

Niebel, Thomas; Rasel, Fabienne; Viete, Steffen

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BIG data – BIG gains? Understanding the link between big data analytics and innovation

Thomas Niebel, Fabienne Rasel and Steffen Viete

Digital Economy Research Department, Centre for European Economic Research (ZEW), Mannheim, Germany

ABSTRACT

This paper analyzes the relationship between firms' use of big data analytics and their innovative performance in terms of product innovations. Since big data technologies provide new data information practices, they create novel decision-making possibilities, which are widely believed to support firms' innovation process. Applying German firm-level data within a knowledge production function framework we find suggestive evidence that big data analytics is a relevant determinant for the likelihood of a firm becoming a product innovator as well as for the market success of product innovations. These results hold for the manufacturing as well as for the service sector but are contingent on firms' investment in IT-specific skills. Overall, the results support the view that big data analytics have the potential to enable innovation.

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1. Introduction

The latest technological trends like connected devices and machines, wearables, and the universal application of sensors as well as (user-generated) online content are drivers of a vast and constantly increasing amount of data. In reference to the large volumes of diverse data and associated new data information practices that have become available to firms, *big data analytics* has become an important topic among practitioners, policy makers and scientists. Broadly speaking, the concept of big data encompasses the amount and complexity of newly available data and the technical challenges of processing them (Dumbill 2013). Depending on the context, big data started to pose challenges to data management along three dimensions: (1) the enormous amount of data (volume), (2) a wide variety of data coming from highly diverse sources (variety), and (3) the pace of data processing (velocity) (Laney 2001). Enormous progress in computing power, storage capacity, and software have been necessary for the surge of big data technologies.

Much of the debate and research has centered around possible implications of big data for firms and businesses. As big data alters the sources and types of information available to decision-makers in the firm, it is expected to impact on established ways of decision- and strategy-making which have traditionally relied on predefined data collected for specific needs (Constantiou and Kallinikos 2015). In particular, data which has become available to firms is often not collected intentionally, but in a heterogeneous and unstructured way (Anderson 2008; Varian 2010). The ability to analyze such data, extract insights and appropriate value from it represents a key challenge to firms. One problem big data poses to decision-making is that correlations identified from the raw data are

CONTACT Thomas Niebel ✉ niebel@zew.de 📧 Centre for European Economic Research (ZEW), Digital Economy Research Department, P.O. Box 103443, D-68304 Mannheim, Germany

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erroneously interpreted as causal relationships or that misleading patterns are found in the data (McAfee and Brynjolfsson 2012; Lazer et al. 2014). Starting from such data patterns found with big data analytics, decisions without potential for improvement or even unwise decisions can be made. That is why the use of big data analytics may not guarantee sustainable, positive effects on firm performance ('Big Gains'). The gray areas with respect to privacy, data protection, the regulatory environment, or an insufficient internet connection are viewed as the other main barriers to the diffusion of big data and related practices.

Despite these challenges associated with big data, a widely shared expectation is that the ongoing changes in how data is being generated and made relevant for firms can help to increase business value through profitable use of data, that previously had even been used to be produced as 'waste' product of business activity before the surge of big data technologies. New data information practices and better informed decision-making can be particularly advantageous for firms' innovation processes, which often involve high uncertainty and risk. In this vein, mining of consumption patterns or social network and consumer sentiment analysis, for instance, might improve the adoption and market success of new products. Data obtained from sensors can facilitate the detection of product defects and the subsequent improvement of existing products. Insights obtained from big data can furthermore reduce the duration and costs of the innovation process. Besides improving the R&D process, big data can also be at the core of the innovation itself. Monitoring transactions and combining different information facilitates the development of new personalized services and other data-intensive innovations. These potentials of big data apply to highly digitized services as well as to more traditional manufacturing industries. For instance, by exploiting real time data on the geospatial position of users, mapping apps now provide drivers with real time information about potential road congestion (Kshetri 2014). Insurance companies started to make use of different data sources and big data technologies to design improved premium policies and new forms of contracts (Varian 2010). A successful example in traditional manufacturing can be found at the Ford Motor Company that started capturing consumer data from vehicles through sensors and remote app-management software. Based on analysis of data from the cars' voice recognition system the company found that surrounding noise affected the performance of the software. This led to an improvement of the system by means of noise reduction technology and the repositioning of microphones (Erevelles, Fukawa, and Swayne 2016). Further potential innovations in the automotive industry based on the steadily growing number of sensors per vehicle are new innovative services like traffic prediction, safety warnings, vehicle diagnostics, and location-based services (Luckow et al. 2015). High potentials are also ascribed to big data technologies in health care, where big data can help to identify drug interactions and design improved drug therapies (Kshetri 2014). Overall, big data is widely expected to enable firms from all industries to create new products and services, improve existing ones, and to develop new business models (e.g. Manyika et al. 2011; Gobble 2013).

High potentials to foster innovation, productivity, and growth are also ascribed to big data by policymakers. For instance, the European Commission (EC) stressed the importance of data for growth and innovation in a knowledge-based economy in their policy report on the strategy for a digital single market. Furthermore, the EC has already taken measures to promote the data-driven economy, e.g. through public-private-partnerships for projects on big data or by supporting the development of standards and interoperability in data usage (European Commission 2014).

Despite the high expectations associated with big data and the prominent position it has gained as a current key technological trend, there is a paucity of empirical evidence on its effect on firm performance overall, and firms' innovation performance in particular. Against this background, we analyze the relation of firms' use of big data and innovation performance using large-scale firm-survey data from German manufacturing and services industries. Extending classical knowledge production functions by firms' use of big data, we find that big data information practices are associated with a higher propensity to innovate, as well as a higher innovation intensity.

Our paper contributes to the literature in various respects: (i) we provide first large-scale empirical evidence based on representative firm-level data on the role of big data for firm performance in terms

of the product innovation activities of manufacturing and service firms. (ii) The paper further contributes to a better understanding of the relationship between data analysis and innovation output across industries and helps to assess the potential benefits of big data analytics.

The remainder of the article is structured as follows. Section 2 reviews the empirical literature on the potential effects of big data analytics on firm performance. Section 3 lays out our empirical framework. Section 4 describes the data and measures. Sections 5 and 6 discuss the descriptive and econometric results. Finally, Section 7 concludes.

2. Related literature

There is a large literature on the productivity effects of investments in information and communication technologies (ICT).¹ Furthermore, there is empirical evidence of complementarity effects between investments in ICT and intangible capital, which is often also referred to as knowledge-based capital (KBC). Bresnahan, Brynjolfsson, and Hitt (2002) and Bloom, Sadun, and Van Reenen (2012) find complementarities between ICT and organizational capital as well as human capital based on analyses of firm-level data. The latter two are part of the more broader concept of knowledge-based capital. Based on analyses with country- and industry-level data, Chen, Niebel, and Saam (2016) and Corrado, Haskel, and Jona-Lasinio (2017) conclude that ICT capital and intangible capital (including R&D, organizational capital and firm-specific human capital) are complements in production.

Similarly, a large literature has dealt with the effects of ICT on the innovation process and the innovative performance of firms. In a broader context, ICT have considerably changed the knowledge generation process of firms. They may lead to efficiency gains and have changed the organizational structure of the firms. Thus, ICT are widely regarded as an enabler for innovation (e.g. Brynjolfsson and Saunders 2010; Spiezia 2011; Brynjolfsson and McAfee 2014; Santoleri 2015). For instance, theories on knowledge management highlight ICT as an organizational innovation which improve the internal dissemination of information and enable firms to harness tacit knowledge, thereby improving the internal organization of the R&D process (e.g. Hempell and Zwick 2008).

