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Intangible Capital and Productivity. Firm-level Evidence from German Manufacturing

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Intangible Capital and Productivity. Firm-level Evidence from German Manufacturing*

Abstract

We study the importance of intangible capital (R&D, software, patents) for the measurement of productivity using firm-level panel data from German manufacturing. We first document a number of facts on the evolution of intangible investment over time, and its distribution across firms. Aggregate intangible investment increased over time. However, the distribution of intangible investment, even more so than that of physical investment, is heavily right-skewed, with many firms investing nothing or little, and a few firms having very large intensities. Intangible investment is also lumpy. Firms that invest more intensively in intangibles (per capita or as sales share) also tend to be more productive. In a second step, we estimate production functions with and without intangible capital using recent control function approaches to account for the simultaneity of input choice and unobserved productivity shocks. We find a positive output elasticity for research and development (R&D) and, to a lesser extent, software and patent investment. Moreover, the production function estimates show substantial heterogeneity in the output elasticities across industries and firms. While intangible capital has small effects for firms with low intangible intensity, there are strong positive effects for high-intensity firms. Finally, including intangibles in a gross output production function reduces productivity dispersion (measured by the 90-10 decile range) on average by 3%, in some industries as much as nearly 9%.

Keywords: intangible capital, productivity, production functions

JEL classification: D24, L60, O30

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1. Introduction

Recent research suggests that the endowment with and accumulation of traditional factors of production such as labor and physical capital explain the output and the growth of firms only to a limited extent. Instead, there might be further, rather intangible factors that affect firm performance, such as research and development (R&D), software, patents, or branding and organization capital (Corrado et al. 2005, 2009; Haskel and Westlake 2018). Yet, the precise role of intangibles is currently not well understood. Many papers relying on aggregate data have used growth accounting methods to show that intangible capital contributes to economic growth.[1] However, focusing on the aggregate captures only part of the story as firms differ widely in their use of intangible capital (Arrighetti et. al 2014). It is necessary to use firm-level data in order to model how intangible capital is distributed across firms and whether there exist any heterogeneities in the returns to intangible capital. Eventually, this may then help to better understand why some firms are more productive than others.

In this paper, we analyze the importance of intangibles for the measurement of firm productivity considering the case of the German manufacturing sector. We use high-quality firm-level panel data from the structural business surveys and the industrial production surveys which are representative for all manufacturing firms with at least 20 persons employed. Our analysis covers the survey years 2009-2015 and includes about 14,000 unique firms per year. We construct firm-level intangible capital stocks based on information on firm expenditures for R&D, patents and licenses (henceforth referred to as *patents*), and software.

We first document a number of facts on the evolution of intangible investment over time and its distribution across firms. We show that on the aggregate level, intangible investment has increased over time and surpassed investment in machinery and equipment in recent years. However, the distribution of intangible investment, even more so than for physical investment, is heavily right-skewed, with many firms investing nothing or little, and a few firms investing a lot. Moreover, we show that investment in intangibles also behaves more “lumpy” than investment in physical capital, i.e., within a firm it is more concentrated in a few years.

The paper then proceeds by estimating production functions with and without intangible capital, separately for different two-digit industries to allow for heterogeneity. We use both an OLS and a Wooldridge (2009) estimator to account for simultaneity of input choice and productivity. We estimate specifications with gross output and value added and perform several robustness checks to assess the stability of our results. Our results show that especially research

[1] See Corrado et al. (2005, 2009) for the US, Giorgio Marrano et al. (2009) for the UK and Fukao et al. (2009) for Japan.

and development (R&D) and, to a lesser extent, software and patent investment, have a positive effect on output. However, the production function estimates show substantial heterogeneity in the output elasticities across industries and firms. While intangible investment has smaller effects for firms with low intensity of intangible capital (per full time employee), there is a strong positive effect for high-intensity firms. We confirm that this gradient is visible in various subsamples, i.e., for both small and large firms, for firms with are part of an enterprise group and those that are not, and for different time periods.

Our analysis further investigates the importance of including intangibles for the measurement of productivity. Firms in the top of the intangible intensity distribution have on average considerably higher "traditional" Total Factor Productivity (TFP) than firms with lower intangible intensity, when TFP is measured as a residual in a regression with labour and physical capital as inputs. Including intangibles in a gross output production function reduces residual productivity dispersion (measured by the 90-10 decile range) on average by 3%, in some industries as much as nearly 9%.

Our paper connects and contributes to the literature in several ways. We connect to previous research that has analyzed the role of intangibles. However, while this research has used selective samples and focused on the role of certain types of intangibles, we use a comprehensive data set from German manufacturing and analyze the importance of different types of intangible assets simultaneously. For example, one strand of the literature has investigated the effect of information and communication technology (ICT) on firm productivity.[2] Another strand of the literature has looked at the effect of R&D.[3] Our comprehensive firm-level data also allow us to analyze heterogeneity, by estimating separate production functions for different industries as well as for firms with different intangible intensity. Moreover, while most of the existing literature focuses on the U.S., the UK or other countries[4], there exists very little evidence on Germany.[5] The German

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[2] This includes, among others, Breshanan et al. (2002) or Brynjolfsson and Hitt (2003) for the U.S.; Bloom et al. (2012) for the UK, Dhyne et al. (2018) for Belgium, and Smeets and Warzynski (2018) for Denmark; as well as Bloom et al (2010) for a cross-country analysis.

[3] This research builds upon the work of Griliches (1979). See Hall et al. (2010) for a literature review, or Hall et al. (2013) as well as Doraszelski and Jaumandreu (2013) for more recent contributions.

[4] Corrado et al. (2005, 2009) for the US, Giorgio Marrano et al. (2009) for the UK and Fukao et al. (2009) for Japan use growth accounting methods with macroeconomic data. Studies using firm-level data and distinguishing between different types of intangibles are Bontempi and Mairesse (2015) and Arrighetti et al. (2014) for Italy, as well as Chappell and Jaffe (2016) for New Zealand.

[5] Belitz et al. (2017) and Crass and Peters (2014) are the German analyses which are closest to our paper. The former also uses German structural business surveys, while the latter uses data from the Mannheim Innovation Panel (MIP). Similar to our paper, these studies estimate production functions with various

case, however, is interesting not only because it is the biggest economy in Europe, but also because German manufacturing is thought to be world class in terms of performance and competitiveness.

We also relate to the literature on the dispersion of TFP. In particular, pronounced and persistent differences in the performance of firms even within relatively narrowly defined industries have often been thought to signal some frictions and distortions of the competition and selection mechanisms and the proper functioning of markets. Syverson (2004) reports that within four-digit SIC industries in the U.S. manufacturing sector, a plant at the 90th percentile of the productivity distribution produces almost twice as much output with the same measured inputs as a plant in the 10th percentile. Hsieh and Klenow (2009) report even larger productivity differences across firms in China or India, with ratios above 5:1. Our results indicate that not accounting for the investment nature of intangibles might lead to overestimating the productivity of firms that make use of them. We find that intangibles as measured by R&D, patents and software play some role in explaining the wide spread of productivity. The effect for the aggregate distribution is not very large, but becomes significant in more narrowly defined industries. Nevertheless, a substantial unexplained variation in productivity remains. Not least, our results are in line with the literature on superstar firms, i.e., firms that achieve extraordinary productivity and profits with relative low intensity of traditional factors of production (Autor et al. 2019).

The remainder of the paper is structured as follows. Section 2 explains the data and the construction of relevant variables. Section 3 presents stylized facts on the evolution of tangible and intangible investment over time and across firms. Section 4 explains the econometric methodology. Section 5 shows the estimation results. Section 6 concludes.

2. Data

2.1. Data Description

The basis for our data are the German structural business surveys and the industrial production surveys in the manufacturing sector for the years 1995 to 2016. These data cover firms with at

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types of intangible capital and also perform separate estimations by industry. We contribute to their analyses by investigating more closely heterogeneity in the use of intangible capital across firms, and by allowing the production functions to vary by intangible intensity at the firm level.

least 20 persons employed and are provided by the Federal Statistical Office of Germany.[6] For these surveys, participation is mandatory for firms and unit nonresponse rates are thus very low.[7]

As different information is collected by different surveys, we combine several different surveys in order to be able to construct intangible capital and assess its importance for measuring TFP. First, we use the investment survey (*Investitionserhebung, IE*) that covers the population of manufacturing firms with at least 20 persons employed (ca. 37,000 per year) and collects information on investment in tangible goods (machinery and buildings) since 1995 and in intangible goods (patents and software) since 2009. Second, we use the cost structure survey (*Kostenstrukturerhebung*, KSE) that is a 40% sample (i.e., ca. 15,000 firm per year) of the investment survey. In order to minimize possible attrition biases, the KSE is drawn as a rotating panel in 1995, 1999, 2003, 2008, 2012, and 2016. It contains information on turnover, intermediate inputs, the number of full-time equivalent employees, internal R&D expenditures, and the number of R&D employees (the latter two variables since 1999). As large firms are oversampled in the KSE (with stratification based on industry, employment, and turnover), we use sampling weights in all analyses.[8]

Overall, this means that our estimations are based on an unbalanced panel of ca. 14,000 firms per year which are available in both cost structure survey and investment survey. Moreover, the period for our main analysis is 2009-2015 since information on investment in patents and software is available only since 2009. Note, however, that, whenever required (e.g., for computing capital stocks), we utilize the full past history (possibly dating back to 1995), as discussed further in Appendix A.

Moreover, we utilize data from the monthly and quarterly production surveys (*Produktionserhebungen*) which contain information on the production value and physical quantities of actually produced goods (not goods for resale) at the nine-digit-level of the PRODCOM classification. We use this information to calculate firm-level prices, which we include as a control variable in the production function to purge out unobserved quality differences in the intermediates that might bias the estimates for the output elasticities and, therefore, TFP (De

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[6] Although the data also include firms in the mining and quarrying industry, we exclude those firms due to lack of comparability with manufacturing.

[7] See Federal Statistical Office (2017, 2018, 2019) for a detailed documentation of the data.

[8] From the years 2008 onwards, weights are directly included in the data sets. This is sufficient for most of our analyses which only cover the years 2009-2016. In the few cases where we require information for preceding years, we construct yearly inverse probability weights (based on 4-digit industry and employment category) ourselves, using the full population of firms in the investment survey (IE).

Loecker et al. 2016). We normalize the firm-product-specific price by the average price of the respective product across all firms (see Bräuer et al. 2019 who use the same data in a different context).[9] In the case of multiproduct firms, we follow Eslava et al. (2004) and construct a price for the composite output of the firm as the weighted average of the prices of all products in a firm's portfolio, using as weights the share of the individual products in the firm's total production value.

The data include time-varying industry classifications at the 4-digit level, which we transform to a consistent NACE Rev. 2 classification using conversion tables provided by Dierks et al. (2019). We keep only manufacturing firms in the 2-digit industries C10 to C33. To avoid issues related to industry switching – in case of either reclassification following NACE revisions or a firm's change in its business model – we drop all firms which ever were in an industry outside of manufacturing.[10]

Finally, we merge information from the official business register on whether the firm is part of an enterprise group, distinguishing between non-grouped firms, firms belonging to groups with a German head, and firms belonging to a group with a foreign head.

2.2. Definition of Key Variables

Depending on the specification, our measure of firm output is either gross output or value added.[11] Our measure for labour input is the number of full-time equivalent employees (including apprentices and interns), plus the number of working proprietors and unpaid family workers. Adjusting for changes in working hours is important given the large increase in part-time employment in Germany since the 1990s (Chalupa and Mai 2018; Burda and Seele 2016). *Physical capital* includes machines and land with and without buildings. *Intangible capital* includes purchased patents, purchased software as well as internal R&D. Our data include annual

[9] In the case of missing price information, we impute the average price of the 4-digit industry. This is mainly relevant for products for which no physical quantities but only monetary values are reported in the data. This applies to ca. 30% of all firm-product observations.

