investment has economic implications beyond this time span, we introduce two alternative innovation measures. Columns (2) and (3) of Table 3 display the association between ICT investment and an indicator for whether product innovations were begun in 2011 and an indicator that combines all innovative activity. The latter takes the value unity when a product innovation had either been started or completed in 2011. As expected, the ICT coefficients are also positive and statistically significant at 10.5 and 13.9 percentage points, respectively. This indicates that ICT investment might indeed have some longer-run implications for the economy.

5.2. Instrumental Variable Results

We now present results from our instrumental variable approach, which is based on the fact that advice from external IT consultants is often the impetus behind a firms' investment in ICT but that these consultants do not directly affect changes in the firms' product portfolio themselves.

Table 2: Association between Investment in ICT and Innovation, Dependent Variable: Product Innovation Realized

	Fully Imputed OLS			Fully Imputed VAD	2010 imputed VAD		Without Imputation VAD	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Firm invested in ICT	0.195***	0.193***	0.193***	0.134***	0.162***	0.085**	0.191***	0.098**
	(0.034)	(0.033)	(0.033)	(0.030)	(0.033)	(0.034)	(0.037)	(0.039)
Log employees	0.001**	0.001	0.001	0.001	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Share academic	0.085***	0.091***	0.088***	0.036***	0.028**	0.025**	0.035***	0.036***
	(0.011)	(0.012)	(0.012)	(0.011)	(0.012)	(0.012)	(0.013)	(0.013)
Share using computer	0.213***	0.171***	0.174***	0.111***	0.076*	0.025	0.081*	0.038
	(0.039)	(0.044)	(0.046)	(0.041)	(0.043)	(0.043)	(0.047)	(0.046)
Firm exports	0.005***	0.003**	0.003**	0.001	0.002	0.001	0.002	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Product innovation realized in t-1				0.350***	0.573***	0.468***	0.519***	0.410***
				(0.050)	(0.043)	(0.069)	(0.046)	(0.070)
Product innovation realized in t-2				0.376***		0.308***		0.345***
				(0.053)		(0.068)		(0.070)
Industry branch fixed effects		yes	yes	yes	yes	yes	yes	yes
Federal State fixed effects			yes	yes	yes	yes	yes	yes
Observations	744	744	744	744	577	436	502	361
R-squared	0.234	0.301	0.311	0.474	0.553	0.662	0.529	0.665

Notes: VAD = Value Added Model. The dependent variable is product innovation realized. The sample consists of firms that responded to the Ifo Innovation Survey in 2012. Columns (1) to (8) contain imputed values for "share using computer" (56 firms), "log no. employees" (39 firms), "log turnover" (101 firms), and "share academic" (118 firms). Column (4) contains imputed values for previous innovations (242 firms in t-1 and 308 firms in t-2). Missing values are imputed with the NACE two-digit average value in the respective year. Columns (5) and (6) shows results for the sample of firms that can be observed in 2011 and 2009 (firms missing in 2010 but responding in 2009 and 2011 are imputed with the average innovation value of 2011 and 2009). Column (7) and (8) are estimations without imputed lags. All specifications contain a full set of dummies for imputed values. A constant is included, but not reported. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The first-stage regression in Column (1) of Table 4 shows that when a firm received an impulse to invest in ICT, it is 39.4 percentage points more likely to have invested in ICT than otherwise. This is after controlling for firm size, industry branch, and Federal State, along with other firm characteristics. At an F-value of 66.87, the instrument is highly relevant. In the second stage, the loss of efficiency that accompanies instrumental variables estimation is notable. The standard error of the ICT effect is about three times larger than the corresponding OLS specification.

Table 3: Association between Investment in ICT and Innovation, Robustness

	Prod. Innovation Realized	Prod. Innovation started	Prod. Innovation Realized/Started
	(1)	(2)	(3)
Firm invested in ICT	0.090**	0.105***	0.139***
	(0.045)	(0.036)	(0.032)
Log employees	0.022	0.039***	0.030***
	(0.015)	(0.013)	(0.011)
Share academic	0.001	0.003**	0.003***
	(0.001)	(0.001)	(0.001)
Share using computer	0.001	0.002**	0.002**
	(0.001)	(0.001)	(0.001)
Firm exports	0.006	0.035	0.080*
	(0.053)	(0.046)	(0.044)
Product innovation realized in t-1	0.311***	0.157***	0.328***
	(0.092)	(0.055)	(0.049)
Product innovation realized in t-2	0.272***	0.207***	0.279***
	(0.092)	(0.059)	(0.051)
Product innovation realized in t-3	0.242***		
	(0.085)		
Industry branch fixed effects	yes	yes	yes
Federal State fixed effects	yes	yes	yes
Observations	265	744	744
R-squared	0.715	0.272	0.426