Further insights into the effects of big data and ICT in general can be obtained from theories of the knowledge production process in firms which build on the idiosyncratic characteristics of knowledge as an economic good, namely limited appropriability, limited excludability and low reproduction costs. As described by Antonelli (2017), these characteristics lead to a trade-off between positive and negative externalities involved in the knowledge creation process. These opposing externalities arise through knowledge spillovers and the resulting availability of a large stock of external knowledge as a quasi-public good on the one hand (Griliches 1979), and, on the other hand, the reduction of incentives for generating new knowledge driven by the ease of imitation (Arrow 1962). In general, ICT will likely reinforce the positive aspect of these externalities and facilitate the integration of external knowledge (Antonelli 2017). Building on the concept of absorptive capacity developed by Cohen and Levinthal (1989, 1990), big data technologies potentially lower the absorption costs of external knowledge, i.e. the costs for identification, retrieval and exploitation of information. Relying on big data enables firms to exploit the continuously increasing amounts of external knowledge that become available in the form of digitized information, such as digitized customer and user knowledge. Big data and related technologies thereby increase the quantity and variety of information available to the firm and associated analytical practices enable firms to generate novel knowledge from this information. In addition to increasing the capacity to absorb external knowledge, various applications of big data analytics, such as predictive maintenance, exemplify how these practices also generate knowledge from internal information. In principle, the successful application of big data analytics allows firms to combine diverse novel knowledge items, integrate external and internal knowledge and appropriate knowledge spillovers from heterogeneous sources.

Applying augmented Crépon–Duguet–Mairesse (CDM) models, which build on the knowledge generation function (Griliches 1979), Polder et al. (2010) and Hall, Lotti, and Mairesse (2013)

empirically show the importance of ICT for the innovation output and subsequently for the productivity of firms. A relatively new stream of empirical literature has started to investigate the distinct effects of big data and data-driven decision making on firm performance. The reports of Manyika et al. (2011) and the OECD (2015) provide a general overview of the definition and application scope of big data analytics and the potential economic benefits of the use of big data technologies and of data-driven innovation.² Up to now, empirical evidence on the potential effects of big data analytics on firm performance has been scarce. There exist only a few empirical studies based on selective U.S. datasets for specific sectors or limited to listed companies (e.g. Brynjolfsson, Hitt, and Kim 2011; Tambe 2014; Brynjolfsson and McElheran 2016a). The common finding from these studies is that firms with more intensive data usage are more productive. Furthermore, some studies show complementarities between big data usage and employment of highly qualified workers (e.g. Tambe 2014; Brynjolfsson and McElheran 2016a).

Concerning the diffusion process of data-related activities, Saunders and Tambe (2015) demonstrate an increasing trend toward the use of data-related activities in U.S. firms within the IT industry in the period from 1996 to 2012. Likewise, Brynjolfsson and McElheran (2016a) find that the use of data-driven decision-making almost tripled in the U.S. during the period from 2005 to 2010, where the adoption was particularly high in larger firms and in firms with more skilled workers and a higher IT capital stock.

With respect to the role of data-driven decision-making for productivity, Brynjolfsson, Hitt, and Kim (2011) find that such practices are associated with a 5–6% increase in productivity and output among publicly traded U.S. firms. Similarly, Brynjolfsson and McElheran (2016a) show that data-related management practices caused a productivity increase of 3% for firms in the U.S. manufacturing sector. However, the authors highlight heterogeneity in the productivity returns of data-related practices with respect to firm characteristics, with the productivity return of data-related management practices appearing to be lower for larger, older and capital-intensive multi-unit firms. In addition, they find evidence for complementarity between data-driven decision-making and a high IT capital stock prior to the adoption of data-related practices as well as complementarity between data practices and the presence of more highly educated workers.

Tambe (2014) shows evidence for labor market complementarities between investments in and productivity returns from a particular big data technology, namely Hadoop, and the availability of employees with the skills for using this big data technology. The hypotheses for labor market complementarities between technology and human capital are supported by findings that indicate that U.S. firms' Hadoop investments yield higher productivity returns in geographic labor markets with high availability of workers with Hadoop skills.

The study probably most closely related to ours is by Wu, Hitt, and Lou (2017). Combining survey data, employee resumes, as well as patent data for a sample of 331 publicly listed firms, they show that firms focusing on organizational process improvements and firms that innovate by recombining existing technologies have a higher demand for employees with data analytics skills. They furthermore show that process improvements and the recombination of existing technologies are more strongly related to productivity in the presence of employees with greater data analytics skills. Overall, the findings on the role of big data analytics in firm performance are compatible with prior evidence on the complementarity and performance effects of ICT. Concerning the exploitation of user generated information for realizing innovation, Bertschek and Kesler (2017) find that firms' adoption of a Facebook page and user activity on this page are significant determinants for the realization of product innovations by firms.

To the best of our knowledge, there is no study yet that explicitly examines the role of big data analytics for innovation performance at the firm level across industries and firm sizes. Based on the findings from the literature on the role of big data in firm performance and generally the contribution of ICT to innovation, we expect a positive relationship between big data analytics and product innovation – however, possibly not uniformly for all firms but rather contingent on potential complementary factors.

3. Empirical framework

We analyze the contribution of big data to firms' innovation performance within the widely used knowledge production function framework introduced by Griliches (1979). This framework postulates a transformation process which links various inputs associated with knowledge accumulation, such as investments in R&D or human capital, to the firms' innovative output. Knowledge production functions have been the workhorse model in understanding the importance of various knowledge sources besides formal R&D. In the present work, we explicitly account for big data in the firms' knowledge production processes in order to provide initial insights into the relevance of big data for firms' innovation activities.

The following section outlines our empirical model of the knowledge production function. We denote y_{1i}^* the latent propensity of firm i to achieve product innovations, given the firm's use of big data analytics, $bigdata_i$, as well as the firm's R&D intensity and other firm- and market-specific characteristics denoted by the vector $\mathbf{c}_{1i}$. For simplicity of the formal exposition of the analysis, let us further collect the variable on the firm's big data use and further control variables in the vector $\mathbf{x}_1 \equiv (bigdata, \mathbf{c}_1)$. The first step of the empirical model of the knowledge production function assumes a linear additive relationship and amounts to

$$y_{1i}^* = \beta_1 bigdata_i + \gamma_1' \mathbf{c}_{1i} + \epsilon_{1i} = \delta_1' \mathbf{x}_{1i} + \epsilon_{1i} \quad (1)$$

where β denotes the parameter of interest, capturing the effect of the firm's engagement in big data analytics on the propensity to innovate. ϵ_{1i} denotes an idiosyncratic error term, which captures unobserved variables affecting y_{1i}^* and is assumed to be identically and independently normally distributed, $\epsilon_{1i} \sim NID(0, \sigma_1^2)$. The observed variable is the innovation success, i.e. the event of introducing a new product to the market, y_{1i} , which is defined by the following observation rule:

$$y_{1i} = \mathbf{1}[y_{1i}^* > 0] \quad (2)$$

where $\mathbf{1}[\cdot]$ is the indicator function taking the value 1 if the condition is satisfied and 0 otherwise. Equations (1) and (2) describe the first part of our analysis, in which we estimate the relationship between the use of big data and firms' innovation propensity via a simple Probit model.³

Beyond the relationship between big data and the propensity to innovate, we want to assess the relationship with the firms' innovation intensities. Thus, let y_{2i}^* denote the firms' potential innovation intensities given the firms' use of big data, R&D intensity and further firm- and market-specific characteristics, such that

$$y_{2i}^* = \beta_2 bigdata_i + \gamma_2' \mathbf{c}_{2i} + \epsilon_{2i} = \delta_2' \mathbf{x}_{2i} + \epsilon_{2i} \quad (3)$$

where, again, $\epsilon_{2i} \sim NID(0, \sigma_2^2)$ denotes the normally distributed idiosyncratic error term and $\mathbf{x}_2 \equiv (bigdata, \mathbf{c}_2)$. In line with much of the empirical literature investigating innovation intensities, the observed innovation intensity, which is typically measured by the sales ratio of innovative products and services, is assumed to be defined by the following observation rule:

$$y_{2i} = \mathbf{1}[y_{2i}^* > 0] y_{2i}^* \quad (4)$$

Equations (3) and (4) together result in the standard Tobit model (Tobin 1958), which takes account of the nonlinear nature of the conditional expectation function $E(y_{2i} | \mathbf{x}_{2i})$ due to the nontrivial fraction of firms which do not generate sales with newly introduced products.⁴

The conditional expectation for the model made up of Equations (3) and (4) is given by

$$E(y_{2i} | \mathbf{x}_{2i}) = \Phi(\delta_2' \mathbf{x}_{2i} / \sigma) \delta_2' \mathbf{x}_{2i} + \sigma \phi(\delta_2' \mathbf{x}_{2i} / \sigma) \quad (5)$$

where $\Phi(\cdot)$ and $\phi(\cdot)$ denote the standard normal cumulative distribution function and density function, respectively.⁵

A potential problem in estimating the Tobit model arises due to its strong and restrictive distributional assumptions. Unlike Ordinary Least Squares estimation, in cases of heteroskedasticity or non-

normality, Tobit estimates will generally be inconsistent.⁶ Due to the limitations of the standard Tobit model, we check our results against the fractional logit model proposed by Papke and Wooldridge (1996). This model builds on the logistic distribution function to model the conditional expectation of a fractional dependent variable

$$E(y_{2i} | \mathbf{x}_{2i}) = \frac{\exp(\delta'_2 \mathbf{x}_{2i})}{1 + \exp(\delta'_2 \mathbf{x}_{2i})}. \quad (6)$$

Using a Bernoulli link function the model is estimated by Maximum Likelihood. Crucially for our application, the fractional logit model allows for y_{2i} to take on the boundaries 0 and 1 with positive probability, as opposed to other common solutions to model proportions, such as using the logit transformation of y_{2i} .