[10] In the context of the conversion from WZ2003 to WZ2008, there have been some industry switchers, mostly manufacturing firms that switched to the service sector. For example, a large number of firms which used to be part of the manufacturing industry D22 "Printing and publishing" are now classified as part of the service industry J58 "Publishing". See Dierks et al. (2019) for a detailed discussion.

[11] Gross output (*Bruttoproduktionswert*) is the sum of turnover from all products of the firm's own production, plus traded commodities, changes in inventories, and the value of self-processed equipment. Value added (*Bruttowertschöpfung*) is gross output minus intermediates, with the latter being the sum of materials, energy, traded commodities, costs for temporary agency workers, other services, rents and leases, and other costs.

investment values that we use to calculate capital stocks applying the Perpetual Inventory Method (PIM) (cf., Appendix A).

We acknowledge that some components of intangible capital are missing in our data. Official business statistics only cover purchased software, measured at the purchase price. Thus, self-processed software is not included (since there are no readily observable market prices for the latter). For similar reasons, the surveys only cover expenditures for purchased patents and licenses and not the value of self-processed patents or licenses. Moreover, R&D only includes activities conducted by the firm itself, not contracted R&D. Other assets such as organizational capital, firm-provided employee training, or brand equity (subsumed under the term “economic competencies” by Corrado et al. 2009) are also missing.

Since our measure of R&D expenditure is a composite of personal expenditures, materials expenditures and investments, we have to avoid double counting of inputs which was often found to bias the returns to R&D downwards (Hall et al. 2010; Hall and Mairesse 1995). In particular, we subtract R&D-related components from the other input variables. As our micro data directly include the firm’s number of R&D employees, we subtract these from the total number of FTE employees when measuring labour input.[12] Moreover, we subtract (i) the investment share of R&D expenditure from investment in machines, and (ii) the materials share of R&D expenditure from intermediate inputs, and add this materials share back to value added. Information on the shares of R&D expenditures on personal, materials, and investments at the 2-digit industry*year level is taken from the *Stifterverband für die Deutsche Wissenschaft e.V.*[13]

We convert all variables to 2015 Euros using price deflators at the 2-digit industry level provided by the Federal Statistical Office of Germany.[14] Moreover, when estimating production functions, we perform an outlier correction for all input and output variables. In particular, we winsorize values at the 1st and 99th percentile of the distribution of each variable per year and we

[12] The number of R&D employees is given in the data as a head count, not as full-time equivalents. We thus assume that a firm’s share of part-time workers is the same for R&D-employees and non-R&D-employees.

[13] For the manufacturing sector as a whole, these shares are 60.6% for personnel, 31.9% for materials, and 7.5% for investment.

[14] The National Accounts data provide separate price deflators for investment in machinery, buildings, and intellectual property (the latter are used for R&D, software, and patents), as well as price deflators for turnover, value added, and intermediates. See also Adler et al. (2014) and Hauf and Schäfer (2019) for a detailed discussion.

also drop firms with an extremely high capital-labour ratio.[15] Finally, all specifications will control for 2-digit industry dummies (when the estimations are pooled for different industries), a dummy for East Germany, and year dummies.

3. Investment in Physical and Intangible Capital: Some Facts

We now use our rich firm-level panel data to present some facts on investment into physical and intangible capital, in particular its development over time and its distribution across industries as well as across and within firms. These findings will later on determine the choice of appropriate specifications of the production functions.

Fact 1: Intangible investment has increased over time.

We first consider in Figure 1 aggregate real investment for the manufacturing sector over the period 1999 to 2016 (with the limitation that, as described in Section 2, software and patent investment are only available in the surveys from 2009 onwards). The numbers are converted to real terms (in 2015 Euros) by using separate price deflators for machinery, buildings, and intangibles.[16] It becomes apparent that the manufacturing sector underwent a major shift from physical investment to investment in intangible capital over the considered period. Investment into machines and equipment increased from 45 billion € in 1999 to 52 billion € in 2016, while R&D spending increased from 39 billion € to 67 billion €. Moreover, on the aggregate level R&D constitutes the main part of intangibles, while software and patents play a smaller role (with 2 billion € and 3 billion € in 2016, respectively).

– Figure 1 here –

[15] In particular, we drop firms where the ratio of the capital stock relative to FTE employees exceeds 2 Mio. Euro for physical capital, and 200,000 Euro for intangible capital. These values lie above the 99th percentile for each variable.

[16] These price deflators come from Germany's National Accounts (*Volkswirtschaftliche Gesamtrechnung, Fachserie 18, Reihe 1.4, Version 18.10.2019*) and vary on the 2-digit industry level.

Fact 2: Intangible investment is highly concentrated among a few firms.

The large role of intangibles on the aggregate level, however, masks that not all firms invest and that the investment is very unequally distributed across firms. Figure 2 shows the share of firms which have invested in the current year, separately for different investment goods. It becomes apparent that investment in physical capital still occurs much more frequently than investment in intangibles. In 2016, almost all firms (89%) had investment in machinery and equipment, whereas only 54% had some form of intangible investment (either R&D, software, or patents). Splitting up the various components of intangibles, software investment is relatively common (with 40% of firms reporting positive values), while investments on patents (13%) and R&D (28%) are performed by a smaller number of firms. However, the share of firms investing in intangibles has increased over time. Considering R&D, the variable for which the longest time series is available in our micro data, the share of firms investing in R&D has increased from 23% in 1999 to 28% in 2016. The incidence of software and patent investment has increased as well.

– Figure 2 here –

As a measure of concentration, Figure 3 shows the top 1% share for each investment type, i.e., the share of total investment in the manufacturing sector conducted by the 1% firms with the highest value.[17] The figure reveals that investment in intangibles is much more concentrated among a few firms than physical investment. Top 1% firms make up between 50% and 58% of physical investment in all years. For intangible investment, however, the shares are considerably higher. Concentration is most pronounced for patents and R&D (both have top 1% shares over 80%) and less so for software (above 60%). Considering the changes over time, concentration of investment has decreased until the mid-2000s and slightly increased since then.

– Figure 3 here –

While the previous analyses have only considered whether a firm has invested in the current year, the infrequent and "lumpy" nature of investment (discussed also in more detail below) makes

[17] Recall that the descriptive statistics in this section include the full sample without dropping outliers. Moreover, the definition of the top 1% firms is done separately for each variable, which means that, for example, a firm that belongs to the top investors in machines does not necessarily belong to the top investors in software.

it worthwhile to also consider investment for a given firm over a longer time period. In Table 1, we thus use the panel structure of our data and consider a firm's 4-year cumulative investment over the 2012-15 period.[18] About 70% of firms had some intangible investment at least once in these 4 years. This share is higher than the yearly investment share (which was about 52-54%) which means that some firms do not invest in intangibles continuously in all years. 62% of firms have invested in software at least once, compared to 33% for R&D, and 25% for patents.

Table 1 also shows the percentiles of the distribution of the different investment types, considering a firm's cumulative 4-year investment over the 2012-15 period. Panel A shows the absolute investment values in TSD Euros, while Panel B shows the share of the respective investment type over the firm's total investment during this period. The distribution of all variables is highly right-skewed, with many firms investing nothing or little, and a few firms investing a lot. This skewness, however, is much stronger for intangible investment. While the median total intangible investment per firm is 28,000 € (see Panel A), the 90th percentile is 3.2 million €, implying a 90/50 ratio of about 114. In contrast, the 90/50 ratio for physical investment is only about 11. As shown in Panel B, the median firm has about 3% of its investment in intangibles, but there are a few firms with very high shares (a firm at the 90th percentile has 62% of its investment in intangibles). Moreover, the table shows that while software investment is more important for the median firm, R&D has much higher values at the top of the distribution.

– Table 1 here –

Table 2 shows the distribution of intangible investment by NACE Rev.2 2-digit industry.[19] The industries where the median firm invests most in intangibles are data processing equipment (1.2 million €), pharmaceutics (875,000 €) and chemicals (691,000 €). The industries electrical equipment, engineering, motor vehicles, and other vehicles also have high values. In contrast, the median firm in the food or wood industry does not invest at all in intangibles. A similar picture emerges when considering intangible investment as share of total investment (Panel B). Besides these differences across industries, Table 2 also reveals large heterogeneities within industries. For example, while the median firm in the motor vehicle industry has an intangible investment of only

[18] The years 2012-15 constitute the most recent "cycle" in the cost structure survey, which is drawn as a 4-year or 5-year rotating panel. We use a balanced panel of firms which are observable in both cost structure survey and investment survey in all 4 years.

[19] We have aggregated a few industries due to small sample sizes (e.g., the industries C19 Coke and C20 Chemistry).

108,000 €, the firm at the 90th percentile invests 12.2 million €. Firms with high intangible investment exist in all industries.

– Table 2 here –

Fact 3: Firms with higher intensity of intangible capital have higher productivity.

We next ask the question how a firm's intangible intensity is correlated with its productivity. We divide the sample into six different groups depending on a firm's intangible capital stock in TSD Euros per FTE employee.[20] In particular, we first identify the group of "non-investors" (firms that have zero intangible capital stock) and then further divide the remaining sample of firms with non-zero intangible capital stock into quintiles of intangible intensity.[21] Figure 4 plots for each of the six groups the distribution of labour productivity defined as value added per FTE employee (Panel A) and "traditional" total factor productivity (TFP, Panel B), whereby TFP is estimated as the residual of a regression of value added on the "traditional" input factors labour and physical capital. Figure 4 reveals that firms with higher intangible intensity on average are more productive and that this association holds for both labour productivity (Panel A) and TFP (Panel B). These findings seem particularly pronounced for the top quintile of intangible investors (highlighted with a dashed line in the graphs).

– Figure 4 here –

Fact 4: Firm-level intangible intensity is correlated with physical capital intensity, industry, and firm size, but there is also substantial variation in intensity within these groups.

Table 3 shows that low- and high-intensity firms also differ in other characteristics.[22] First, one can ask whether firms with high intensity of intangible capital also use physical capital more

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[20] The intangible capital stock is constructed using the Perpetual Inventory Method, see Appendix A.

[21] The definition of quintiles is done separately for each year, meaning that a firm can be in different quintiles in different years.

[22] Since we consider the 2012-15 period and firms can be in different quintiles in each year, the number of unique firms for all six groups together is higher than the number of firms in the sample.

intensively. As it turns out, this relationship is not monotonous. Firms who do invest in intangible capital have higher physical capital intensity than noninvestors. However, firms in the top quintile of intangible intensity actually have slightly *lower* physical capital intensity than the third and fourth quintile of investors. This suggests that for firms with very high intangible intensity, intangible capital is more of a substitute for physical capital. Moreover, high-intensity firms are concentrated in different industries (chemical, data processing, electrical equipment). Nevertheless, there is also substantial heterogeneity within industries. For example, take one of the largest industries, engineering. While engineering firms are disproportionately found in the top intensity quintile, there is also a substantial number of engineering firms which have a zero intangible capital stock. With respect to the number of persons employed, firms with high intangible intensity are on average larger, but there is still a non-negligible number of small firms in the top quintile (ca. 16% in the top quintile of investors are smaller than 50 persons employed).

– Table 3 here –

Fact 5: Intangible investment is "lumpy".

Finally, there are also some interesting patterns with respect to the distribution of investment *within* firms over several years, which we show in Figure 5. The previous literature has documented that investment is "lumpy", i.e., that most of a firm's investment is concentrated in a few years (Cooper and Haltiwanger 2006, Nilsen and Schintarelli 2003, Doms and Dunne 1998). However, these papers have so far only focused on physical capital and little is known about intangibles. We calculate, for each firm in our panel, its cumulative investment over the 4-year period 2012-15 and ask what share of this cumulative investment falls in the year with the highest, second highest, etc. value. We then average these shares over all firms in the sample.