Notes: The sample consists of firms that responded to the Ifo Innovation Survey in 2012. All specifications contain imputed values for “share using computer” (56 firms), “log no. employees” (39 firms), “log turnover” (101 firms), and “share academic” (118 firms). They also contain imputed values for previous innovations (242 firms in t-1 and 308 firms in t-2). Missing values are imputed with the NACE two-digit average value in the respective year. A full set of dummies for imputed values is included. A constant is included, but not reported. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The 2SLS estimates are still statistically significant at the 10 percent level when controlling for the same set of covariates as the baseline specification. The estimated effect in Column (2) Table 4 is, at 18.1, about 4.7 percentage points higher compared to the latter. The increase in the point estimate from IV – compared to the previously obtained 13.4 percentage points (cf. Table 2) – may be due to the LATE interpretation of our instrument that we observe IV estimates above the expected population effect. Maybe firms who hire an IT consultant are different in their innovation and investment behavior from those who do not.

Table 4: Results from Instrumental Variables Estimation

	First Stage	2SLS	2SLS
	(1)	(2)	(3)
IT consultant	0.394***		
	(0.030)		
Firm invested in ICT		0.181*	0.113
		(0.098)	(0.093)
Log employees	0.022*	0.035***	0.015
	(0.013)	(0.011)	(0.010)
Share academic	-0.001	0.002	0.002
	(0.002)	(0.001)	(0.001)
Share using computer	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
Firm exports	-0.080	0.114***	0.109***
	(0.052)	(0.041)	(0.038)
Product innovation realized in t-1	0.077	0.346***	0.304***
	(0.053)	(0.042)	(0.039)
Product innovation realized in t-2	0.143**	0.369***	0.293***
	(0.058)	(0.047)	(0.043)
Process innovation realized			0.337***
			(0.032)
Industry branch fixed effects	yes	yes	yes
Federal State fixed effects	yes	yes	yes
F-stat. of excluded instruments	66.87		
Observations	744	744	744
R-squared	0.225	0.473	0.554

Notes: The dependent variable is product innovation realized. The sample consists of firms that responded to the Ifo Innovation Survey in 2012. All specifications contain imputed values for "share using computer" (56 firms), "log no. employees" (39 firms), "log turnover" (101 firms), and "share academic" (118 firms). They also contain imputed values for previous innovations (242 firms in t-1 and 308 firms in t-2). Missing values are imputed with the NACE two-digit average value in the respective year. A full set of dummies for imputed values is included. A constant is included, but not reported. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

As discussed in Section 3, there are circumstances under which the exclusion restriction could be violated. A general, firm-wide reorganization is one way in which external IT consultants might be linked to product innovation other than through ICT investment. IT consultants will likely affect process innovations which often come along with product innovations. If this reorganization were connected to redirecting a firm's general strategy, for example, due to a change in the top management, such an event would be one obvious threat to the validity of the instrumental variable. We account for this possibility of contemporaneous correlation and additionally include current process innovations in the regression. This dummy variable takes the value unity if a process innovation has been started or introduced in the current year. Column (3) shows this specification: when controlling for current process innovations, the ICT coefficient is no longer statistically significant at conventional levels; it decreases in magnitude to 11.3 percentage points, a value that is within the same order of magnitude as our baseline result. Process innovations might in fact be a bad control to product innovations as the literature sees them as complementary (Bresnahan et al., 2002). If this were the case, controlling for process innovations would lead to the underestimation of the total effect of ICT investments.

5.3. Propensity Score and Direct Matching

Table 5 provides results for regression-adjusted matching for different matching algorithms. The algorithms we use are nearest neighbor, five-nearest neighbors, Epanechnikov kernel, and radius caliper matching. Overall, the results are of the same order of magnitude as the OLS estimates. They range between 13.2 and 14.2 percentage points and they remain highly statistically significant for all algorithms used. The need for carefully chosen comparison groups is highlighted in the Appendix. Figure A-5 displays the distribution of propensity scores for treated and untreated firms. Only a few firms fall off support at the left tale and the distribution of the likelihood of investing in ICT is slightly less flat and somewhat more skewed to the left for firms that actually invested. Table A-1 provides t-tests for the hypothesis that the means of the firm characteristics do not differ by ICT investment status. The test is conducted before and after matching. The table reveals large, significant differences in the characteristics between investing firms and non-investing firms. In the absence of propensity score matching, the two types of firms differ in every characteristic, apart from the share of academics and non-response in *t-1*. After matching has been conducted, the means no longer statistically differ from each other.