The standard Tobit and the fractional logit model discussed above assume that the observed innovation intensity is the result of a single process influenced by the same set of determinants. As the innovation intensity is a fractional variable with a lot of observations clustering at zero, one possible concern is that a single model fitted to all data might be insufficient. In particular, while big data might be related to the propensity to innovate, it could at the same time be unrelated to the innovation intensity, i.e. the market success of the firms' innovations, conditional on being an innovator. In that case, the simple Tobit model in Equations (3) and (4) is too restrictive. Alternatively, we can consider a framework in which the models for the propensity to innovate and for the innovation intensity conditional on being an innovator differ. Overall, there is no consensus in the empirical innovation literature whether a one stage model, such as the simple Tobit model described above, or an alternative two stage model is more appropriate to model firms' innovation intensities.⁷ We therefore also estimate an alternative two stage model. In particular, we consider that, alternative to Equation (4), the observed innovation intensity is defined by the observation rule

$$y_{2i} = \mathbf{1}[y_{1i}^* > 0]y_{2i}^* \quad (7)$$

such that the sales ratio of innovations is observed if the firm's propensity to innovate is sufficiently large (e.g. Raymond et al. 2015). In addition, let the unobserved errors $(\epsilon_{1i}, \epsilon_{2i})$ be jointly normally distributed with covariance σ_{12} . Equations (3) and (7) together with the distributional assumptions on the error terms yield the Tobit Type II or Heckman Selection model, in which the conditional expectations of interest are given by:

$$E(y_{1i} | \mathbf{x}_{1i}, \mathbf{x}_{2i}) = \Phi(\delta'_1 \mathbf{x}_{1i}) \quad (8)$$

$$E(y_{2i} | \mathbf{x}_{1i}, \mathbf{x}_{2i}, y_{1i} = 1) = \delta'_2 \mathbf{x}_{2i} + \sigma_{12} \frac{\phi(\delta'_1 \mathbf{x}_{1i})}{\Phi(\delta'_1 \mathbf{x}_{1i})} \quad (9)$$

Given both models, the simple Tobit as well as the Heckman Selection model, are being used in the empirical innovation literature, we estimate both to check the robustness of our findings to the common modeling assumptions.

The main caveat here is that our study is subject to common endogeneity concerns in the empirical literature on the value of ICT. Omitted variables might confound the relation between the use of big data and firms' innovation performance. The main advantage of our data is the wide variety of background characteristics we can account for. In particular, our data contain rich information on firms' use of alternative digital technologies, which help to disentangle the quality and features of big data analytics activities from the firms' general ICT intensities as well as the use of legacy systems. Since the empirical literature on ICT performance generally suffers from a lack of good instrumental variables, reverse causation is another common endogeneity concern. We note that our study runs the risk of being confounded by reverse causation since we are only able to provide controlled correlation applying a new cross-sectional dataset. Nevertheless, we believe

that our analysis is an important first step in understanding how firms make use of big data analytics and in shedding light on the often discussed role of big data technologies in the innovation process of firms.

4. Data and measures

Our analysis is based on the ZEW ICT survey which is a survey of manufacturing and services firms located in Germany with five or more employees. In total, six waves were collected in 2000, 2002, 2004, 2007, 2010 and 2015. We exploit the 2015 wave, which is the first to contain information on the firms' use of big data. About 4400 firms were interviewed about their characteristics and particularly about their ICT usage. The data were collected via computer-aided telephone interviews (CATI) based on a sample stratified with respect to industry and firm size. The respondent is usually from the board of management or the head of the IT department.⁸

4.1. Big data analytics

Any empirical analysis on the topic has to take into account that big data is a heterogeneous concept. It comprises various types and volumes of digitized information, depending on the capabilities of the firm, as well as various specific analytical tools and technologies, depending on the industrial context (Manyika et al. 2011). Thus, big data cannot generally be defined or measured by any specific software or size of the database. Focusing on the novelty of big data technologies and architectures Apache Hadoop, for instance, defines big data as data that *'could not be captured, managed, and processed by general computers within an acceptable scope'* (Chen, Mao, and Liu 2014, p. 173). Another insightful delineation of big data can be found in Chen, Chiang, and Storey (2012). The authors describe big data as digitized information and analytical technologies which have not been incorporated into standard commercial business intelligence platforms and enterprise software systems.⁹ In this vein, the authors highlight new web-based, mobile and sensor-generated data as well as techniques such as opinion mining, social network analysis or machine learning techniques.¹⁰

In our empirical application the main variable of interest is a dummy variable that is equal to one if the firm indicated to use big data technologies. More precisely, the following question was asked in the survey:

Up next a question about so-called big data, i.e. the processing of large amounts of data. Does your company systematically analyze large amounts of data to support business operations?

Overall 22% of firms in our estimation sample indicated that they rely on big data to support their business operations (see Table 1). As our indicator for the usage of big data is based on subjective assessment by the firm, we want to contextualize this measure. We therefore make use of supplementary data, available for a subsample of 1598 firms, which contain more detailed information about the application of automated data generation, processing and transmission for various purposes. These data-related practices range from the automated exchange of information with suppliers and customers to the use of automated data processing to customize products or services. In Table 6 in the appendix we evaluate our big data measure against these specific data-driven practices. In general, firms which indicated to rely on big data employ the data-related practices that were covered in the survey more often. The most common practices among firms relying on big data are the provision of digital assistance systems for employees and the automated information exchange with suppliers and customers. The least common is the use of embedded sensors in final products (Column 2). Except for the use of embedded sensors, considerably more firms indicated to apply any of the data-driven practice than firms indicated to rely on big data (Column 3). This suggests that survey participants correctly perceived big data as data and related analytical technologies which qualitatively exceed conventional data applications. Overall, among the firms which indicate to rely on big data, the vast majority of 91% also indicate to use data-related practices for at least one of the purposes included in the survey (Column 2).

4.2. Innovation outcomes

Our data include items on innovation and R&D activities following the Community Innovation Survey (CIS) and the guidelines of the Oslo Manual by the OECD and Eurostat (Mortensen and Bloch 2005). In particular, we consider the event of introducing a product innovation to the market as the first outcome of the knowledge production process. The relevant measure is a binary indicator, which takes the value one if the firm has introduced a new or substantially improved product or service to the market over the past three years (*Product Innovation*). The product can be new to the market overall or new to the firm. In addition to the propensity to innovate, we investigate the intensity of innovation, which we measure by the share in total sales resulting from new products in the year 2013 (% of Sales New Product). In contrast to a mere innovation count, the sales share of innovations weights each innovation by its success in total turnover. In this way, our innovation intensity measure captures the market success of product innovations (Mairesse and Mohnen 2002; Laursen and Salter 2006).