– Figure 5 here –

Figure 5 shows clear evidence that investment in intangible capital behaves more "lumpy" than investment in physical capital. 60% of the total intangible investment over the last 4 years happens in the year with the largest investment, compared to 52% for physical capital. Most concentrated are investments in patents and software, while R&D is slightly less concentrated.[23]

[23] Appendix Figure B1 shows the same analyses for a longer period of 8 years, with the restriction that the number of firms which are observable over 8 consecutive years is much smaller (N= 3629 firms) and

The latter might be driven by the fact that R&D spending also includes expenditure for R&D personnel, which behaves more smoothly over time. The pattern of "lumpy" investment, in particular when it comes to intangibles, shows that investment in a given year can be a misleading indicator of a firm's long-term investment and capital stock.Thus, when calculating capital stocks for tangible and intangible capital, it is necessary to observe firms over a longer period of time in the data. This is a key advantage of the panel data we use.

4. Assessing Productivity: Production Function Estimation

4.1. The Basic Setup

We estimate an "augmented" Cobb-Douglas production function for firm i in time period t

$$Y_{it} = M_{it}^{\beta_m} \cdot L_{it}^{\beta_l} \cdot TK_{it}^{\beta_{tk}} \cdot IK_{it}^{\beta_{ik}} \cdot A_{it}$$

where Y is output (measured as gross output), M are intermediate inputs, L is labour, TK is tangible capital, IK is intangible capital, and A is total factor productivity (TFP). Note that we will use both the sum of all intangible components (R&D, software, patents) as well as the three components separately. Taking logs on both sides gives the estimating equation

$$y_{it} = \beta_0 + \beta_m \cdot m_{it} + \beta_l \cdot l_{it} + \beta_{tk} \cdot tk_{it} + \beta_{ik} \cdot ik_{it} + \omega_{it} + u_{it} \qquad (1)$$

where lower-case letters denote logarithms and log TFP can we written as $\log A_{it} = \beta_0 + \omega_{it} + u_{it}$. ω_{it} is a firm-specific productivity component which is observed to the firm but unobserved to the econometrician and u_{it} is a stochastic residual. The difference between ω_{it} and u_{it} is that the former affects the firm's input choice, while the latter does not.[24]

An alternative specification to that in (1) is to use log value added as the dependent variable and don't include the log intermediate inputs. In principle, both approaches identify different parameters concerning, for example, the effect of intangibles. Either we identify the effect of intangibles on gross output, holding capital, labour, and intermediates fixed, or we identify the effect of intangibles on value added, holding labour and capital fixed. Moreover, as has been

consists mostly of larger firms. When considering the longer 8-year period, the patterns become smoother, as expected, but the key results remain.

[24] Our final specification will additionally include a set of control variables, namely year dummies, industry dummies (when pooling estimates across industries), and a dummy for East Germany.

shown by Gandhi et al. (2017) or Bartelsman and Wolf (2018), the patterns of estimated TFP dispersion also can differ substantially between both approaches (dispersion is typically much higher in a value added specification). We will show how our results vary between the different approaches, while most of the literature has only used either one of the specifications.

Another specification issue is how to treat firms with zero capital stocks because these observations would drop out when taking logs. As shown in Section 3, there is a large number of firms which do not invest in intangibles. On the one hand, we apply a frequently used strategy in the literature which is to recode the missing log values by some number and additionally control for a missing dummy.[25] Another strategy, implemented in Section 5.3., is that we estimate separate production functions for non-investors and investors, while also dividing the sample of investors into quintiles of different intangible intensity.

4.2. Wooldridge (2009) estimator accounting for simultaneity of inputs

A long literature, going back to Marschak and Andrews (1944), has recognized that OLS estimation of equation (1) is biased if firms make their input choices upon productivity ω_{it} (which is observed to the firm, but unobserved to the econometrician). Various proxy variable methods for dealing with this bias have been proposed in the literature.[26] The common idea of all approaches is that inverting the demand function for a particularly flexible input (in our case: energy) provides a proxy for productivity. In the following, we adopt this approach and estimate the production function following Wooldridge (2009).[27] The method generally distinguishes between state variables and flexible variables. For state variables, their realization in period t is decided based on the information in period t-1 and is thus not affected by the productivity shock arriving in t. Flexible variables are determined in response to the shock. In line with the existing literature, physical capital is considered a state variable since the installation of new machinery is associated with adjustment costs. In our baseline specification, we assume also intangible capital to be a state variable. One rationale for this is the lumpiness of intangible investment (cf., Figure 5 in section 3). This holds especially for patents and software investment, suggesting that investment in these

[25] An alternative strategy would involve a sample selection model in order to explicitly model the firm's decision whether to invest in intangibles or not (as done by, e.g., Hall et al. 2013). We abstain from this strategy as we don't have a good instrumental variable affecting the firm's decision whether to invest.

[26] This includes Olley and Pakes (1996), Levinsohn and Petrin (2003), Wooldridge (2009), or Ackerberg et al. (2015).

[27] The estimations are conducted in Stata using the module prodest developed by Rovigatti and Mollisi (2018).

assets requires large fixed costs and can't be changed readily from one year to the next. Intermediate inputs are considered flexible. Concerning labour, we follow most of the literature which has considered labour a flexible variable as firms are able to hire and dismiss employees.[28] Nevertheless, we also experiment with alternative specifications with intangibles considered as flexible and labour considered as state and found our results to be robust.

We then use energy expenditures, e_t, to proxy for unobserved productivity in time t, since energy is thought to react flexibly to productivity shocks. Assume that the demand for the proxy variable in period t is a function of the contemporaneous unobserved productivity and the state variables (here: tangible and intangible capital):

$$e_t = g(\omega_t, tk_t, ik_t)$$

where the firm index from now on will be omitted to simplify notation. Assuming the proxy demand function is monotonous in ω_t, we can invert the demand function to arrive at an expression for productivity:

$$\omega_t = g^{-1}(e_t, tk_t, ik_t)$$

Moreover, assume that productivity follows a first-order Markov process

$$\omega_t = E(\omega_t|\omega_{t-1}) + a_t$$

where a_t is a "productivity shock" that is (assumed to be) uncorrelated with the state variables tk_t, ik_t. The flexible inputs m_t, l_t and the proxy variable e_t are allowed to be correlated with the productivity shock (this is the simultaneity problem), but the *lagged* values of these variables are uncorrelated with the shock. A sufficient condition is that

$$E(a_t|tk_t, ik_t, m_{t-1}, l_{t-1}, e_{t-1}, \ldots, tk_1, ik_1, m_1, l_1, e_1) = 0$$

which means that

[28] While firing costs in Germany are typically larger than in Anglo-Saxon countries due to employee protection laws, there does exist some flexibility due to, e.g., part-time or temporary agency work which have risen considerably in Germany in the recent decades (Chalupa and Mai 2018, Burda and Seele 2016).

$$E(\omega_t | tk_t, ik_t, tk_{t-1}, ik_{t-1}, m_{t-1}, l_{t-1}, e_{t-1}, \ldots, tk_1, ik_1, m_1, l_1, e_1) = E(\omega_t | \omega_{t-1}) \equiv f(g^{-1}(e_{t-1}, tk_{t-1}, ik_{t-1}))$$

Putting the two expressions for productivity, $\omega_t = g^{-1}(e_t, tk_t, ik_t)$ and $\omega_t = f\left(g^{-1}(e_{t-1}, tk_{t-1}, ik_{t-1})\right) + a_t$, into equation (1) yields the two-equation system

$$y_t = \beta_0 + \beta_m \cdot m_t + \beta_l \cdot l_t + \beta_{tk} \cdot tk_t + \beta_{ik} \cdot ik_t + g^{-1}(e_t, tk_t, ik_t) + u_t \qquad (2a)$$

$$y_t = \beta_0 + \beta_m \cdot m_t + \beta_l \cdot l_t + \beta_{tk} \cdot tk_t + \beta_{ik} \cdot ik_t + f\left(g^{-1}(e_{t-1}, tk_{t-1}, ik_{t-1})\right) + a_t + u_t \qquad (2b)$$

Wooldridge (2009) proposed to estimate estimations (2a) and (2b) jointly using the Generalized Method of Moments (GMM). The identifying moment conditions are

$$E(u_t | tk_t, ik_t, m_t, l_t, e_t, tk_{t-1}, ik_{t-1}, m_{t-1}, l_{t-1}, e_{t-1}, \ldots, tk_1, ik_1, m_1, l_1, e_1) = 0$$

$$E(u_t + a_t | tk_t, ik_t, tk_{t-1}, ik_{t-1}, m_{t-1}, l_{t-1}, e_{t-1}, \ldots, tk_1, ik_1, m_1, l_1, e_1) = 0$$

This means that the state variables tk_t, ik_t act as their own instruments, while the endogenous variables m_t, l_t and e_t are instrumented with their lags. Additionally, we model the unknown function $f(g(e_{t-1}, tk_{t-1}, ik_{t-1}))$ as a second-order polynomial in $e_{t-1}, tk_{t-1}, ik_{t-1}$ and their first-order interactions.

5. Estimation of Production Functions: Results

5.1. Aggregate Results

Table 4 shows the production function estimates when pooling all firms in the manufacturing sector and estimating the equation with OLS. First consider Table 4a, which shows the results from the gross output specification. Column 2 shows that a 1% increase in intangible capital is associated with a 0.013% increase in output, holding all other inputs fixed. Considering the different subcomponents of intangible capital, the effects are larger for R&D (with an elasticity of 0.017 in the full specification in column 6), and smaller for software (0.008) and patents (0.001). Due to the positive correlation among the different intangibles, the effect of the different subcomponents are bigger when they are included separately in the regression (columns 3-5) than when they are included jointly (column 6). The effect of patents, for example, is only positive and significant when not controlling for the other intangibles (column 5). Regarding the "traditional" input variables, we find a coefficient of roughly 0.72 for intermediates, 0.24-0.25 for labour, and 0.033-0.035 for physical capital. The elasticities of the "traditional" inputs become smaller when intangibles are added, although the differences are not that big. Returns to scale are very close to one in all specifications.

Table 4b shows the results of the value added specification.[29] The coefficient of intangible capital is 0.053, as shown in column 2. Again, we find the biggest effect of R&D (0.052 in the full specification in column 6), followed by software (0.032) and patents (0.010). Interestingly, returns to scale in the value added specification are in the order of 1.04-1.09 and thus bigger than in the gross output specification.[30]

– Table 4 here –

In Table 5, we compare our previous OLS results to a Fixed Effects (FE) regression and the Wooldridge control function approach. First consider the FE model in column 2 of Tables 5a and 5b. We confirm a pattern documented previously in the literature (e.g., Bloom et al. 2019), namely that the elasticities drop considerably compared to OLS. On the one hand, this can be seen as indicating the endogeneity of inputs. On the other hand, measurement error in the input variables likely causes a bias towards zero in the FE model, which means that the FE results should be seen as a lower bound. But even in the FE model, the coefficients of R&D and software remain positive and strongly significant.

Next consider the Wooldridge specifications in columns 3-5 (3-6) of Table 5a (5b). We present all possible alternatives, with labour and intangibles treated either fixed or flexible (physical capital is always considered as state variable while intermediates are always considered flexible). The effects of R&D and software remain positive and significant in all Wooldridge-specifications, and the magnitudes do not change very much either. For example, the R&D elasticity always remains in the order of 0.015-0.019 (gross output specification) and 0.047-0.053 (value added specification). Interestingly, the results also do not depend that much on whether the intangibles are treated as state or as flexible variables. The coefficient of physical capital becomes much larger in the Wooldridge specification compared to OLS, a result consistent with Levinsohn

[29] Note that the number of observations is slightly lower in the value added specification because there are a few firms with negative value added which drop out when taking logs.

[30] This result is consistent with Gandhi et al. (2017).

and Petrin (2003). The labour coefficient becomes smaller, in particular in the value added specification (Table 5b).

– Table 5 here –

5.2. Heterogeneities by Industry

Given the large heterogeneity in intangible use across industries (cf., Section 3), it is an important question as to whether the elasticities also differ and whether the assumption of all firms operating with a common production technology is tenable. For example, the previous literature has found that elasticities of ICT capital (Bloom et al. 2010) or R&D (Belitz et al. 2017) tend to be higher in industries that use these inputs more intensively.