The pattern shown in the propensity score matching is seen again in the direct matching approach presented in Table 6. Here, the estimated ICT coefficient ranges between 15.0 and 20.4 percentage points. The coefficient remains significant at the 1 percent level throughout all specifications despite the low number of observations that remain in the matched sample after imposing identical firm characteristics in multiple dimensions. Depending on the matching algorithm, only between 214 and 315 firms remain in the matched sample. Table A-2 in the Appendix shows the balancing test for the group means by ICT investment. Here, the matched sample exhibits identical means for all characteristics that were exactly matched. The means of the number of employees are not identical since for this variable no exact match is imposed. Nevertheless, the means are not statistically distinguishable.

Table 5: Propensity Score Matching Results, Dependent Variable: Product Innovation Realized

	1-n-n (1)	5-n-n (2)	kernel (3)	caliper (4)
Firm invested in ICT	0.137***	0.132***	0.134***	0.142***
	(0.032)	(0.029)	(0.029)	(0.032)
Log employees	0.047***	0.051***	0.054***	0.044***
	(0.013)	(0.012)	(0.012)	(0.014)
Share academic	0.003*	0.002*	0.002	0.003*
	(0.001)	(0.001)	(0.001)	(0.001)
Share using computer	0.002***	0.001	0.001	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
Firm exports	0.148***	0.110**	0.112**	0.161***
	(0.053)	(0.047)	(0.046)	(0.054)
Product innovation realized in t-1	0.278***	0.289***	0.282***	0.277***
	(0.048)	(0.045)	(0.045)	(0.048)
Product innovation realized in t-2	0.382***	0.378***	0.367***	0.379***
	(0.054)	(0.049)	(0.049)	(0.054)
Industry branch fixed effects	yes	yes	yes	yes
Federal State fixed effects	yes	yes	yes	yes
Observations	600	712	723	588
R-squared	0.479	0.448	0.450	0.476

Notes: The dependent variable is product innovation realized. The matching algorithms in Column (1) are nearest neighbor (with replacement), in Column (2) five-nearest-neighbors (with replacement), in Column (3) Epanechnikov kernel, and in Column (4) radius caliper (0.01). Missing values are imputed with the NACE two-digit average value in the respective year. A full set of dummies for imputed values is included. A constant is included, but not reported. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Taken together, the characteristics we control for should be a good reflection of a firm's situation. The results indicate that the propensity score and the direct matching processes successfully generated comparable counterfactual observations as each investing firm has common support. We thus conclude that ICT investment has a positive effect on product innovation. In a next step, we estimate our instrumental variable regression on the matched sample. The results are shown in Table A-3 in the Appendix. Columns (1) to (4) are based on samples generated with propensity score matching algorithms, Columns (5) to (8) on samples obtained with direct matching. The ICT investment coefficient ranges between 11 (rounded) and 19.5 percentage points.

Table 6: Direct Matching Results, Dependent Variable: Product Innovation Realized

	1-n-n	5-n-n	kernel	caliper
	(1)	(2)	(3)	(4)
Firm invested in ICT	0.204***	0.168***	0.159***	0.150***
	(0.054)	(0.040)	(0.042)	(0.043)
Log employees	0.049**	0.037**	0.032*	0.047**
	(0.024)	(0.017)	(0.019)	(0.018)
Share academic	0.004**	0.003**	0.002	0.003*
	(0.002)	(0.001)	(0.002)	(0.002)
Share using computer	-0.001	-0.000	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Firm exports	0.036	0.076		
	(0.083)	(0.060)		
Product innovation realized in t-1	0.337***	0.292***	0.392***	0.300***
	(0.090)	(0.077)	(0.089)	(0.082)
Product innovation realized in t-2	0.408***	0.462***	0.382***	0.470***
	(0.092)	(0.077)	(0.086)	(0.082)
Industry branch fixed effects	yes	yes	yes	yes
Federal State fixed effects	yes	yes	yes	yes
Observations	230	328	277	288
R-squared	0.573	0.633	0.666	0.645

Notes: The dependent variable is product innovation realized. The matching algorithms in column (1) are nearest neighbor (with replacement), in Column (2) five-nearest-neighbors (with replacement), in column (3) Epanechnikov kernel, and in Column (4) radius caliper (0.01). Missing values are imputed with the NACE two-digit average value in the respective year. A full set of dummies for imputed values is included. A constant is included, but not reported. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The only exception is Column (5), which also contains the least observations with only 230 firms in the sample. In this specification the coefficient is practically zero. The results are not statistically significant –apart from Column (7) – which is statistically significant at the 10 percent level. The small sample sizes may well be the reasons for the imprecisely estimated coefficients of ICT investment.