4.3. Control variables

Following the empirical innovation literature, we control for an extensive set of firm characteristics which have been shown to affect innovation performance. We measure R&D intensity, the potentially single most important input factor to knowledge production, as R&D expenditures over total sales (% of R&D Expenses). The firms' R&D intensities affect the propensity to innovate as well as the firms' innovation successes (Pakes and Griliches 1980) and reflect the relative importance of innovation activities for the firm. Firms which are making use of big data analytics are in general likely to be more intensive ICT users. Similarly, ICT intensity can be expected to positively affect firms' innovation performance (Hempell and Zwick 2008). Therefore, we control for firms' ICT intensities by the share of employees who mainly work with personal computers (% of Emp. Predom. Using PC) as well as the share of employees with access to the internet in the workplace (% of Emp. Using Internet). Furthermore, as the use of enterprise software systems has been shown to be related to firms' innovation activities (Engelstätter 2012), we include a binary variable into the model indicating whether or not the firm has an enterprise software system implemented (*Enterprise Software*). We note that our additional measures on the firms' ICT use capture the effect of mature software systems and data technologies, which lack the quality of large-scale data analytics, such as structured data collected through standard Enterprise Resource Planning Systems (ERP) and stored in conventional relational database management systems. Furthermore, firms' innovative capabilities are affected by the employees' human capital, their knowledge, abilities and creativity (Vinding 2006). Thus, we control for the share of highly skilled employees, i.e. workers with degrees from universities and technical colleges (% Highly Qualified Employees), as well as the share of employees with vocational training (% Medium Qualified Employees). In order to account for the firm's investment in IT-specific knowledge, we control for the share of employees who participated in IT-specific training over the past year (% of Emp. IT-Training). We furthermore account for the age structure of the workforce by controlling for the share of employees below 30 years of age (% of Employees < Age 30) and above 50 years of age (% of Employees > Age 50). As the maturity of the firm might affect both, the use of cutting-edge technology as well as their innovative capabilities (Huergo and Jaumandreu 2004), we control for the years since the founding year of the firm (*Age*). Younger firms might also achieve higher sales shares with new products merely because they have fewer established products in their portfolio. Firm size has been found to be an important determinant of technology adoption (Haller and Siedschlag 2011). Likewise, potential relations between firm size and innovation have already been found by Schumpeter (1942). Overall, larger firms can be expected to have better internal financial resources and enjoy economies of scale and scope, which benefits both, technology adoption as well as innovative capabilities. We thus control for firm size measured by the log of the number of employees (*Employees*). As the likelihood of innovating has been shown by some studies

to increase with physical capital intensity (e.g. Lööf and Heshmati 2006), we control for the log of gross investments (*Investment*). The exposure to international product markets affects the potential market size for new products as well as the competitive pressure to innovate (Hottenrott and Lopes-Bento 2016). We thus include an indicator for whether the firm exports to foreign markets (*Exporter*) and whether it is part of a multinational enterprise (*Multinational*). As Brynjolfsson and McElheran (2016b) show that multi-unit firms are more likely to adopt data driven decision-making, we additionally account for the firms' ownership structure by a binary variable indicating whether the firm is part of a national enterprise group (*Group*). Finally, we account for structural regional differences between the two former German states by a binary indicator for firms' location in former Eastern Germany (*East Germany*) as well as structural differences between industries by including a set of 16 industry dummies constructed from 3-digit NACE industry codes.¹¹

5. Descriptive statistics

Table 1 provides summary statistics on the variables used in the analysis. The share of firms that introduced new products or services amounts to 48% and the average share of sales due to new products and services is 8.4%. In our estimation sample, 22% of firms rely on big data to support their decision-making. With a share of 56%, considerably more firms have implemented an enterprise software system. About 45% of employees predominately work with computers. The average number of employees in the sample is 89, so the sample mainly consists of small and medium-sized enterprises. We apply the data to shed light on the incidence of data driven decision-making and to discover which firms exploit data strategically for their decision-making. Figure A1 provides the in-sample share of firms which are using big data analytics by industry. Overall, the use of data analytics is higher in the service sector. As noted by other authors as well (e.g. Chen, Mao, and Liu 2014), data driven decision-making has proliferated in the financial sector, where over half of the firms in the sample indicated that they systematically apply data as a form of strategic support for their business operations. Firms in the retail and wholesale trade sectors also make intensive use of data in their decision-making process with a diffusion of around 30%. Amongst the manufacturing industries, big data is used most intensively in the chemicals and motor vehicles sectors, by around 23% of the firms in each sector. The sector in which the least firms rely on data for their decision-making

Table 1. Summary statistics: estimation sample.

	<i>N</i>	Mean	SD	Min	Max
Product Innovation	2706	0.48	0.50	0	1
% of Sales New Product	2706	0.084	0.15	0	1
Big Data	2706	0.22	0.41	0	1
% of Emp. Predom. Using PC	2706	0.45	0.34	0	1
% of Emp. Using Internet	2706	0.57	0.37	0	1
Enterprise Software	2706	0.56	0.50	0	1
% of R&D Expenses	2706	0.050	0.11	0	1
Employees	2706	89.3	243.5	5	4100
Employees (in logs)	2706	3.43	1.30	1.61	8.32
Investment in Mill. Euro	2706	0.88	4.61	0.00050	130
Investment (in logs)	2706	-2.03	1.83	-7.60	4.87
Exporter	2706	0.45	0.50	0	1
% Highly Qualified Employees	2706	0.19	0.24	0	1
% Medium Qualified Employees	2706	0.63	0.27	0	1
% of Employees < Age 30	2706	0.24	0.17	0	1
% of Employees > Age 50	2706	0.27	0.19	0	1
East Germany	2706	0.25	0.43	0	1
% of Emp. IT-Training	2706	0.092	0.19	0	1
Age (in logs)	2706	3.17	0.92	0	6.39
Group	2706	0.29	0.46	0	1
Multinational	2706	0.093	0.29	0	1

Source: ZEW ICT-Survey 2015.

is manufacturing of consumer goods with a diffusion rate of only 13%. [Figure A1](#) also depicts the share of firms innovating by industry. Among manufacturers of chemicals, electronics and machinery as well as in the ICT service sector over 70% of firms introduced new products or services within the previous three years. The share of innovating firms is lowest in the transport service sector with only 23%. Overall, the variation over industries depicted in [Figure A1](#) does not provide a clear picture on the relation between the use of big data and innovation performance. While some sectors with a high diffusion of big data also exhibit high shares of innovating firms, this is certainly not true for all industries. For example, while in the manufacturing of machinery industry around 71% of the firms innovate, only 16% rely on big data for their decision-making.

To further investigate which firms exploit data strategically for their decision-making, [Table 8](#) provides summary statistics of firm characteristics conditional on the firms' use of big data. In general, firms which have introduced big data technologies are using ICT more intensively overall, are larger in terms of employees and investments, have higher R&D expenditures, more likely to belong to a multi plant or multinational firm and are more likely to export their goods and services. Importantly, firms using big data analytics are on average more innovative, both at the extensive and intensive margin. Still, a thorough investigation of the relation between big data and firms' innovation performance calls for a multivariate analysis as outlined above.

6. Econometric results

The following section provides the main estimation results. [Table 2](#) presents the estimation results of the Probit models analyzing the relation between big data utilization and the firms' innovation propensity for the full sample as well as for the estimation sample split into the manufacturing and service sector, respectively. The estimate of the coefficient on the big data indicator is positive and statistically significant in all three estimations. Moreover, the estimated relation between a firm's use of big data and the likelihood of that same firm introducing a new product or service to the market is economically meaningful. Looking at the results for the full sample in column (1), the firms' application of big data analytics is associated with a 6.7 percentage point increase in the propensity to innovate. Interestingly, the results are of comparable magnitude when differentiating between manufacturing and service firms in columns (2) and (3). The respective results show that firms using big data analytics are 6.5 percentage points more likely to innovate in the manufacturing sector and 6.8 percentage points more likely to innovate in the service sector. Looking at the estimated coefficients on other control variables, in particular those for other measures of ICT use by the firm, we find that the firms' general ICT intensity measured by the share of employees working predominantly with PCs is not significantly related to innovation propensity. Our estimation results furthermore confirm existing research on the positive relation between enterprise software and innovation (e.g. Engelstätter 2012). ERP Systems typically serve for the planning and controlling of business processes across different sections of the value chain. They moreover constitute a platform to integrate more specific applications, such as Supply Chain Management or Customer Relationship Management Software. While firms using ERP Systems are typically integrating information across different business processes and engage in data driven decision-making, the features of classical ERP Software systems lack the quality of big data analytics in terms of the amount of data that is being processed and the software tools which are used to analyze the data. Furthermore, ERP systems are used to process data that has been purposefully generated by the firm through business transactions while big data often stems from heterogeneous sources outside of the firm. Importantly, our measure for big data use explains the firms' innovation propensity beyond the effect of these legacy software systems. Further strong predictors for how likely a firm is to innovate over all three models are the firm's R&D intensity and export status as well as whether or not the firm belongs to a multinational enterprise.