Table 6 shows separate estimations by 2-digit industry (NACE Rev. 2). We first split the sample into industries with a high intensity of intangible capital (C19-C20 chemical, C21 Pharmaceutical, C26 Data processing equipment, C27 Electrical equipment, C28 Engineering, C29 Motor vehicles, C30 Other vehicles) and industries with a low intensity (all else). The classification follows Table 3 which shows intangible investment for each industry. We show the results of the Wooldridge gross output specification as our baseline, while the value added and OLS results are reported in Appendix B (Tables B1-B3).

– Table 6 here –

The R&D elasticity for the sample of high-intensity industries is 0.027, as compared to an elasticity of 0.014 of low-intensity industries. The software elasticity differs only slightly between the two groups (0.010 for the “high” group, 0.006 for the “low” group), while the patents elasticity is close to zero and insignificant for both groups. Further disaggregating to the 2-digit industry level reveals that the R&D elasticities are high for C26 Data processing equipment (0.057), C19-C20 Chemical (0.031) or C27 Electrical equipment (0.033), and typically lower for other industries that use intangible capital less intensively. However, there are some exceptions to this pattern. C30 Other Vehicles, a high-intensity industry, does not show any positive intangible effect, while the low-intensity industries C13-15 Textiles (0.016), C25 Fabricated Metal Products (0.016) or C31-32 Furniture (0.036) show positive effects. Moreover, patent investment only has a positive effect for two industries, C21 Pharmaceutical and C17 Paper. Positive effects for software are present in both high-intensity and low-intensity industries. When considering the results of the value added specification (in Appendix Table B1), we again find that the R&D coefficients are higher for most of the high-intensity industries, while the pattern is more dispersed for the software and patent coefficients.

Overall, we can confirm that the effects of intangible capital are heterogeneous across industries. While there is some evidence that industries with higher intangible intensity tend to have higher returns to intangible capital, this pattern is far from uniform. It does not hold for all industries and not for all types of intangible capital. One reason for this may be that intangible intensity shows strong variation also within industries (as we had shown in Section 3). We thus consider in the next subsection another dimension of heterogeneity – intangible intensity at the firm level.

5.3. Heterogeneities by Intangible Intensity at the Firm Level

We next consider separate production functions for firms of different intangible intensity. We follow our procedure in Section 3 and distinguish between six groups. The first group consists of firms with a zero intangible capital stock ("noninvestors", henceforth). The remaining sample of firms with a positive intangible capital stock is further divided into five quintiles of intangible intensity (intangible capital stock per FTE employee).[31]

Table 7 shows the results. Table 7a shows that the effect of total intangible capital is relatively small for firms in the lowest to third quintile of intangible capital (in the order of 0.006-0.016), but increases to 0.049 for the fourth quintile and to 0.165 for the top quintile. The top quintile stands out from the other groups not only because the coefficient for intangibles is the largest, but also because the effect is much larger than that of physical capital. For all other groups, the effect of physical capital is larger than that of intangible capital. Table 7b further splits the different subcomponents of intangible capital and finds that these patterns are mainly driven by R&D, whose elasticity increases from 0.007 in the lowest quintile to 0.162 in the top quintile. In contrast, the effect of software is comparable across the quintiles, while patents show no significant effect.

– Table 7 here –

[31] Since we define the quintiles separately for each year, a firm can be in different quintiles in different years.

Figure 6 shows how the quintile intensity gradient changes if we additionally slice the data by firm size and enterprise group membership.[32] First, considering firm size, some studies have found the returns to ICT to increase with firm size (Dhyne et al. 2018), while this was not confirmed in other studies (Bloom et al. 2010). In Panel A of Figure 6, we plot the elasticities of intangible capital from separate regressions for the quintiles*firm size cells. The figure reveals that small firms typically have larger returns to intangible capital than big firms. However, within each firm size category, the returns are considerably larger for firms in the top intangible intensity quintile. This confirms our previous results.

Another dimension we investigate is whether the firm is member of an enterprise group (in Panel B of Figure 6). One might conjecture that grouped firms have more resources or better management practices which allow them to invest more in intangibles and reap higher returns from them.[33] Moreover, firms belonging to a group might (partly) share a common intangible pool. We merge the relevant information from the official business registry and distinguish between (i) firms which are not member of a group, (ii) firms belonging to a group with a German head, and (iii) firms belonging to a group with a foreign head. Yet, there is no strong evidence that intangibles have different effects depending on group membership. Again, the strong positive effect of intangibles for the top intensity quintile is present for both non-group firms and group firms.

The findings regarding enterprise groups are also informative for another reason. Since the units of observation in our data are legal units in the manufacturing sector, one might be concerned that some firms have outsourced part of their intangibles to other firms (possibly outside the manufacturing sector) which would lead to an underreporting of intangibles for the affected firms. This outsourcing (and the associated measurement error) is likely to be less relevant for firms which are not part of an enterprise group structure. Therefore, our finding that the results remain robust for non-grouped firms is at least suggestive evidence that this measurement issue is not too extreme.

– Figure 6 here –

[32] Small firms are those with less than 50 persons employed and less than 10 million € turnover, medium firms are those with less than 250 persons employed and less than 50 million € turnover, and large firms all others.

[33] See, for example, evidence in Bloom et al. (2012) for the UK that US-owned multinationals have larger returns to IT than other multinationals or than domestic firms.

Finally, we show additional specifications in Appendix B that reveal similar findings. First, we show the coefficients of the value added and the Wooldridge specifications (Table B4). The general pattern – a coefficient for intangible capital that increases with the intensity of intangibles use – remains robust, although the magnitudes differ. Similarly, for firms in the top quintile of the intangible intensity the effect of intangible capital exceeds the effect of physical capital. Second, we present in Appendix B Table B5 the estimations separately for the 2009-2011 and 2012-2015 time periods.[34] The effects of the intangibles for firms in different intangible intensity quintiles do not change from the first to the second period in a systematic way. The coefficients for firms in the lowest and the highest quintiles drop from 2009-2011 to 2012-2015, while those for firms in the 3rd and 4th quintile increase. However, the strong gradient in intangible intensity is visible in both periods.

5.4. Implications for Productivity Dispersion

Previous literature has documented large productivity differences across firms within industries (Syverson 2011). We now ask how much of this dispersion can be explained by intangible capital, a factor which has often been neglected in previous analyses. To that end, we estimate log TFP in regressions with and without intangible capital according to the formula

$$\log TFP_i = y_i - \{\widehat{\beta_m} \cdot m_i + \widehat{\beta_l} \cdot l_i + \widehat{\beta_{tk}} \cdot tk_i + \widehat{\beta_{ik}} \cdot ik_i + \widehat{\beta_{ikmiss}} \cdot (ik_i = missing) + \beta_{price} \cdot price + \beta_{pricemiss} \cdot (price_i = missing)\}$$

and compute the gap between the 90th and the 10th percentile of the distribution of estimated log TFP.[35] We perform the estimations separately by 2-digit industry.

Table 8 shows the results and reveals three main findings. First, the level of TFP dispersion is generally largest in the industries C19/20 Coke/Chemical, C21 Pharmaceutical, C26 Data processing equipment, and C30 Other Vehicles, which belong to the industries with higher intangible intensity (cf., Table 2). Second, the level of TFP dispersion in all industries is substantially larger in the value added than in the gross output specification, by a factor of about

[34] Note that the choice of these time periods follows the rotating panel structure in the KSE, which was drawn anew in 2008, and 2012 and that we consider a balanced panel of firms which appeared in all years of a respective "KSE cycle". From the 2008-11 cycle we consider only the years 2009-11 as software and patent investment was only included from 2009 onward.

[35] Note that we include a dummy for missing intangibles in all regressions which has to be included in the formula for estimated log TFP.

2-3.[36] For example, in the C26 Data processing equipment industry, the 90-10 log TFP difference after controlling for intangibles is 0.469 in the gross output case, meaning that a firm at the 90th percentile is (exp(0.469)-1)*100%=60% more productive than a firm at the 10th percentile. For the value added specification, the 90-10 log difference is 1.135, corresponding to a (exp(1.135)-1)*100%=211% difference. Third, the impact of adding intangibles on the 90-10 gap varies across industries and tends to be larger in industries where both the intensity of intangibles use and its output elasticity are larger. For example, in the C26 data processing equipment industry, accounting for intangibles decreases the 90-10 gap by 8.6% in the gross output specification and by 14.5% in the value added specification. In contrast, the reduction is only -0.8% and -2.1%, respectively, in the C13-15 Textiles industry where the impact of intangibles is smaller.

– Table 8 here –

5.5. Additional Robustness Checks

We finally discuss a number of additional specification issues and robustness checks.

The role of adjusting for double-counting of inputs. As described in Section 2, our baseline estimates correct the inputs for "double counting" by subtracting the respective R&D components from labour inputs and intermediate inputs, and, in turn, adding them to value added in the value added specification. In Appendix B Table B6, we compare the results without and with adjusting for double-counting. It becomes clear that the adjustment indeed makes a difference in the sense that the R&D elasticities become much larger in magnitude and more precisely estimated. These results confirm previous evidence by, e.g., Hall and Mairesse (1995, 2010).

Including temporary agency workers. A further robustness check concerns the treatment of temporary agency workers. In the cost structure survey, these workers are not included in the number of persons employed and expenditures for them are counted as an intermediate input. We now aim to add the number of temporary agency workers to the number of persons employed and add the expenditures back to value added. However, the number of temporary agency workers is not directly recorded in the survey. We thus calculate the firm's average wage per non-R&D-

[36] This is in line with Gandhi et al. (2017) or Bartelsman and Wolf (2018) and demonstrates that differences in specifications have to be taken into account when comparing different papers.

worker[37] and divide total costs for temporary agency workers by this wage to achieve the total number of temporary agency workers. We find that the share of temporary agency workers is only about 0.6% for the median firm, but that there are a few firms for which the share is higher (the 90th percentile is 14%). With respect to the production function estimates, Table B7 shows that adding temporary agency workers increases the labour coefficient only marginally (from 0.232 to 0.247 in the OLS gross output specification). The coefficients of the intangible variables are not much affected either.

The role of controlling for firm-level price data. Our baseline estimates include controls for firm-specific prices that are constructed using the industrial production survey. The previous literature has emphasized that firm-specific prices should be used to account for unobserved differences in the quality of inputs (De Loecker et al. 2016). However, as shown in Appendix Table B8, the coefficient estimates are similar when prices are not controlled for. These results parallel previous analyses by Mairesse and Jaumandreu (2005) on French and Spanish manufacturing firms.

6. Summary and conclusions

German manufacturing firms increasingly invest in intangible capital compared to physical capital, yet little has been known so far about whether these investments affect productivity and whether they can explain productivity dispersion across firms. In this paper, we have used data from the structural business surveys, which are representative for all German manufacturing firms with 20 or more persons employed. We have estimated production functions comparing the results of a large number of different specifications. The results show positive output elasticities for R&D and software investment, while the evidence is more mixed for patent investment. At the same time, the effects show substantial heterogeneities between firms with high intensity of intangible investment, which show larger output elasticities, and firms with lower intensity of intangible investment, for which the elasticities are lower.

Regarding productivity dispersion, we find that including intangibles in a production function reduces TFP dispersion, in particular in specific industries which use intangibles more intensively. Albeit non-negligible, the effects are not huge, suggesting that the type of intangible capital we can measure in our data – self-processed R&D, and purchased software and patents – might not be the main factor explaining TFP dispersion. Future research is therefore required to

[37] This assumes that temporary agency workers and regular workers cost the same from the firm perspective.

determine the role of the remaining factors, such as other forms of intangible capital (e.g., organization and branding capital), management quality, market power, or market distortions.