5.4. General Discussion

The results presented in the previous subsections of Section 5 mostly suggest that ICT investment does enable manufacturing firms to innovate. Controlling for pre-treatment outcomes and Federal State and industry fixed effects, the ICT coefficient remains relatively stable throughout OLS, matching, and IV regressions. According to our estimations, a manufacturing firm that made a major investment in ICT is between 11 and 18 percentage points more likely to introduce a product innovation within the next two years. Evaluated at the average probability of introducing a product innovation of 42 percent, this is an economically important effect.

Our dataset raises some issues concerning the generalizability of the presented findings to the entire population of firms. First, our study uses only firms in the manufacturing sector, which differs from other sectors in the way firms use ICT. Second, maybe the results are not applicable to all other countries. Germany is specific in its ICT capacity, i.e. in the way in which relevant stakeholders such as businesses, governments and private users make use of ICT. In 2013, it ranked among the top 13 countries (out of 144) in the World Economic Forum's (2013) Network Readiness Index (NRI). This implies that lower ranked countries with less capacity to make use of ICT may not benefit as much from an increased investment.

Furthermore, the time span we can observe is relatively short. We can follow the aftermath of ICT investment for only two years, which raises the following issues: first, is it realistic that benefits of ICT manifest within two years and, second, if there are economic benefits of ICT investment beyond this period, our results would underestimate its effect. We argue that due to the fast-developing nature of ICT, the assumption of a short lag until manifestation of effects from new ICT equipment is realistic. Firms invest in these technologies with the expectation that they will pay off in the near future.

In line with this reasoning, most of the economic benefits of ICT should occur within the first few years after acquisition. The common depreciation period for IT equipment in Germany covers three years. This is the expected time span of use for the equipment in the firm before it is replaced. But if the time span employed is not sufficiently long to capture all future benefits that ICT investment generates for the firms, our estimates would provide a lower bound to the longer-term effect.

There are moreover other characteristics that are likely to influence firm's investment in ICT and that may be correlated with innovative activity. One example would be an increased aggregate demand for ICT capital since the end of the recent economic crisis. But this would occur on a national level and affect all firms in Germany, and should not bias our results.

6. Conclusion and Outlook

Investment in ICT is generally believed to be an important factor in increasing firm performance. We provided micro evidence at the firm level on how ICT investment affects product innovation. The results reveal that ICT investment has a consistently positive effect on firms' innovative behavior. This finding holds across the value-added model, instrumental variables estimations, and regression-adjusted matching. Our estimates suggest that there are substantial economic benefits from increased spending on ICT. Controlling for firms' history of innovative activity, we find in various specifications that a manufacturing firm that made major investments in ICT is between 11 and 18 percentage points more likely to introduce a product innovation within the following two years. Evaluated at the average probability of introducing a product innovation of 42 percent, this is an economically important effect. Our findings have important implications beyond the single firm. Innovations are major drivers of aggregate growth and ICT investments thus have the potential to benefit the aggregate economy.

Our results may not necessarily be generalizable to the entire population of firms. First, the instrumental variable approach most likely identifies a local average treatment effect that may not apply to all firms since we expect it to measure the effect for a subset of firms that were induced to invest in ICT by external consultants. Moreover, our study uses only manufacturing firms, an industry that differs from other sectors in the way ICT is used. Moreover, the data allow us to study only relatively short-term effects of ICT investment, and thus we cannot predict the effect of this type of investment on long-run development.

Nevertheless, we contribute to the literature by providing firm-level evidence in which we account for the self-selection of firms to invest in ICT. Our findings are important as they suggest that new ICT capital acts as an important catalyst for new products in the manufacturing sector. Further research should be conducted – ideally using panel data – to provide a better understanding of the role that ICT investment may play in innovative behavior, to discover the kinds of processes it is a substitute for, and to look more closely at how the decision to invest in ICT is formed.