[Table 3](#) reports the results from the Tobit and the Fractional Logit estimations modeling the sales share of new products, i.e. the market success of firms' innovations. The table reports

Table 2. Dependent variable: dummy for product innovation – probit regression – average marginal effects.

	(1) Full sample	(2) Manufacturing	(3) Services
Big Data	0.067*** (0.023)	0.065* (0.035)	0.068** (0.029)
% of Emp. Predom. Using PC	−0.012 (0.042)	−0.104 (0.075)	0.050 (0.051)
% of Emp. Using Internet	0.074** (0.036)	0.076 (0.050)	0.067 (0.052)
Enterprise Software	0.081*** (0.020)	0.112*** (0.030)	0.059** (0.026)
% of R&D Expenses	0.905*** (0.158)	1.104*** (0.267)	0.774*** (0.176)
Employees (in logs)	0.011 (0.012)	0.015 (0.017)	0.010 (0.015)
Investment (in logs)	0.024*** (0.007)	0.018* (0.011)	0.029*** (0.010)
Exporter	0.164*** (0.021)	0.144*** (0.029)	0.183*** (0.032)
% Highly Qualified Employees	0.154** (0.062)	0.353*** (0.124)	0.041 (0.080)
% Medium Qualified Employees	−0.043 (0.043)	−0.020 (0.056)	−0.099 (0.069)
% of Employees < Age 30	−0.028 (0.052)	−0.069 (0.077)	−0.006 (0.071)
% of Employees > Age 50	−0.015 (0.049)	−0.054 (0.070)	0.022 (0.070)
East Germany	0.005 (0.021)	0.032 (0.028)	−0.036 (0.030)
% of Emp. IT-Training	0.137*** (0.052)	0.165 (0.125)	0.126** (0.055)
Age (in logs)	−0.010 (0.010)	0.004 (0.014)	−0.025* (0.014)
Group	0.036* (0.020)	0.056* (0.030)	0.014 (0.028)
Multinational	0.135*** (0.036)	0.133*** (0.047)	0.123** (0.055)
Industry Dummies	Yes	Yes	Yes
Pseudo R^2	0.209	0.182	0.216
Observations	2706	1404	1302
Log likelihood	−1481.155	−788.318	−683.426

Robust standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All models include an intercept.

Source: ZEW ICT-Survey 2015.

average marginal effects on the conditional expectations in Equations (5) and (6). Overall, results show that the use of big data is not only related to firms' innovation status, but also to their innovation intensity. Over both empirical models in all three samples, big data is positively and statistically significantly associated with the sales share of innovations. Again the estimates are economically meaningful and of equal magnitude for the full sample and within the manufacturing and the service sector. In particular, for the full sample (columns (1) and (2)) the use of big data is associated with a 2.5–2.9 percentage point increase in the sales share from innovations. All other coefficients are in line with prior expectations. R&D intensity is a strong predictor of the sales share of innovations. Over most specifications, a firms' age is negatively associated with innovation intensity. Thus, younger firms achieve a larger share of their sales with newly introduced products or services.

Finally, we turn to the estimation results of the Heckman Selection Model. Theoretically, the model is identified by the functional form assumptions. That is, even if the set of regressors in both equations of the model is identical ($\mathbf{x}_1 = \mathbf{x}_2$), the model is identified due to the nonlinearity of the inverse Mills ratio in the second equation.¹² However, in practice it is desirable to have at least one exclusion restriction, i.e. a variable that enters the selection equation but not the second

Table 3. Dependent variable: % share of new products in turnover-tobit/fracreg regressions.

	Full sample		Manufacturing		Services	
	(1) Tobit	(2) FracReg	(3) Tobit	(4) FracReg	(5) Tobit	(6) FracReg
Big Data	0.025*** (0.006)	0.029*** (0.008)	0.026*** (0.009)	0.032*** (0.011)	0.026*** (0.008)	0.029*** (0.010)
% of Emp. Predom. Using PC	0.004 (0.012)	0.007 (0.013)	−0.009 (0.019)	−0.003 (0.022)	0.015 (0.014)	0.019 (0.015)
% of Emp. Using Internet	0.016* (0.010)	0.014 (0.011)	0.021 (0.013)	0.022 (0.015)	0.014 (0.014)	0.007 (0.018)
Enterprise Software	0.020*** (0.005)	0.018*** (0.006)	0.032*** (0.007)	0.030*** (0.008)	0.012* (0.007)	0.011 (0.008)
% of R&D Expenses	0.253*** (0.020)	0.196*** (0.024)	0.321*** (0.035)	0.243*** (0.050)	0.199*** (0.023)	0.158*** (0.024)
Employees (in logs)	−0.007** (0.003)	−0.014*** (0.004)	−0.004 (0.005)	−0.009* (0.005)	−0.009** (0.004)	−0.019*** (0.005)
Investment (in logs)	0.007*** (0.002)	0.008*** (0.003)	0.003 (0.003)	0.002 (0.004)	0.011*** (0.003)	0.014*** (0.004)
Exporter	0.037*** (0.005)	0.030*** (0.007)	0.034*** (0.007)	0.028*** (0.009)	0.038*** (0.008)	0.029*** (0.010)
% Highly Qualified Employees	0.034** (0.016)	0.026 (0.020)	0.055** (0.028)	0.027 (0.032)	0.013 (0.022)	0.026 (0.023)
% Medium Qualified Employees	−0.015 (0.012)	−0.018 (0.015)	−0.019 (0.015)	−0.032 (0.020)	−0.020 (0.019)	−0.001 (0.021)
% of Employees < Age 30	0.001 (0.014)	0.013 (0.017)	0.015 (0.021)	0.036 (0.023)	−0.011 (0.018)	−0.003 (0.023)
% of Employees > Age 50	−0.001 (0.013)	0.001 (0.015)	−0.008 (0.019)	−0.000 (0.023)	0.007 (0.018)	0.005 (0.020)
East Germany	0.002 (0.006)	0.002 (0.006)	0.012 (0.008)	0.013 (0.009)	−0.009 (0.008)	−0.009 (0.008)
% of Emp. IT-Training	0.027** (0.012)	0.019 (0.015)	0.007 (0.025)	−0.002 (0.023)	0.031** (0.014)	0.027* (0.016)
Age (in logs)	−0.008*** (0.003)	−0.012*** (0.003)	−0.004 (0.004)	−0.008* (0.004)	−0.011*** (0.004)	−0.015*** (0.005)
Group	0.008 (0.006)	0.007 (0.007)	0.015* (0.008)	0.016 (0.010)	0.001 (0.007)	−0.002 (0.009)
Multinational	0.024*** (0.009)	0.023** (0.009)	0.015 (0.011)	0.011 (0.011)	0.035** (0.014)	0.039** (0.016)
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.363	0.092	0.398	0.069	0.335	0.127
Observations	2706	2706	1404	1404	1302	1302
Censored	1432		633		799	
Uncensored	1274		771		503	
Log likelihood	−659.328	−709.616	−257.934	−410.628	−376.715	−295.430

Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in columns 2, 4, and 6. All models include an intercept.

Source: ZEW ICT-Survey 2015.

equation, for more reliable identification of the model parameters (e.g. Wooldridge 2010, p.805ff). Ideally, the exclusion restriction is selected on theoretical grounds. However, there is no variable available which would theoretically affect the firms' likelihood of innovating while leaving the firms' innovation intensity unaffected. We thus follow, for instance, Andries and Czarnitzki (2014) or Peters and Schmiele (2010) and search empirically for an exclusion restriction in order to ensure that identification of the model parameters does not merely rest on functional form assumptions. When including the full set of variables in both equations of the model, the firms' export status is strongly and significantly related to the firms' propensity to innovate, whereas the respective parameter estimate in the second equation is very small and statistically insignificant (see Table 9 in the appendix for the respective estimation results). We thus rely on the firms' export status as an exclusion restriction.¹³ We note, however, that the validity of our exclusion restriction cannot be tested.