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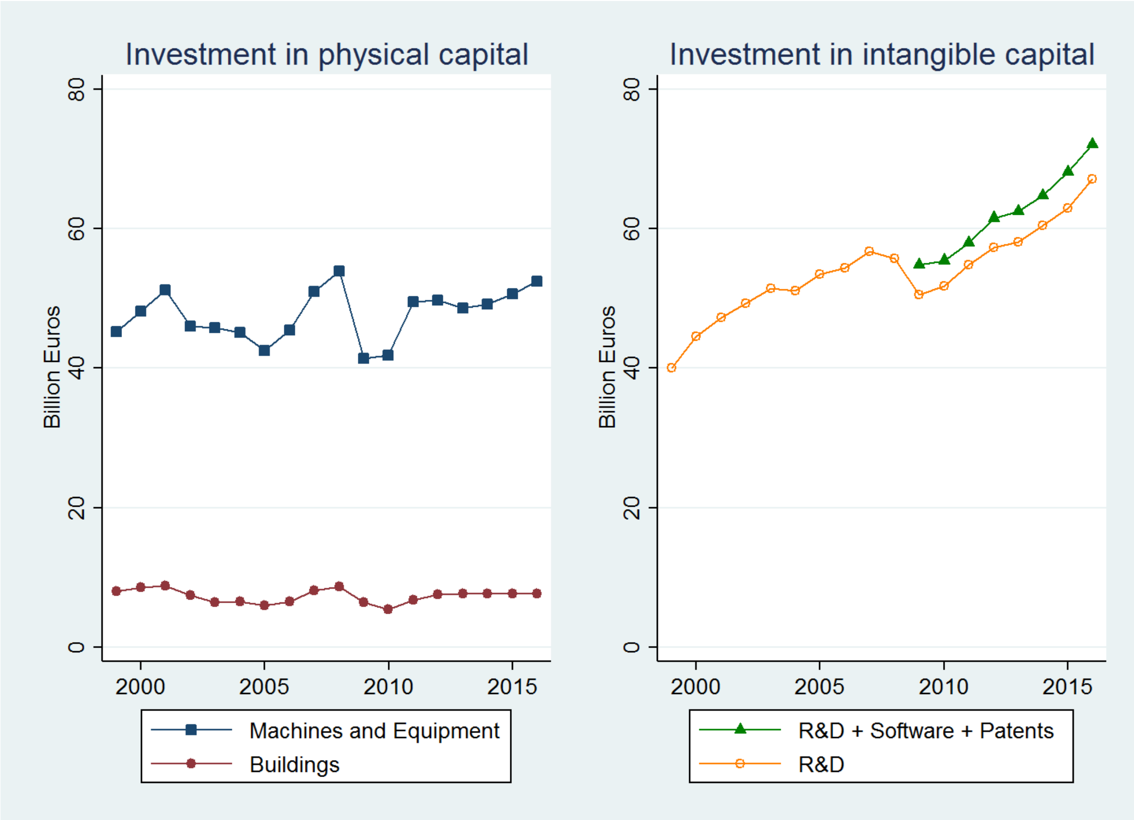
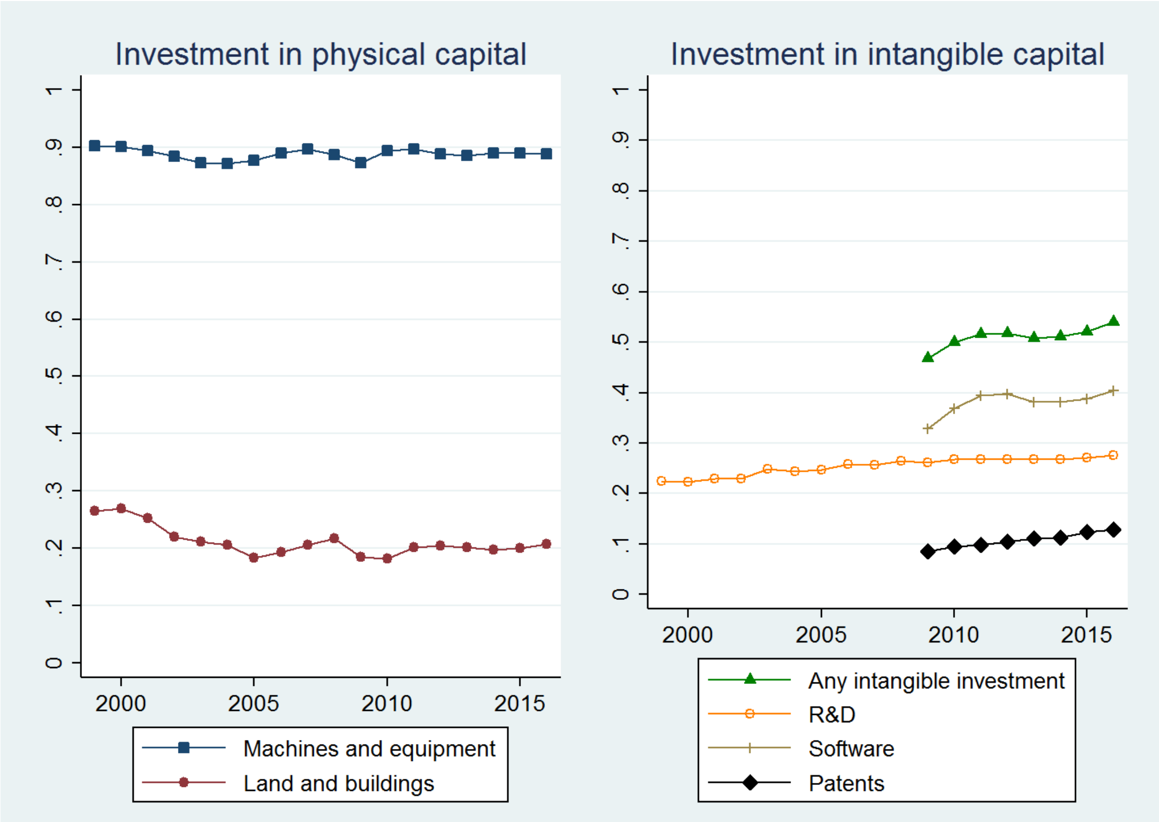
Figure 1: Aggregate real investment in German manufacturing, in billion €



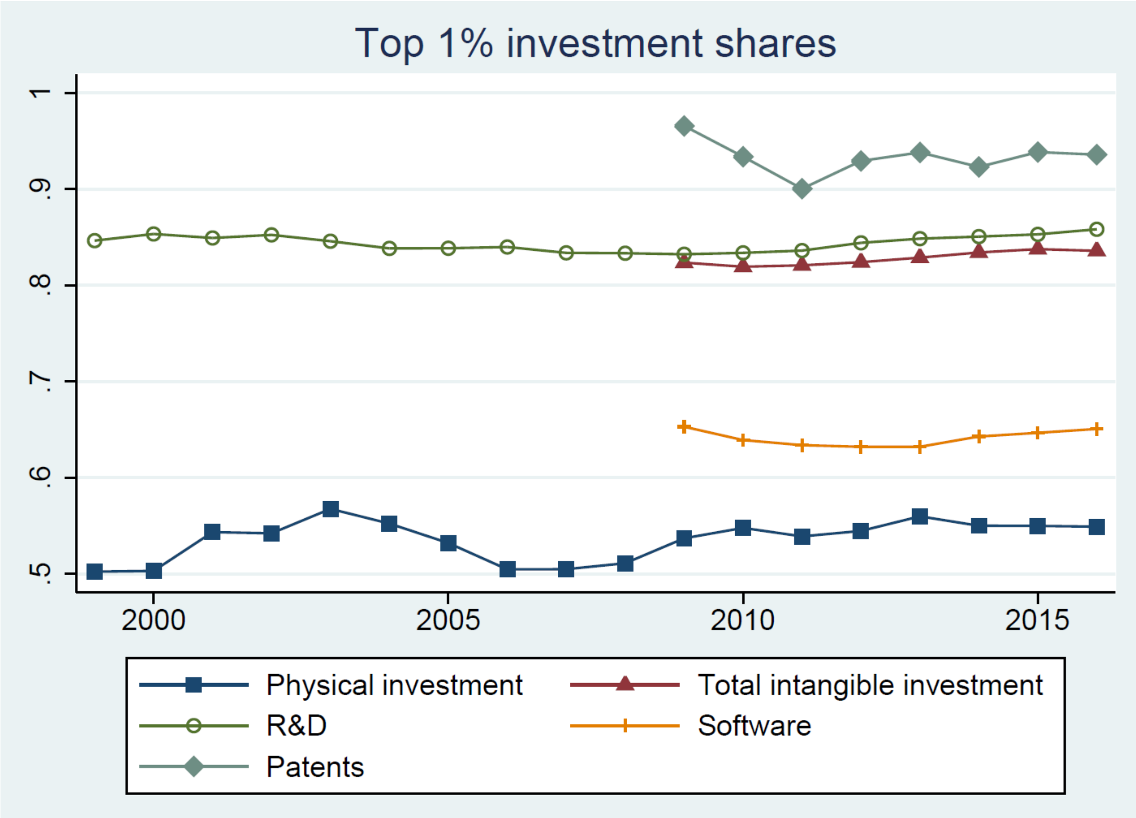
Note: Investment series are deflated to 2015 Euros using separate price indices for machinery, buildings, and intangible capital. Price indices vary at the 2-digit industry level and are taken from the German National Accounts. Source: German structural business surveys covering firms in the manufacturing sector with 20 or more persons employed, own calculation. Survey weights are used.

Figure 2: Share of firms which have invested in the current year



Source: German structural business surveys covering firms in the manufacturing sector with 20 or more persons employed, own calculation. Survey weights are used.

Figure 3: Share of investment in each year which is conducted by the top 1% firms



Source: German structural business surveys covering firms in the manufacturing sector with 20 or more persons employed, own calculation. Survey weights are used.

Table 1: Percentiles of 4-year cumulative investment in TSD Euros

(Firm's cumulative investment over the 2012-2015 period, in 2015 Euros, balanced panel of N=13,585 firms)

1A: Total investment in TSD €

	Share >0	P10	P25	P50	P75	P90	P95
Total physical investment	0.967	66	226	775	2,649	8,780	17,830
Machines and Equipment	0.967	62	205	669	2,228	7,053	14,838
Land and buildings	0.362	0	0	0	99	1,158	3,102
Total intangible investment	0.698	0	0	28	414	3,202	9,163
R&D	0.331	0	0	0	207	2,668	8,039
Software	0.615	0	0	7	62	265	591
Patents	0.252	0	0	0	0	52	223

1B: Share of intangible investment over total investment

	Share >0	P10	P25	P50	P75	P90	P95
Total physical investment	0.967	0.30	0.73	0.96	1	1	1
Machines and Equipment	0.967	0.21	0.53	0.88	1	1	1
Land and buildings	0.362	0	0	0	0.04	0.29	0.47
Total intangible investment	0.698	0	0	0.03	0.23	0.62	0.80
R&D	0.331	0	0	0	0.11	0.54	0.73
Software	0.615	0	0	0	0.03	0.09	0.14
Patents	0.252	0	0	0	0	0.02	0.05

Note: The calculations use a balanced sample of N=13,585 firms which are in both cost structure survey and investment survey over the whole period 2012-2015. Survey weights are used. Values are expressed in 2015 Euros. Source: German structural business surveys covering firms in the manufacturing sector with 20 or more persons employed, own calculation.