Appendix

Figure A-1: Excerpt from the Ifo Innovation Survey, 2012 Questionnaire

1. Product innovations: In 2011, we

   Introduced ☐

   Started ☐

   Aborted ☐ a product innovation

2. Process innovations: In 2011, we

   Introduced ☐

   Started ☐

   Aborted ☐ a process innovation

3. What percentage of employees (in %) need the following equipment on a daily basis in order to perform their professional activities?

   Computer ______%

   Internet ______%

4. Did you invest in the **last two years** in substantial innovations of ICT-equipment?

   Yes ☐ ___________€ (if unknown, please estimate)

   No ☐ (proceed to question 7)

5. If yes, which type of ICT-equipment did you invest in mostly?

   ☐ IT-Equipment (computers und hardware)

   ☐ Communications-equipment

   ☐ Software

6. If yes, to what degree did the ICT-Investments require internal reorganizations?

   ☐ No restructuring

   ☐ Low degree of restructuring

   ☐ High degree of restructuring

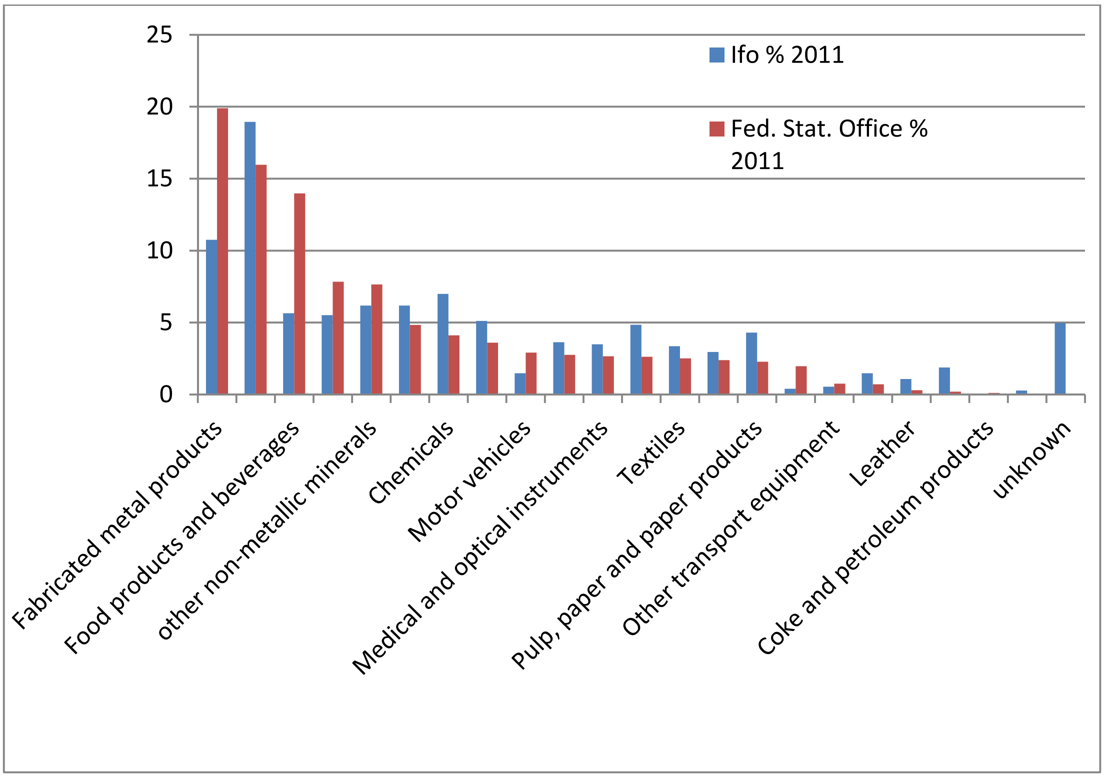
7. Impulses to invest in ICT stem from

   ☐ Internal IT-department ☐ Suppliers

   ☐ Internal IT-management ☐ Other business partners

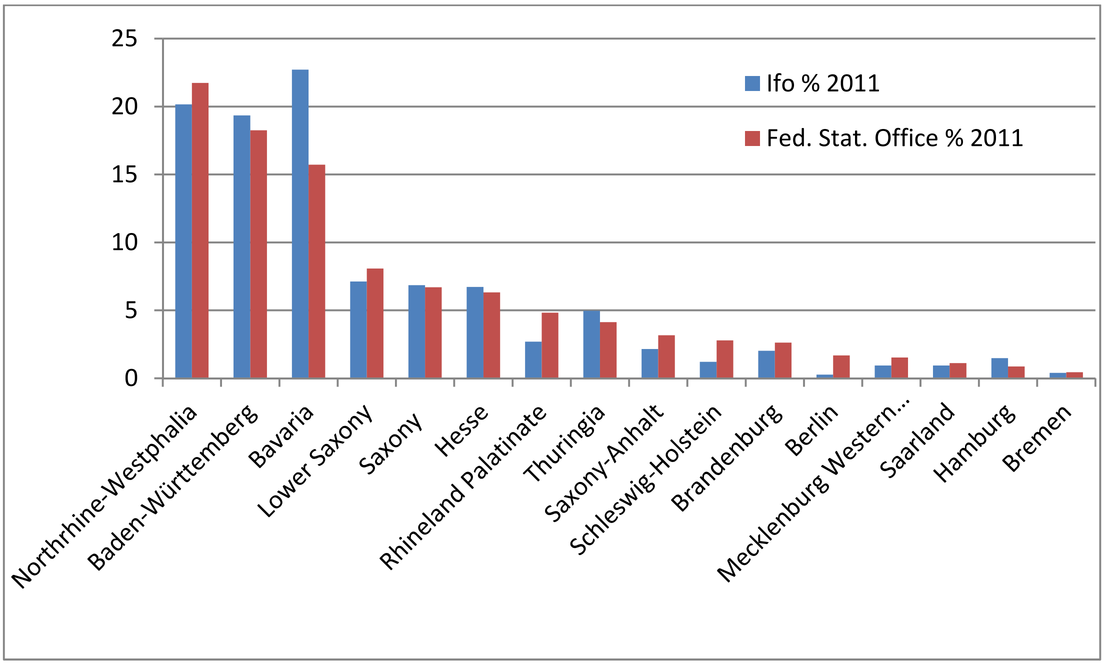
   ☐ External IT consultancy ☐ Customers

Figure A-2: The distribution of NACE codes in the Ifo Innovation Survey 2011



Data source: Ifo Institute (2012) and Federal Statistical Office (2014)

Figure A-3: The distribution of Federal States in the Ifo Innovation Survey 2011



Data source: Ifo Institute (2012) and Federal Statistical Office (2014)