Table 4. Heckman selection model with exclusion restriction (export status), marginal effects.

	Full sample		Manufacturing		Services	
	(1) 1st	(2) 2nd	(3) 1st	(4) 2nd	(5) 1st	(6) 2nd
Big Data	0.066*** (0.022)	0.023*** (0.008)	0.065* (0.035)	0.025** (0.010)	0.067** (0.030)	0.025** (0.013)
% of Emp. Predom. Using PC	−0.014 (0.043)	0.001 (0.017)	−0.108 (0.072)	0.015 (0.022)	0.048 (0.054)	−0.011 (0.027)
% of Emp. Using Internet	0.074** (0.036)	−0.005 (0.014)	0.075 (0.050)	0.010 (0.016)	0.069 (0.053)	−0.024 (0.028)
Enterprise Software	0.082*** (0.020)	−0.007 (0.008)	0.112*** (0.030)	−0.002 (0.010)	0.059** (0.026)	−0.012 (0.013)
% of R&D Expenses	0.940*** (0.112)	0.223*** (0.025)	1.210*** (0.203)	0.285*** (0.039)	0.789*** (0.128)	0.182*** (0.036)
Employees (in logs)	0.011 (0.012)	−0.020*** (0.004)	0.015 (0.017)	−0.011* (0.006)	0.010 (0.015)	−0.031*** (0.007)
Investment (in logs)	0.024*** (0.008)	0.004 (0.003)	0.018 (0.011)	−0.005 (0.004)	0.029*** (0.010)	0.014*** (0.005)
Exporter	0.162*** (0.021)		0.138*** (0.029)		0.181*** (0.031)	
% Highly Qualified Employees	0.155** (0.062)	0.003 (0.023)	0.358*** (0.114)	−0.037 (0.034)	0.040 (0.081)	0.043 (0.040)
% Medium Qualified Employees	−0.040 (0.043)	−0.010 (0.017)	−0.018 (0.057)	−0.026 (0.019)	−0.099 (0.069)	0.032 (0.036)
% of Employees < Age 30	−0.027 (0.051)	0.028 (0.020)	−0.069 (0.076)	0.069*** (0.026)	−0.004 (0.069)	−0.007 (0.032)
% of Employees > Age 50	−0.015 (0.048)	0.007 (0.019)	−0.050 (0.068)	0.005 (0.023)	0.018 (0.069)	0.018 (0.034)
East Germany	0.005 (0.021)	0.001 (0.008)	0.032 (0.028)	0.005 (0.009)	−0.036 (0.030)	−0.001 (0.015)
% of Emp. IT-Training	0.133*** (0.051)	0.005 (0.017)	0.166 (0.113)	−0.016 (0.028)	0.119** (0.056)	0.018 (0.022)
Age (in logs)	−0.010 (0.010)	−0.013*** (0.004)	0.004 (0.013)	−0.009* (0.005)	−0.025* (0.014)	−0.019*** (0.007)
Group	0.034* (0.021)	−0.000 (0.007)	0.054* (0.031)	0.007 (0.010)	0.014 (0.028)	−0.009 (0.012)
Multinational	0.134*** (0.036)	0.012 (0.010)	0.130*** (0.047)	−0.004 (0.012)	0.123** (0.055)	0.033* (0.019)
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2706	2706	1404	1404	1302	1302
$\hat{\sigma}_{12}$	−0.232		−0.283		−0.250	
LR-Test $H_0: \sigma_{12} = 0$ [$\chi^2(1)$], p -Val	0.166		0.113		0.391	
Log Likelihood	−969.745		−412.029		−524.323	

Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.0125$. All models include an intercept.

Source: ZEW ICT-Survey 2015.

Table 4 reports the average marginal effects of the Heckman model estimation. For each of the three samples, the first column reports the partial effects on the propensity to innovate while the second column reports the expected innovation intensity, conditional on being an innovator, according to Equation (9). Overall, the previous results are confirmed by the estimation of the selection model. The application of big data analytics is associated with a 6.5–6.7 percentage point higher innovation propensity over all samples. The estimated partial effect on the innovation intensity conditional on being an innovator ranges between 2.3 percentage points in the full sample and 2.5 percentage points in the manufacturing and service sector samples. Note that, in contrast, the use of enterprise software is only positively and statistically significantly related to the propensity to innovate, while the estimated partial effect on the conditional innovation intensity is negative, small and statistically insignificant.

Finally, it should be noted that over all three samples we cannot reject independence between the two equations comprising the model. Consequently, we can re-estimate the equation modeling the

Table 5. Dependent variable: dummy for product innovation – probit regression by skill group – average marginal effects.

	General human capital		IT-specific skills	
	(1) low	(2) high	(3) low	(4) high
Big Data	0.075** (0.033)	0.066** (0.030)	0.044 (0.034)	0.096*** (0.029)
% of Emp. Predom. Using PC	−0.128** (0.064)	0.089 (0.058)	−0.006 (0.059)	−0.033 (0.061)
% of Emp. Using Internet	0.092* (0.049)	0.010 (0.050)	0.110** (0.046)	0.041 (0.056)
Enterprise Software	0.112*** (0.028)	0.044 (0.028)	0.099*** (0.026)	0.046 (0.030)
% of R&D Expenses	0.684*** (0.204)	0.995*** (0.220)	0.805*** (0.190)	0.960*** (0.270)
Employees (in logs)	0.006 (0.017)	0.011 (0.016)	0.017 (0.016)	−0.009 (0.017)
Investment (in logs)	0.031*** (0.010)	0.021** (0.011)	0.017* (0.009)	0.035*** (0.012)
Exporter	0.167*** (0.030)	0.160*** (0.030)	0.151*** (0.028)	0.181*** (0.032)
% Highly Qualified Employees	0.334* (0.176)	0.167 (0.106)	0.175** (0.083)	0.080 (0.095)
% Medium Qualified Employees	−0.015 (0.055)	−0.118* (0.072)	0.000 (0.055)	−0.147** (0.074)
% of Employees < Age 30	−0.078 (0.076)	0.017 (0.072)	−0.133** (0.067)	0.119 (0.082)
% of Employees > Age 50	0.033 (0.067)	−0.067 (0.072)	−0.055 (0.062)	0.007 (0.081)
East Germany	0.015 (0.031)	−0.005 (0.028)	0.015 (0.027)	−0.017 (0.031)
% of Emp. IT-Training	0.219*** (0.083)	0.101 (0.064)	0.192 (0.589)	0.084 (0.065)
Age (in logs)	−0.014 (0.014)	−0.004 (0.014)	−0.018 (0.013)	−0.003 (0.015)
Group	0.047 (0.029)	0.024 (0.029)	0.035 (0.029)	0.031 (0.029)
Multinational	0.089 (0.057)	0.158*** (0.043)	0.092* (0.056)	0.163*** (0.043)
Industry Dummies	Yes	Yes	Yes	Yes
Pseudo R^2	0.192	0.239	0.186	0.215
Observations	1394	1312	1491	1215
Log likelihood	−765.502	−688.597	−813.189	−647.612

Robust standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All models include an intercept.

Source: ZEW ICT-Survey 2015.

firms' innovation intensity on the subsample of innovating companies only. In fact, all the above results were confirmed and detailed regression results are thus omitted for the sake of brevity.

As outlined in Section 2, existing empirical evidence has thus far highlighted the notion that the returns to employing big data analytics is contingent on human capital and the skills of the workforce (e.g. Brynjolfsson and McElheran 2016a). In particular, big data technologies are often discussed to be driving demand for new skills in data mining and visualization. Empirically, Tambe (2014) provides evidence that positive returns to Hadoop investments depend on the firm operating in labor markets with a sufficient supply of relevant technical skills.

Exploring these previous findings in the context of innovation, we conduct a further split sample analysis differentiating between firms with low vs. high general human capital and firms with low vs. high investment in the IT skills of their employees. Specifically, we define a firm as a low (high) human capital firm if the share of employees with degrees from universities and technical colleges is below (above) the industry specific median. Similarly, firms are defined as having low (high) investment in IT-specific skills if the share of employees who participated in IT-specific training in the previous year is below (above) the industry specific median.