Table 2: Percentiles of 4-year cumulative investment, by 2-digit industry (2012-2015)

2A: Total intangible investment in TSD €

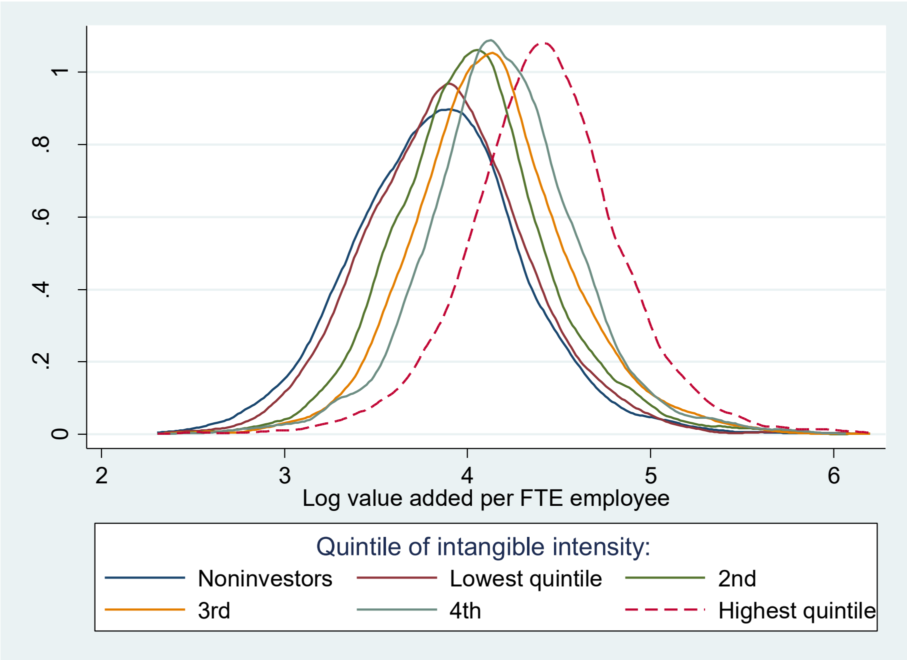
	Share >0	**p10**	**p25**	**p50**	**p75**	**p90**	**p95**	**N**
Total manufacturing	0.698	**0**	**0**	**28**	**414**	**3,202**	**9,163**	**13,585**
10-12. Food	0.466	0	0	0	26	365	1,280	1,951
13-15. Textiles	0.714	0	0	36	382	1,800	3,117	518
16. Wood	0.510	0	0	0	49	247	925	310
17. Paper	0.767	0	1	47	319	1,485	3,804	382
18. Printing	0.688	0	0	19	81	296	549	268
19-20. Chemicals	0.890	0	46	691	3,421	12,895	24,970	798
21. Pharmaceutical	0.951	7	81	875	4,976	29,367	141,754	167
22. Rubber/Plastic	0.737	0	0	37	297	1,676	3,633	742
23. Glass	0.711	0	0	24	301	1,587	4,232	605
24. Metal Production	0.792	0	3	71	539	3,020	6,930	576
25. Metal Products	0.652	0	0	14	112	724	2,074	1,731
26. Data Proc. Eq.	0.912	1	64	1,198	4,580	20,493	39,204	620
27. Electrical eq.	0.812	0	8	240	2,778	10,172	22,390	913
28. Engineering	0.829	0	11	155	1,540	8,119	21,801	1,913
29. Motor Vehicles	0.774	0	2	108	1,542	12,172	69,800	495
30. Other Vehicles	0.845	0	19	233	2,941	12,495	44,143	192
31-32. Furniture	0.637	0	0	11	243	2,234	7,378	825
33. Repairing	0.562	0	0	2	30	421	1,158	579

2B: Share of intangible investment over total investment

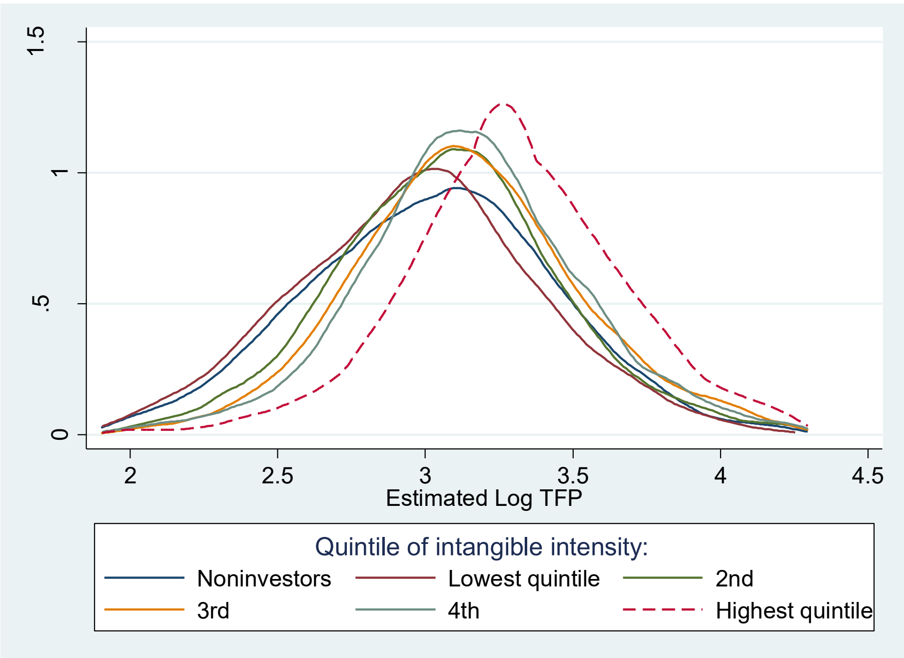
	Share >0	**p10**	**p25**	**p50**	**p75**	**p90**	**p95**	**N**
Total manufacturing	0.698	***0.00***	***0.00***	***0.03***	***0.23***	***0.62***	***0.80***	***13,585***
10-12. Food	0.466	0.00	0.00	0.00	0.02	0.09	0.20	1,951
13-15. Textiles	0.714	0.00	0.00	0.06	0.31	0.56	0.81	518
16. Wood	0.510	0.00	0.00	0.00	0.05	0.21	0.32	310
17. Paper	0.767	0.00	0.00	0.02	0.10	0.23	0.40	382
18. Printing	0.688	0.00	0.00	0.02	0.11	0.21	0.42	268
19-20. Chemicals	0.890	0.00	0.02	0.21	0.54	0.75	0.84	798
21. Pharmaceutical	0.951	0.00	0.02	0.18	0.52	0.74	0.80	167
22. Rubber/Plastic	0.737	0.00	0.00	0.03	0.14	0.40	0.54	742
23. Glass	0.711	0.00	0.00	0.02	0.16	0.37	0.54	605
24. Metal Production	0.792	0.00	0.00	0.03	0.12	0.27	0.39	576
25. Metal Products	0.652	0.00	0.00	0.02	0.11	0.34	0.51	1,731
26. Data Proc. Eq.	0.912	0.00	0.07	0.55	0.82	0.90	0.94	620
27. Electrical eq.	0.812	0.00	0.02	0.23	0.61	0.81	0.90	913
28. Engineering	0.829	0.00	0.02	0.16	0.54	0.79	0.87	1,913
29. Motor Vehicles	0.774	0.00	0.00	0.05	0.31	0.69	0.82	495
30. Other Vehicles	0.845	0.00	0.02	0.18	0.52	0.75	0.85	192
31-32. Furniture	0.637	0.00	0.00	0.02	0.23	0.65	0.82	825
33. Repairing	0.562	0.00	0.00	0.01	0.07	0.30	0.55	579

Figure 4. Distribution of productivity, by firm's intangible intensity (intangible capital stock per FTE employee)

4A. Labour productivity



4B. "Traditional" Total Factor Productivity (TFP)



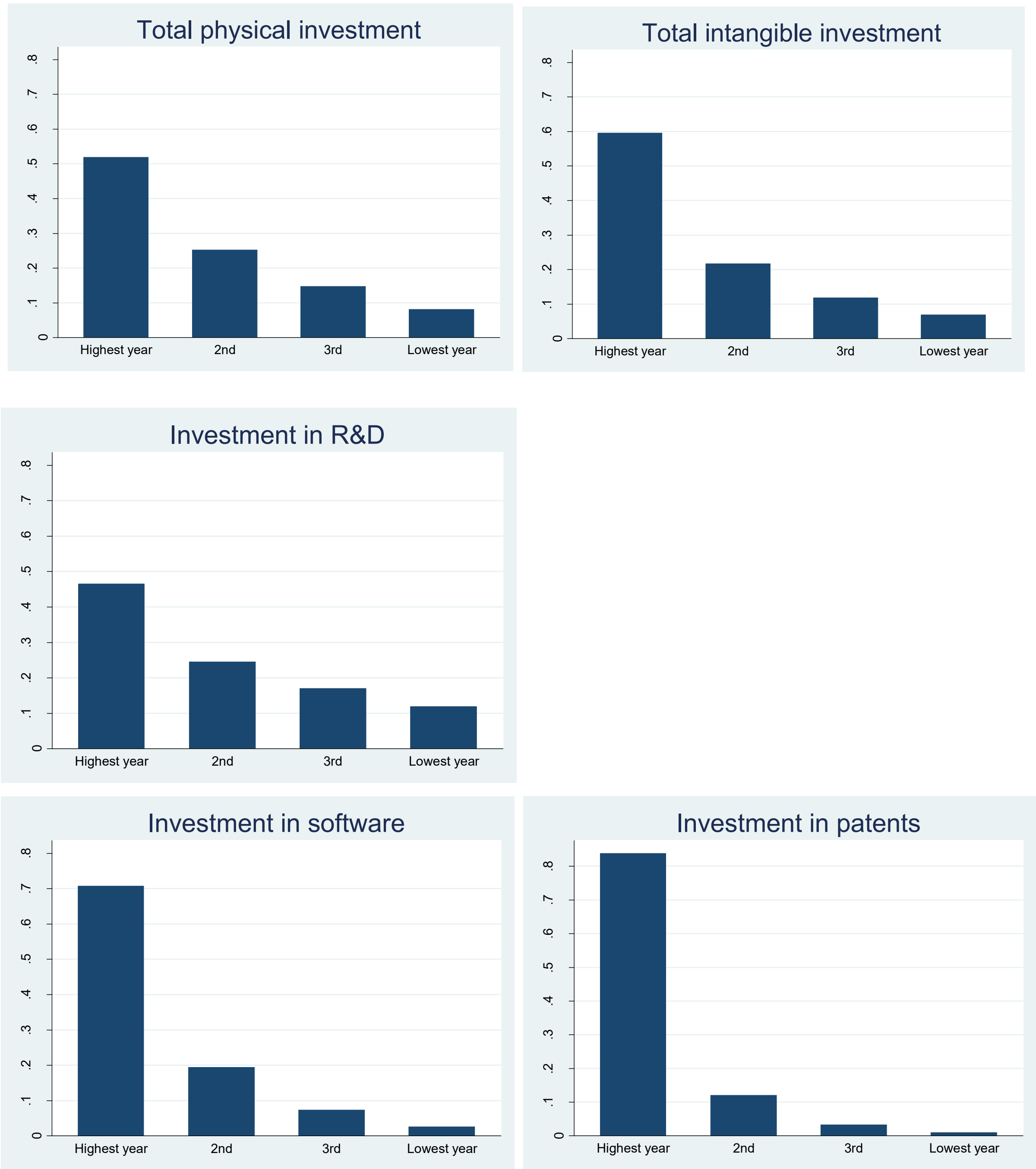
Note: "Noninvestors" are firms with a zero intangible capital stock. The sample of firms with positive intangible capital stock is divided into quintiles of intangible intensity (intangible capital stock per FTE employee). Labour productivity is defined as log value added per FTE employee. "Traditional" TFP is the residual of a regression of value added on physical capital and labour. Source: German structural business surveys 2009-2015 covering firms in the manufacturing sector with 20 or more persons employed, own calculation. Survey weights are used.