Figure A-4: The distribution of firms, by size of employment

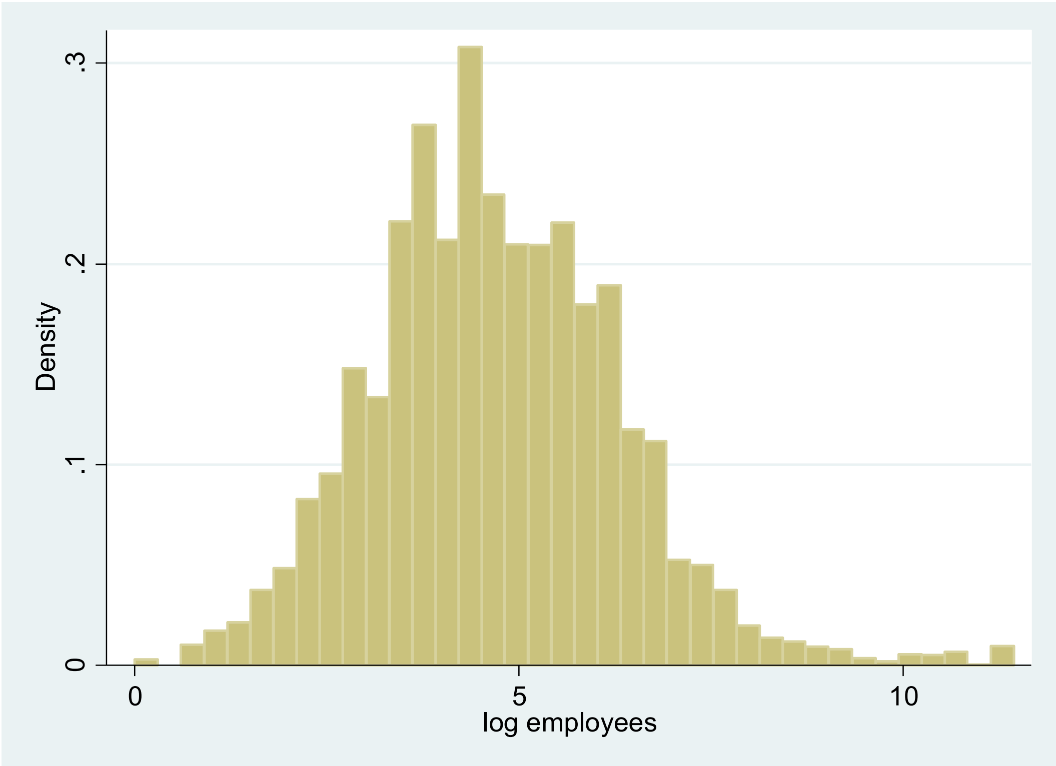
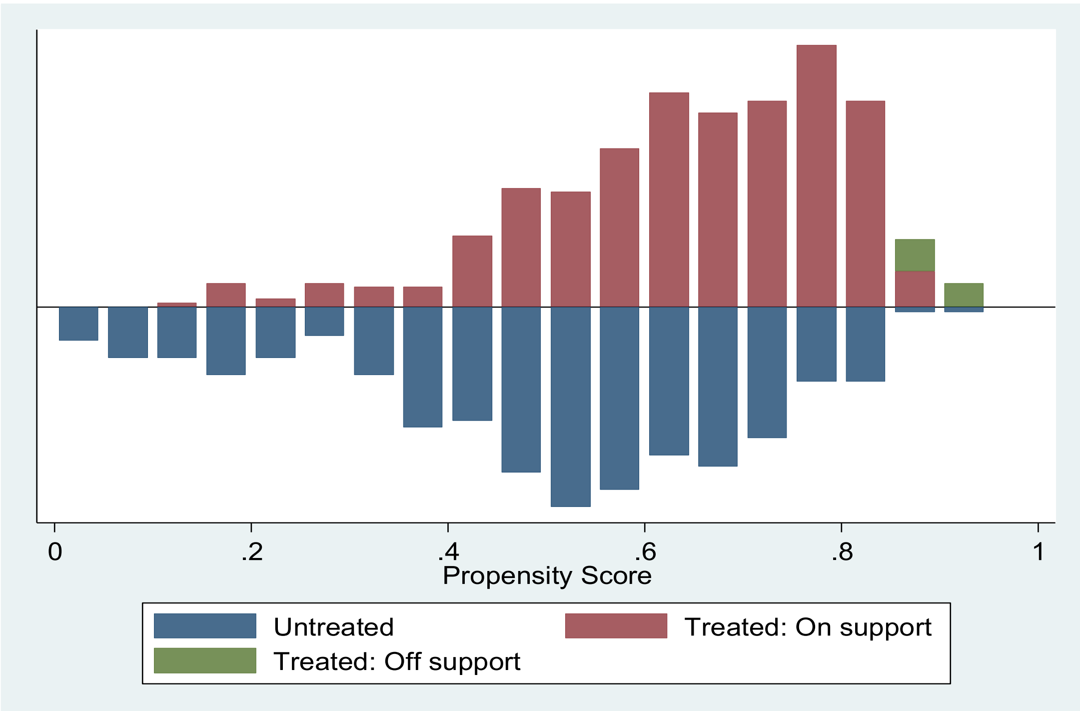


Figure A-5: The distribution of propensity scores for treated and untreated firms



Notes: The graph shows the distribution of the probabilities of firms to invest in ICT, by their respective treatment status. The algorithm used in obtaining the graph is radius caliper (0.01) matching.

Table A-1: Balancing Score Test, Mean Comparison by ICT Investment, Before and After Propensity Score Matching

		Mean			t-test	
Variable	Sample	Treated	Control	%bias	t-test	p>|t|
Product innovation realized	unmatched	0.54	0.30	50.40	6.71	0.00
	matched	0.53	0.42	23.60	3.32	0.00
Log no. employees	unmatched	4.76	4.30	30.70	4.09	0.00
	matched	4.64	4.77	-8.40	-1.30	0.19
Share academic	unmatched	12.12	10.94	9.10	1.25	0.21
	matched	12.03	12.28	-1.90	-0.31	0.76
Share using computer	unmatched	53.59	49.03	16.80	2.25	0.03
	matched	53.55	53.90	-1.30	-0.19	0.85
Firm exports	unmatched	0.79	0.70	22.10	3.00	0.00
	matched	0.80	0.84	-9.80	-1.60	0.11
Product innovation realized in t-1	unmatched	0.49	0.37	28.60	3.82	0.00
	matched	0.47	0.51	-10.00	-1.45	0.15
Product innovation realized in t-2	unmatched	0.48	0.36	32.40	4.35	0.00
	matched	0.47	0.49	-6.00	-0.89	0.37
Non-response in t-1	unmatched	0.34	0.30	8.20	1.09	0.27
	matched	0.34	0.36	-3.00	-0.43	0.67
Non-response in t-2	unmatched	0.46	0.35	21.50	2.87	0.00
	matched	0.46	0.49	-6.80	-0.96	0.34

Notes: Radius caliper (0.01) matching. 588 observations are in the sample. Federal State dummies, industry branch dummies (at NACE two-digit), and a full set of dummies for missing values as well as dummies for non-response enter the matching process but are not reported.