Table 5 shows the regression results for Probit models analyzing the relation between big data utilization and the firms' innovation propensity. Columns 1 and 2 show the result for firms with low and high general human capital and columns 3 and 4 the respective results for firms with low and high investment in IT-specific skills. Interestingly, while the relation of big data analytics and the propensity to innovate is not contingent on general human capital in our data, it appears to be, in fact, contingent on the firm's investment in specific IT skills. For firms with low investment in IT skills, the parameter estimate reduces in magnitude and we cannot reject the null hypothesis of no association between big data analytics and the propensity to innovate. For firms with high investment in IT-specific skills the point estimate is now more than twice as large as for firms with low investment. We note that this finding does not carry over to the intensity of innovation, where results are similar to our previous findings, irrespective of the modeling assumptions.¹⁴ Overall, the estimation results support findings on the importance of the acquisition of technical skills for the successful use of big data analytics and show them to be of particular relevance in the context of firms' innovative performance.

7. Conclusions

This paper investigates the relationship between the use of big data analytics and firms' innovative performance. As big data and associated technologies are changing the way information is generated and made relevant, they are widely expected to affect established ways of decision-making within the firm. Better informed decision-making based on novel data practices can be particularly advantageous for business processes involving high uncertainty and risk. Therefore, big data analytics has raised expectations of being particularly beneficial for the firms' innovation process. In addition to improving the innovation process through new and higher quality information, big data technologies can furthermore be at the core of the innovation itself and generate new innovative digital products and services.

We provide large-scale empirical evidence on this widely discussed relation between big data analytics and innovation. Our empirical analysis exploits survey data on 2706 manufacturing and service firms in Germany within a classical knowledge production function framework. Our results show that the use of big data analytics is associated with a higher propensity to innovate, as well as a higher innovation intensity, which we measure by the sales share resulting from new products or services and which constitutes a measure of the market success of the firms' innovations. Importantly, this relation holds when we control for the use of mature software systems and data technologies, such as Enterprise Resource Planning Software, which lack more sophisticated features encompassed by big data analytics.

As the knowledge production process and innovative output likely differ between manufacturing and service firms, we investigate potential effect heterogeneity with regard to the two sectors. Interestingly, the associations we measure are of similar magnitude among firms in the manufacturing and service industries. Our empirical results furthermore suggest that, while the relation between a firm's use of big data and the likelihood of the firm innovating is not contingent on general human capital, it is contingent on firms' investment in IT-specific knowledge and skills.

Our results are robust with respect to various alternative specifications and econometric methods. As we provide evidence on the usage of big data in firms at an early stage, the main limitation of this study is that data availability does not allow to establish causal links, as discussed above. Nevertheless, by providing first empirical evidence based on representative data, this study makes an important contribution towards a better understanding of the potential benefits of big data technologies for firms' innovative performance. Overall, our results are consistent with positive returns of big data analytics in terms of product innovations at the extensive and intensive margin. They support the view that knowledge gained from digitized data by means of big data analytics can be a relevant intangible asset in the innovation process. In this way, our study is relevant for managers making investment decisions in big data related technologies. Taking up the discussions on the effects of

ICT on knowledge production, our results are in line with the notion that big data reduces costs of knowledge absorption, while at the same time exerting little effects on the negative externalities involved in the knowledge creation process brought about by low appropriability and ease of imitation by competitors. Overall, big data thus helps to magnify the positive side of knowledge spillovers involved in knowledge production.

As we provide results based on large-scale data that are representative for a wide variety of manufacturing and service industries, our analysis is also valuable for policy makers. Over recent years, a steadily growing number of policy initiatives have started to promote the use of data as a key asset for increasingly knowledge based economies. In the EU, for instance, such initiatives range from financial support, the layout of new regulations supporting the free flow of data, public private partnerships to develop incentives to share data and knowledge transfer, to the establishment of uniform standards.¹⁵ Our analysis emphasizes the value of such initiatives for the economy's innovativeness but also hints at the role of supporting education for relevant skills and abilities as a necessary complement. Given the ongoing advancements in technologies to generate, store and process data as well as the increasing evidence on their economic value to which this paper contributes, big data will likely play a key role in the ongoing digital transformation of businesses and the associated generation of innovation and new business models.

Notes

1. For an overview see e.g. Draca, Sadun, and Van Reenen (2007), Van Reenen et al. (2010) and Cardona, Kretschmer, and Strobel (2013).
2. Goodridge and Haskel (2015) develop an economic framework to determine the importance of big data for GDP and for GDP growth. Applying their framework to the UK, they find that big data in the form of transformed data and data-based knowledge accounted for 0.02% of growth in market sector value added from 2005 to 2012.
3. Given the distributional assumption in Equation (1), we have $P(y_{1i} = 1 | \mathbf{x}_{1i}) = P(y_{1i}^* > 0 | \mathbf{x}_{1i}) = P(\epsilon_{1i} \leq \mathbf{x}_{1i}'\beta) = \Phi(\mathbf{x}_{1i}'\beta)$ under the normalization restriction $\sigma_1^2 = 1$, which we estimate by Maximum Likelihood.
4. Note that, in line with the general literature, in the Tobit model with zero lower limit we ignore the upper limit of the innovation intensity. However, as the share of observations at the upper limit (of 1) is well below 1%, we regard the effect of upper limiting cases on the estimates to be negligible.
5. For a more detailed description of Tobit type models see for instance Amemiya (1984) or Maddala (1986).
6. Note that the assumption of normality and constant variance of ϵ_{2i} is crucial in deriving the conditional expectation in Equation (5).
7. See for instance Cassiman and Veugelers (2006), Andries and Czarnitzki (2014) or Hottenrott and Lopes-Bento (2016) for other studies applying both types of models to model innovation shares.
8. For more information about the survey see Bertschek, Ohnemus, and Viète (2018). The data are available at the ZEW Research Data Centre – <http://kooperationen.zew.de/en/zew-fdz>.
9. In order to better differentiate big data in accordance with this definition, we will control for the use of such legacy systems in the empirical application.
10. For an extensive review of definitions of the big data phenomenon see for instance Wamba et al. (2015).
11. Table 7 provides an overview of the industries and their distribution in the estimation sample.
12. The inverse Mills ratio corresponds to the term $\phi(\delta_1' \mathbf{x}_{1i}) / \Phi(\delta_1' \mathbf{x}_{1i})$ in Equation (9).
13. As a robustness check, we used enterprise software as well as firms' export status together with enterprise software as exclusion restrictions with substantially similar results (results not reported; available upon request).
14. Estimation tables for the innovation intensity equations using split samples by human capital and investment in IT-specific skills are excluded for brevity.
15. See for example <http://ec.europa.eu/digital-single-market/en/policies/big-data>.

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Disclosure statement

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Appendix

Table A1. Data practices employed by firms relying on big data.

	(1)		(2)		(3)	
	No big data		Use big data		Total	
	N	Mean	N	Mean	N	Mean
Big Data					1598	0.22
We use automated data recording, processing and transmission in order to ...						
... make internal processes more efficient, e.g. reduce material or energy consumption.	1246	0.32	352	0.48	1598	0.36
... provide our employees with digital assistance systems, e.g. in logistics, production, maintenance.	1246	0.48	352	0.70	1598	0.53
... exchange information with suppliers and customers.	1246	0.48	352	0.65	1598	0.52
... customize products/services to individual customer needs.	1246	0.31	352	0.47	1598	0.34
... adapt internal processes flexibly or fix errors.	1246	0.39	352	0.60	1598	0.44
Firm supplies products with embedded RFID-Chips, QR-codes, sensors	1246	0.09	352	0.14	1598	0.10
At least one of the above	1246	0.74	352	0.91	1598	0.78

Note: All differences in proportions between firms with and without big data applications are statistically significant at the 0.01 level.

Source: ZEW ICT-Survey 2015 and supplementary survey 2015/2016.

Table A2. Distribution of firms across industries: estimation sample.

	N	Percentage
Manufacture of Consumer Goods	448	16.56
Manufacture of Chemicals	94	3.47
Manufacture of Basic Materials	249	9.20
Manufacture of Metals	193	7.13
Manufacture of Electronics	177	6.54
Manufacture of Machinery	165	6.10
Manufacture of Motor Vehicles	78	2.88
Retail Trade	158	5.84
Wholesale Trade	129	4.77
Transport Services	149	5.51
Media Services	125	4.62
ICT Services	158	5.84
Financial Services	129	4.77
Consulting, Advertising	158	5.84
Technical Services	128	4.73
Business Services	168	6.21
Total	2706	100.00

Source: ZEW ICT-Survey 2015.