Table 3: Characteristics of firms - by intangible intensity (intangible capital stock per FTE employee)

		Quintile of intangible intensity:				
	Noninvestors	**Lowest quintile**	**2nd quintile**	**3rd quintile**	**4th quintile**	**Highest quintile**
Intangible capital stock per FTE employee, in TSD Euros	0.000	0.064	0.363	1.464	7.466	51.436
Physical capital stock per FTE employee, in TSD Euros	56.538	70.886	80.277	91.571	90.558	81.475
Value added per FTE employee, in TSD Euros	49.521	53.078	60.308	66.434	70.792	88.966
Number of persons employed:						
20-34	0.357	0.193	0.170	0.142	0.098	0.064
35-49	0.281	0.206	0.209	0.163	0.138	0.090
50-99	0.244	0.313	0.316	0.305	0.252	0.211
100-249	0.095	0.217	0.229	0.271	0.298	0.281
250+	0.023	0.071	0.076	0.119	0.214	0.355
2-digit industry:						
10-12. Food	0.272	0.181	0.108	0.091	0.071	0.024
13-15. Textiles	0.023	0.022	0.027	0.034	0.038	0.018
16. Wood	0.035	0.037	0.021	0.029	0.016	0.004
17. Paper	0.018	0.024	0.029	0.030	0.025	0.007
18. Printing	0.031	0.032	0.042	0.053	0.016	0.005
19-20. Chemicals	0.011	0.016	0.022	0.027	0.047	0.106
21. Pharmaceutical	0.002	0.003	0.007	0.007	0.008	0.020
22. Rubber/Plastic	0.061	0.098	0.090	0.091	0.102	0.041
23. Glass	0.034	0.048	0.041	0.048	0.055	0.025
24. Metal Production	0.019	0.030	0.032	0.038	0.035	0.010
25. Metal Products	0.211	0.202	0.223	0.206	0.161	0.066
26. Data Proc. Eq.	0.013	0.019	0.027	0.024	0.042	0.160
27. Electrical eq.	0.031	0.034	0.040	0.043	0.062	0.130
28. Engineering	0.081	0.100	0.143	0.154	0.206	0.260
29. Motor Vehicles	0.020	0.024	0.032	0.025	0.031	0.039
30. Other Vehicles	0.003	0.005	0.006	0.006	0.011	0.015
31-32. Furniture	0.081	0.070	0.063	0.066	0.059	0.055
33. Repairing	0.054	0.058	0.048	0.027	0.016	0.015
N firms*years	10,133	7,435	7,570	8,285	9,365	10,758
N firms	2,924	2,712	3,154	3,168	3,025	2,964

Note: "Noninvestors" are firms with a zero intangible capital stock. The sample of firms with positive intangible capital stock is further divided into quintiles of intangible intensity (intangible capital stock per FTE employee). Values are expressed in 2015 Euros. Source: German structural business surveys 2009-2015 covering firms in the manufacturing sector with 20 or more persons employed, own calculation. Survey weights are used.

Figure 5: Share of a firm's cumulative 4-year investment which happened in the largest, 2nd, 3rd, lowest year



Note: The calculations use a balanced sample of N=13,585 firms which are in both the cost structure survey and the investment survey over the whole period 2012-2015. Source: German structural business surveys covering firms in the manufacturing sector with 20 or more persons employed, own calculation. Survey weights are used.

Table 4. OLS Production Functions, pooled for all manufacturing industries

Table 4a: Gross output specification

	(1)	(2)	(3)	(4)	(5)	(6)
Intermediates	0.724***	0.718***	0.720***	0.722***	0.723***	0.719***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Labour	0.250***	0.239***	0.239***	0.243***	0.248***	0.235***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Physical Capital	0.035***	0.033***	0.035***	0.034***	0.035***	0.034***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Intangible Capital		0.013***				
		(0.001)				
R&D			0.018***			0.017***
			(0.001)			(0.001)
Software				0.011***		0.008***
				(0.001)		(0.001)
Patents					0.006***	0.001
					(0.001)	(0.001)
Returns to scale	1.009	1.004	1.012	1.010	1.012	1.013
N Firms*Years	95,638	95,638	95,638	95,638	95,638	95,638
N Firms	22,439	22,439	22,439	22,439	22,439	22,439
r2	0.985	0.986	0.986	0.986	0.985	0.986

Table 4b: Value added specification

	(1)	(2)	(3)	(4)	(5)	(6)
Labour	0.923***	0.854***	0.869***	0.882***	0.909***	0.843***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Physical Capital	0.155***	0.136***	0.147***	0.142***	0.152***	0.138***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Intangible Capital		0.053***				
		(0.001)				
R&D			0.059***			0.052***
			(0.002)			(0.002)
Software				0.047***		0.032***
				(0.002)		(0.002)
Patents					0.025***	0.010***
					(0.002)	(0.002)
Returns to scale	1.077	1.043	1.076	1.071	1.086	1.074
N Firms * Years	95,310	95,310	95,310	95,310	95,310	95,310
N Firms	22,428	22,428	22,428	22,428	22,428	22,428
r2	0.877	0.886	0.884	0.881	0.878	0.886

Note: Standard errors in parentheses, clustered at the firm level, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Further controls are firm-level prices, dummies for missing intangible capital variables and missing firm-level prices, 2-digit industry dummies, year dummies, and a dummy for East Germany. Survey weights are used. Source: German structural business surveys 2009-2015 covering firms in the manufacturing sector with 20 or more persons employed, own calculation.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Production Functions: OLS, Fixed Effects, and Wooldridge specifications

Table 5a: Gross output specification

	(1) OLS	(2) FE	(3) WO Lab flexible, Intang flexible	(4) WO Lab fix, Intang flexible	(5) WO Lab flexible, Intang fixed	(6) WO Lab fixed, Intang fixed
Intermediates	0.719^{***}	0.694^{***}	0.717^{***}	0.684^{***}	0.702^{***}	0.675^{***}
	(0.002)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
Labour	0.235^{***}	0.168^{***}	0.229^{***}	0.233^{***}	0.232^{***}	0.233^{***}
	(0.003)	(0.005)	(0.001)	(0.004)	(0.001)	(0.004)
Physical Capital	0.034^{***}	0.020^{***}	0.092^{***}	0.095^{***}	0.089^{***}	0.093^{***}
	(0.001)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
R&D	0.017^{***}	0.008^{***}	0.015^{***}	0.017^{***}	0.018^{***}	0.019^{***}
	(0.001)	(0.002)	(0.000)	(0.000)	(0.003)	(0.003)
Software	0.008^{***}	0.003^{***}	0.008^{***}	0.009^{***}	0.007^{***}	0.008^{***}
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Patents	0.001	0.000	-0.002^{***}	0.000	-0.000	0.001
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
N Firms * Years	95,638	95,638	73,157	73,157	73,157	73,157
N Firms	22,439	22,439	22,428	22,428	22,428	22,428

Table 5b: Value added specification

	(1) OLS	(2) FE	(3) WO Lab free, Intang free	(4) WO Lab fix, Intang free	(5) WO Lab free, Intang fixed
Labour	0.843^{***}	0.558^{***}	0.694^{***}	0.688^{***}	0.690^{***}
	(0.005)	(0.012)	(0.002)	(0.010)	(0.002)
Physical Capital	0.138^{***}	0.069^{***}	0.268^{***}	0.266^{***}	0.256^{***}
	(0.003)	(0.008)	(0.011)	(0.011)	(0.011)
R&D	0.052^{***}	0.020^{***}	0.051^{***}	0.053^{***}	0.047^{***}
	(0.002)	(0.005)	(0.001)	(0.001)	(0.007)
Software	0.032^{***}	0.013^{***}	0.025^{***}	0.026^{***}	0.026^{***}
	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)
Patents	0.010^{***}	0.003	0.004^{***}	0.005^{***}	0.005
	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)
N Firms *Years	95,310	95,310	72,759	72,759	72,759
N Firms	22,428	22,428	22,417	22,417	22,417

Note: The Wooldridge estimations use energy input as the proxy variable. Standard errors in parentheses, clustered at the firm level, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Further controls are firm-level prices, dummies for missing intangible capital variables and missing firm-level prices, 2-digit industry dummies, year dummies, and a dummy for East Germany. Survey weights are used. Source: German structural business surveys 2009-2015 covering firms in the manufacturing sector with 20 or more persons employed, own calculation.

Table 6: Production Functions, separate estimations by 2-digit industry (Gross output specification, Wooldridge)

	(1) Inter-mediates	(2) Labour	(3) Phys. Capital	(4) R&D	(5) Software	(6) Patents
All high-intensity industries	*0.704****	*0.217****	*0.104****	*0.027****	*0.010****	*0.001*
	(0.003)	*(0.002)*	*(0.008)*	*(0.004)*	*(0.002)*	*(0.002)*
19/20: Coke/Chemical	0.752***	0.166***	0.101***	0.031***	0.007	-0.000
	(0.008)	(0.004)	(0.022)	(0.012)	(0.004)	(0.004)
21: Pharma	0.792***	0.270***	0.027	0.032	0.012	0.018*
	(0.013)	(0.010)	(0.038)	(0.020)	(0.009)	(0.011)
26: Data Processing Eq.	0.633***	0.247***	0.123***	0.057***	0.002	0.002
	(0.009)	(0.006)	(0.027)	(0.014)	(0.006)	(0.006)
27: Electrical Eq.	0.703***	0.244***	0.045***	0.033***	0.017***	-0.008*
	(0.007)	(0.004)	(0.015)	(0.010)	(0.004)	(0.004)
28: Engineering	0.672***	0.244***	0.115***	0.025***	0.012***	0.002
	(0.005)	(0.003)	(0.011)	(0.007)	(0.003)	(0.003)
29: Motor Vehicles	0.759***	0.193***	0.095***	0.019**	0.004	-0.002
	(0.008)	(0.004)	(0.022)	(0.008)	(0.005)	(0.005)
30: Other Vehicles	0.710***	0.242***	0.003	-0.020	-0.006	-0.004
	(0.017)	(0.011)	(0.038)	(0.017)	(0.009)	(0.007)
All low-intensity industries	*0.727****	*0.230****	*0.083****	*0.014****	*0.006****	*-0.000*
	(0.002)	*(0.001)*	*(0.006)*	*(0.004)*	*(0.001)*	*(0.002)*
10-12: Food	0.786***	0.190***	0.064***	-0.002	0.010***	-0.003
	(0.005)	(0.002)	(0.015)	(0.009)	(0.004)	(0.004)
13-15: Textiles	0.739***	0.240***	0.128***	0.016*	0.002	0.001
	(0.005)	(0.004)	(0.032)	(0.009)	(0.005)	(0.006)
16: Wood	0.757***	0.225***	0.036**	0.020	0.005	-0.001
	(0.007)	(0.005)	(0.018)	(0.023)	(0.005)	(0.007)
17: Paper	0.780***	0.190***	0.015	0.008	0.002	0.010*
	(0.008)	(0.005)	(0.017)	(0.012)	(0.005)	(0.006)
18: Printing	0.612***	0.299***	0.046*	-0.031	0.013*	0.019
	(0.010)	(0.008)	(0.025)	(0.056)	(0.008)	(0.014)
22: Rubber/Plastic	0.718***	0.223***	0.093***	0.009	0.001	-0.002
	(0.006)	(0.003)	(0.016)	(0.009)	(0.003)	(0.004)
23: Glass	0.739***	0.204***	0.103***	-0.006	0.005	-0.003
	(0.007)	(0.004)	(0.021)	(0.015)	(0.004)	(0.006)
24: Basic Metals	0.724***	0.186***	0.098***	0.005	0.002	-0.002
	(0.007)	(0.003)	(0.018)	(0.009)	(0.003)	(0.005)
25: Fabricated Metal Products	0.678***	0.273***	0.089***	0.016**	0.006**	0.003
	(0.004)	(0.003)	(0.010)	(0.008)	(0.003)	(0.004)
31-32: Furniture	0.642***	0.272***	0.163***	0.036**	-0.002	-0.001
	(0.006)	(0.005)	(0.019)	(0.014)	(0.005)	(0.006)
33: Repairing	0.648***	0.355***	0.008	0.015	0.007	-0.007
	(0.005)	(0.005)	(0.023)	(0.017)	(0.006)	(0.009)

Note: See Table 5.