Table A-2: Balancing Score Test, Mean Comparison by ICT Investment, Before and After Direct Matching

		Mean			t-test	
	Sample	Treated	Control	%bias	t-test	p>|t|
Product innovation realized	unmatched	0.54	0.30	50.40	6.71	0.00
	matched	0.58	0.44	29.60	2.74	0.01
Log no. employees	unmatched	4.76	4.30	30.70	4.09	0.00
	matched	4.69	4.57	8.30	0.88	0.38
Share academic	unmatched	2.65	2.43	19.50	2.60	0.01
	matched	2.88	2.88	0.00	0.00	1.00
Share using computer	unmatched	2.72	2.50	19.40	2.59	0.01
	matched	2.79	2.79	0.00	0.00	1.00
Firm exports	unmatched	0.79	0.70	22.10	3.00	0.00
	matched	0.80	0.64	35.30	3.30	0.00
Product innovation realized in t-1	unmatched	0.49	0.37	28.60	3.82	0.00
	matched	0.49	0.49	0.00	0.00	1.00
Product innovation realized in t-2	unmatched	0.48	0.36	32.40	4.35	0.00
	matched	0.48	0.48	0.00	0.00	1.00
Non-response in t-1	unmatched	0.34	0.30	8.20	1.09	0.27
	matched	0.21	0.21	0.00	0.00	1.00
Non-response in t-2	unmatched	0.46	0.35	21.50	2.87	0.00
	matched	0.28	0.28	0.00	0.00	1.00

Notes: Radius caliper (0.1) matching. All variables except “log no. employees” are used for exact matching. This variable enters the matching process as propensity score from a probit regression. “Share using computer” and “share academic” are rescaled as size ranges to allow for exact matching within four categories (by quartile).

Table A-3: Instrumental Variables Results on Matched Samples

	Propensity Score Matching Samples				Direct Matching Samples			
	1-n-n	5-n-n	kernel	caliper	1-n-n	5-n-n	kernel	caliper
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Firm invested in ICT	0.105	0.110	0.112	0.109	0.006	0.175	0.195*	0.172
	(0.120)	(0.093)	(0.093)	(0.122)	(0.145)	(0.110)	(0.109)	(0.135)
Log employees	0.001	0.001	0.001	0.001	-0.001	-0.000	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Share academic	0.015	0.013	0.014	0.013	0.015	0.011	-0.004	0.014
	(0.012)	(0.011)	(0.011)	(0.012)	(0.022)	(0.015)	(0.017)	(0.017)
Share using computer	0.130***	0.117***	0.120***	0.138***	0.064	0.063	0.092*	0.082
	(0.044)	(0.039)	(0.039)	(0.045)	(0.075)	(0.052)	(0.055)	(0.061)
Firm exports	0.002	0.002	0.002	0.002	0.003*	0.003**	0.003*	0.003*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Product innovation realized in t-1	0.284***	0.297***	0.296***	0.285***	0.232***	0.199***	0.277***	0.214***
	(0.044)	(0.040)	(0.039)	(0.044)	(0.081)	(0.066)	(0.078)	(0.071)
Product innovation realized in t-2	0.329***	0.302***	0.299***	0.331***	0.363***	0.405***	0.329***	0.388***
	(0.048)	(0.044)	(0.044)	(0.049)	(0.081)	(0.066)	(0.074)	(0.071)
Industry branch fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Federal State fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Observations	600	712	723	588	230	328	277	288
R-squared	0.543	0.547	0.549	0.537	0.582	0.666	0.686	0.638

Notes: The dependent variable is product innovation realized. All specification show instrumental variables estimations applied to matched samples. Columns (1) to (4) are based on samples obtained with propensity score matching methods, Columns (5) to (8) are based on samples obtained with direct matching methods. The matching algorithms in column (1) and (5)are nearest neighbor (with replacement), in Column (2) and (6) five-nearest-neighbors (with replacement), in column (3) and (7) Epanechnikov kernel, and in Column (4) and (8) radius caliper (0.01). Missing values are imputed with the NACE two-digit average value in the respective year. A full set of dummies for imputed values is included. A constant is included, but not reported. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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