Table A3. Summary statistics by big data use of firms: estimation sample.

	No big data		Use big data		Total	
	N	Mean	N	Mean	N	Mean
Product Innovation	2121	0.44	585	0.60	2706	0.48
% of Sales New Product	2121	0.07	585	0.12	2706	0.08
Big Data	2121	0.00	585	1.00	2706	0.22
% of Emp. Predom. Using PC	2121	0.42	585	0.55	2706	0.45
% of Emp. Using Internet	2121	0.55	585	0.65	2706	0.57
Enterprise Software	2121	0.50	585	0.77	2706	0.56
% of R&D Expenses	2121	0.04	585	0.07	2706	0.05
Employees	2121	62.22	585	187.53	2706	89.31
Employees (in logs)	2121	3.23	585	4.17	2706	3.43
Investment in Mill. Euro	2121	0.53	585	2.12	2706	0.88
Investment (in logs)	2121	-2.29	585	-1.09	2706	-2.03
Exporter	2121	0.44	585	0.49	2706	0.45
% Highly Qualified Employees	2121	0.19	585	0.21	2706	0.19
% Medium Qualified Employees	2121	0.63	585	0.61	2706	0.63
% of Employees < Age 30	2121	0.23	585	0.26	2706	0.24
% of Employees > Age 50	2121	0.28	585	0.26	2706	0.27
East Germany	2121	0.25	585	0.22	2706	0.25
% of Emp. IT-Training	2121	0.08	585	0.13	2706	0.09
Age (in logs)	2121	3.13	585	3.31	2706	3.17
Group	2121	0.26	585	0.43	2706	0.29
Multinational	2121	0.08	585	0.15	2706	0.09

Source: ZEW ICT-Survey 2015.

Table A4. Heckman selection model (without exclusion restriction), marginal effects.

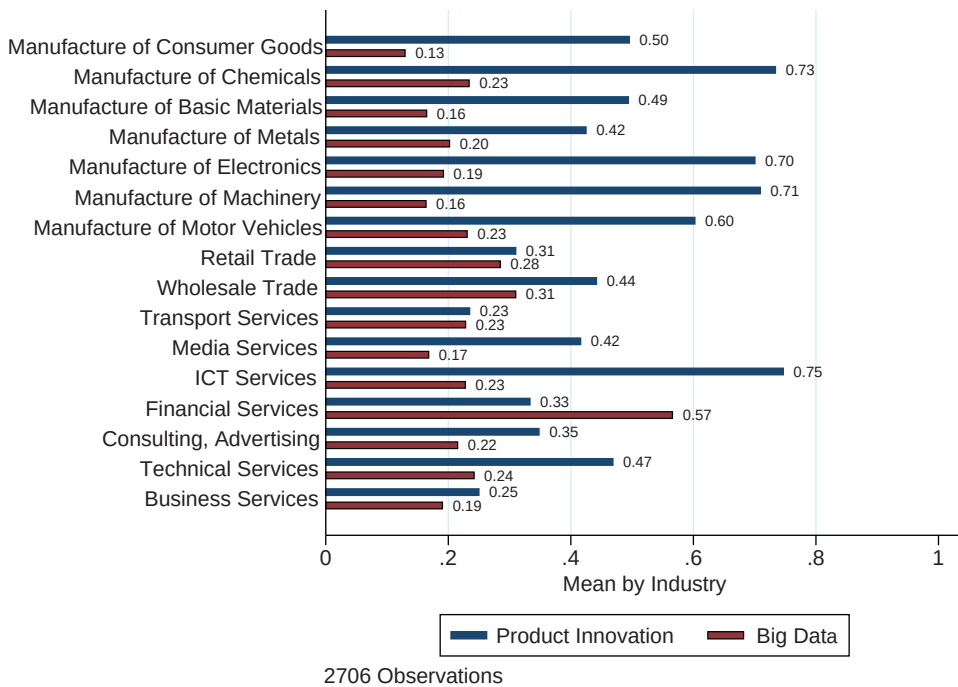
	Full sample		Manufacturing		Services	
	(1) 1st	(2) 2nd	(3) 1st	(4) 2nd	(5) 1st	(6) 2nd
Big Data	0.066*** (0.022)	0.022*** (0.008)	0.065* (0.034)	0.024** (0.011)	0.067** (0.030)	0.025* (0.013)
% of Emp. Predom. Using PC	-0.015 (0.043)	0.001 (0.017)	-0.110 (0.072)	0.017 (0.023)	0.048 (0.054)	-0.013 (0.028)
% of Emp. Using Internet	0.074** (0.036)	-0.005 (0.014)	0.075 (0.050)	0.010 (0.016)	0.069 (0.053)	-0.025 (0.028)
Enterprise Software	0.082*** (0.020)	-0.007 (0.008)	0.112*** (0.030)	-0.002 (0.010)	0.059** (0.026)	-0.014 (0.013)
% of R&D Expenses	0.947*** (0.111)	0.223*** (0.026)	1.224*** (0.202)	0.286*** (0.040)	0.792*** (0.127)	0.180*** (0.037)
Employees (in logs)	0.011 (0.012)	-0.020*** (0.005)	0.015 (0.017)	-0.010* (0.006)	0.010 (0.015)	-0.031*** (0.008)
Investment (in logs)	0.024*** (0.008)	0.004 (0.003)	0.018 (0.011)	-0.005 (0.004)	0.029*** (0.010)	0.014*** (0.005)
Exporter	0.164*** (0.021)	-0.007 (0.008)	0.141*** (0.029)	-0.010 (0.011)	0.184*** (0.031)	-0.010 (0.014)
% Highly Qualified Employees	0.154** (0.062)	0.002 (0.023)	0.358*** (0.113)	-0.039 (0.035)	0.040 (0.081)	0.045 (0.041)
% Medium Qualified Employees	-0.040 (0.043)	-0.010 (0.017)	-0.018 (0.057)	-0.027 (0.019)	-0.099 (0.068)	0.034 (0.037)
% of Employees < Age 30	-0.026 (0.051)	0.027 (0.020)	-0.068 (0.076)	0.068*** (0.026)	-0.004 (0.069)	-0.008 (0.033)
% of Employees > Age 50	-0.015 (0.048)	0.007 (0.020)	-0.049 (0.067)	0.006 (0.024)	0.017 (0.069)	0.017 (0.035)
East Germany	0.005 (0.021)	0.000 (0.008)	0.032 (0.028)	0.004 (0.010)	-0.036 (0.030)	-0.001 (0.016)
% of Emp. IT-Training	0.133*** (0.051)	0.004 (0.017)	0.166 (0.113)	-0.017 (0.028)	0.118** (0.055)	0.017 (0.023)
Age (in logs)	-0.010 (0.010)	-0.013*** (0.004)	0.004 (0.013)	-0.009* (0.005)	-0.025* (0.014)	-0.019*** (0.007)
Group	0.034* (0.014)	-0.001 (0.007)	0.054* (0.014)	0.007 (0.007)	0.014 (0.014)	-0.010 (0.014)

(Continued)

Table A4. Continued.

	Full sample		Manufacturing		Services	
	(1) 1st	(2) 2nd	(3) 1st	(4) 2nd	(5) 1st	(6) 2nd
Multinational	(0.021) 0.133***	(0.008) 0.012	(0.031) 0.129***	(0.010) -0.004	(0.028) 0.122**	(0.013) 0.036*
Industry Dummies	(0.036) Yes	(0.010) Yes	(0.047) Yes	(0.012) Yes	(0.055) Yes	(0.020) Yes
Observations	2706	2706	1404	1404	1302	1302
$\hat{\sigma}_{12}$	-0.270		-0.316		-0.311	
LR-Test $H_0 : \sigma_{12} = 0[\chi^2(1)]$, p -Val	0.113		0.068		0.262	
Log Likelihood	-969.413		-411.619		-524.052	

Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All models include an intercept.
Source: ZEW ICT-Survey 2015.

**Figure A1.** Industry means of product innovation and big data: estimation sample.

Source: ZEW ICT survey 2015.