Table 7: Production Functions, separate estimations by quintile of intangible intensity (Gross output specification, Wooldridge)

Table 7a: All intangibles pooled

		Quintiles of intangible intensity:				
	Noninvestors	Lowest quintile	2nd quintile	3rd quintile	4th quintile	Highest quintile
Intermediates	0.685***	0.680***	0.700***	0.718***	0.702***	0.692***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)
Labour	0.260***	0.249***	0.238***	0.230***	0.203***	0.212***
	(0.002)	(0.003)	(0.005)	(0.004)	(0.003)	(0.003)
Physical Capital	0.087***	0.078***	0.129***	0.069***	0.163***	0.076***
	(0.009)	(0.014)	(0.015)	(0.012)	(0.012)	(0.011)
Intangible Capital		0.006*	0.016***	0.010*	0.049***	0.165***
		(0.003)	(0.005)	(0.006)	(0.007)	(0.012)
N Firms* Years	14,895	8,200	7,313	8,895	11,230	13,892
N Firms	5,862	4,369	5,069	5,055	4,762	4,374

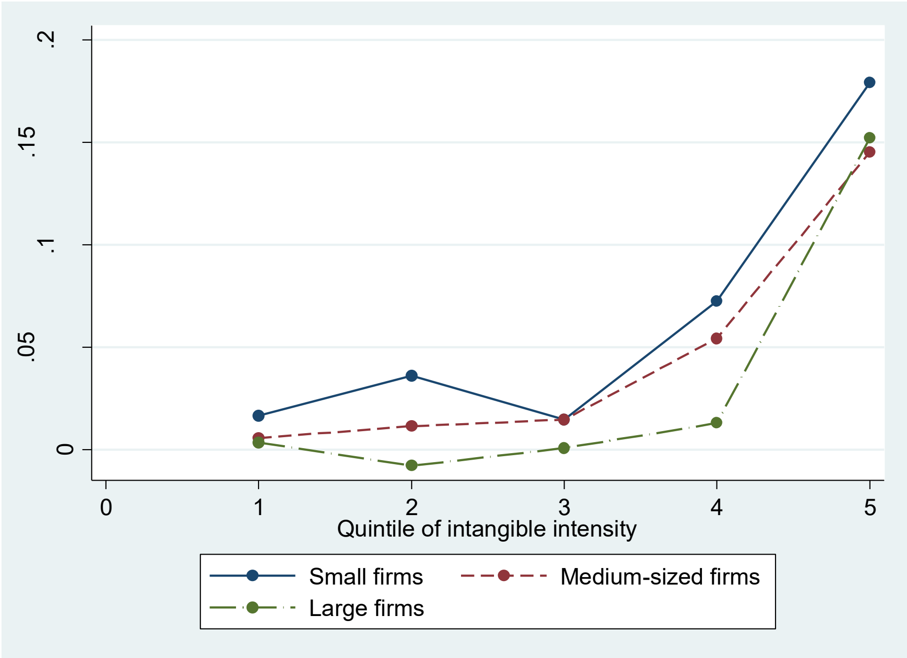
Table 7b: Different types of intangibles

		Quintiles of intangible intensity:				
	Noninvestors	Lowest quintile	2nd quintile	3rd quintile	4th quintile	Highest quintile
Intermediates	0.685***	0.682***	0.706***	0.718***	0.702***	0.686***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)
Labour	0.260***	0.248***	0.232***	0.220***	0.200***	0.209***
	(0.002)	(0.003)	(0.005)	(0.004)	(0.003)	(0.003)
Physical Capital	0.087***	0.079***	0.121***	0.056***	0.153***	0.077***
	(0.009)	(0.013)	(0.015)	(0.012)	(0.012)	(0.011)
R&D		0.007	-0.012	-0.004	0.044***	0.162***
		(0.028)	(0.012)	(0.007)	(0.006)	(0.011)
Software		0.006**	0.012***	0.012***	0.012***	0.003
		(0.003)	(0.004)	(0.003)	(0.002)	(0.003)
Patents		-0.001	0.005	0.005	0.001	-0.002
		(0.006)	(0.005)	(0.004)	(0.003)	(0.002)
N Firms* Years	14,895	8,200	7,313	8,895	11,230	13,892
N Firms	5,862	4,369	5,069	5,055	4,762	4,374

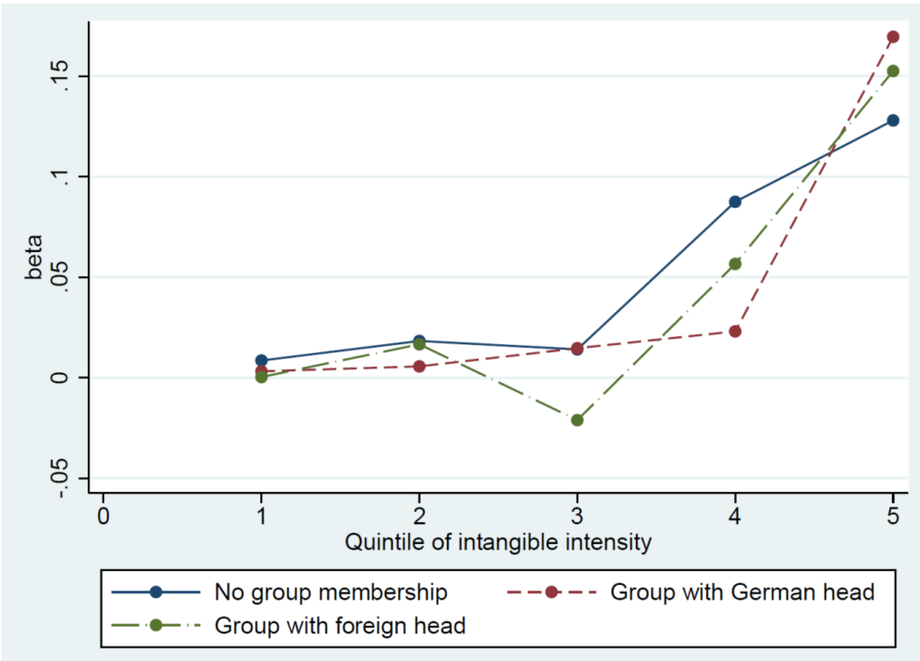
Note: "Noninvestors" are firms with a zero intangible capital stock. The sample of firms with positive intangible capital stock is further divided into quintiles of intangible intensity (intangible capital stock per FTE employee). Standard errors in parentheses, clustered at the firm level, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Further controls are firm-level prices, dummies for missing intangible capital variables and missing firm-level prices, 2-digit industry dummies, year dummies, and a dummy for East Germany. Survey weights are used. Source: German structural business surveys 2009-2015 covering firms in the manufacturing sector with 20 or more persons employed, own calculation.

Figure 6. Effect of intangible capital, by quintile and enterprise group/firm size

6a. Effect of intangible capital, by quintile and firm size



6b. Effect of intangible capital, by quintile and enterprise group membership



Note: The graphs plot the coefficient of intangible capital in a gross output production function additionally controlling for intermediates, labour, and physical capital. The Wooldridge (2009) estimator is used with energy as the proxy variable. Graph 6a perform the regressions separately by enterprise group category and quintile, while Graph 6b perform the regressions separately by firm size category and quintile. Source: German structural business surveys 2009-2015 covering firms in the manufacturing sector with 20 or more persons employed, own calculation.

Table 8: The Role of Intangibles for Productivity Dispersion

Difference between the 90th and the 10th percentile of estimated log Total Factor Productivity (TFP) without and with controlling for intangibles

	Gross output specification			Value added specification		
	90-10 log diff. without in-tangibles	90-10 log diff. with in-tangibles	% difference	90-10 log diff. without in-tangibles	90-10 log diff. with intangibles	% difference
Total manufacturing	*0.364*	*0.354*	*-2.7%*	*1.048*	*0.989*	*-5.7%*
19/20: Coke/Chemical	0.369	0.359	-2.8%	1.180	1.135	-3.8%
21: Pharma	0.439	0.420	-4.2%	1.203	1.109	-7.8%
26: Data Processing Eq.	0.513	0.469	-8.6%	1.327	1.135	-14.5%
27: Electrical Eq.	0.373	0.357	-4.2%	1.096	0.987	-10.0%
28: Engineering	0.354	0.347	-2.0%	0.980	0.926	-5.5%
29: Motor Vehicles	0.353	0.344	-2.7%	1.041	0.999	-4.0%
30: Other Vehicles	0.420	0.407	-3.0%	1.231	1.194	-3%
10-12: Food	0.394	0.389	-1.2%	1.076	0.993	-7.7%
13-15: Textiles	0.340	0.337	-0.8%	1.105	1.082	-2.1%
16: Wood	0.273	0.272	-0.3%	0.879	0.882	0.4%
17: Paper	0.269	0.266	-0.9%	0.928	0.905	-2.4%
18: Printing	0.401	0.394	-1.7%	0.852	0.850	-0.1%
22: Rubber/Plastic	0.298	0.295	-0.9%	0.883	0.865	-2.1%
23: Glass	0.337	0.331	-1.8%	1.047	0.995	-5.0%
24: Basic Metals	0.270	0.269	-0.3%	0.989	0.964	-2.5%
25: Fabricated Metal Products	0.369	0.364	-1.4%	0.898	0.888	-1.1%
31-32: Furniture	0.399	0.382	-4.4%	0.916	0.877	-4.2%
33: Repairing	0.383	0.382	-0.1%	0.894	0.872	-2.5%

Note: TFP estimates are based on OLS specifications. Source: German structural business surveys 2009-2015 covering firms in the manufacturing sector with 20 or more persons employed, own calculation.

Appendix A: Construction of physical and intangible capital stocks

We use the Perpetual Inventory Method (PIM) to transform our panel data on yearly investment flows into capital stocks. For capital good $\theta \in$ (machines, buildings, software, patents, R&D) the real capital stock of firm *i* in industry *j* in year *t* is calculated as follows:

$$K_{ijt}^{\theta} = \left(1 - \delta_{jt}^{\theta}\right) * K_{i,j,t-1}^{\theta} + I^{\theta}{}_{ijt}$$

where δ_{jt}^{θ} denotes the yearly depreciation rate and $I^{\theta}{}_{ijt}$ yearly real investment.

Price deflators. To transform nominal investment flows into real ones, we use price deflators provided by the National Accounts of the Federal Statistical Office of Germany.[38] The deflators are provided on a yearly basis since 1991 at the level of 2-digit industries, and there are also separate deflators for investments in machines, buildings, and intellectual capital. We use the latter for investments in software, patents, and R&D. The values are expressed in 2015 Euros.

Depreciation rates. We determine the depreciation rate for machines and buildings by using industry-level data from the German national accounts on the yearly values of depreciations divided by the yearly gross capital stock of machines and buildings, respectively:

$$\delta^{\theta}{}_{jt} = \frac{Depr_{jt}^{\theta}}{K_{jt}^{\theta}}$$

These yearly depreciation rates vary between 6.6% and 7.8% for machinery and equipment, and between 2.3% and 3.8% for buildings. Regarding the depreciation rates of intangible capital, we follow most of the literature and use fixed rates for all industries and years, in

[38] The national accounts data on industry-level price deflators, depreciations, gross capital stock, and number of employees are included in the Fachserie 18, Reihe 1.4., available at: https://www.destatis.de/DE/Themen/Wirtschaft/Volkswirtschaftliche-Gesamtrechnungen-Inlandsprodukt/Publikationen/Downloads-Inlandsprodukt/inlandsprodukt-endgueltig-pdf-2180140.html

particular 33% for software, and 20% for patents and R&D (Corrado et al. 2009).[39] We thus assume that intangible capital depreciates at a faster rate than physical capital.

Initial capital stocks. Finally, an important issue is the construction of the initial capital stock in t=0, i.e., the capital stock in the first year a firm is observed in the sample with information on investment flows. Our baseline method of constructing the initial capital stock is used frequently in the literature. Hall and Mairesse (1995) construct an initial capital stock by simply dividing a firm's investment in t=0 by the depreciation rate plus a fixed annual growth rate. We modify this formula by using the average investment during the firm's first three years in the data (to account for the fact that many firms have zero investments in a single year). This gives an initial capital stock for period t=0

$$K^{\theta}{}_{ij0} = \frac{1}{3} * \sum_{\{t=1\}}^{3} \frac{I_{ijt}^{\theta}}{\delta_{jt}^{\theta} + r_{ij}^{\theta}}$$

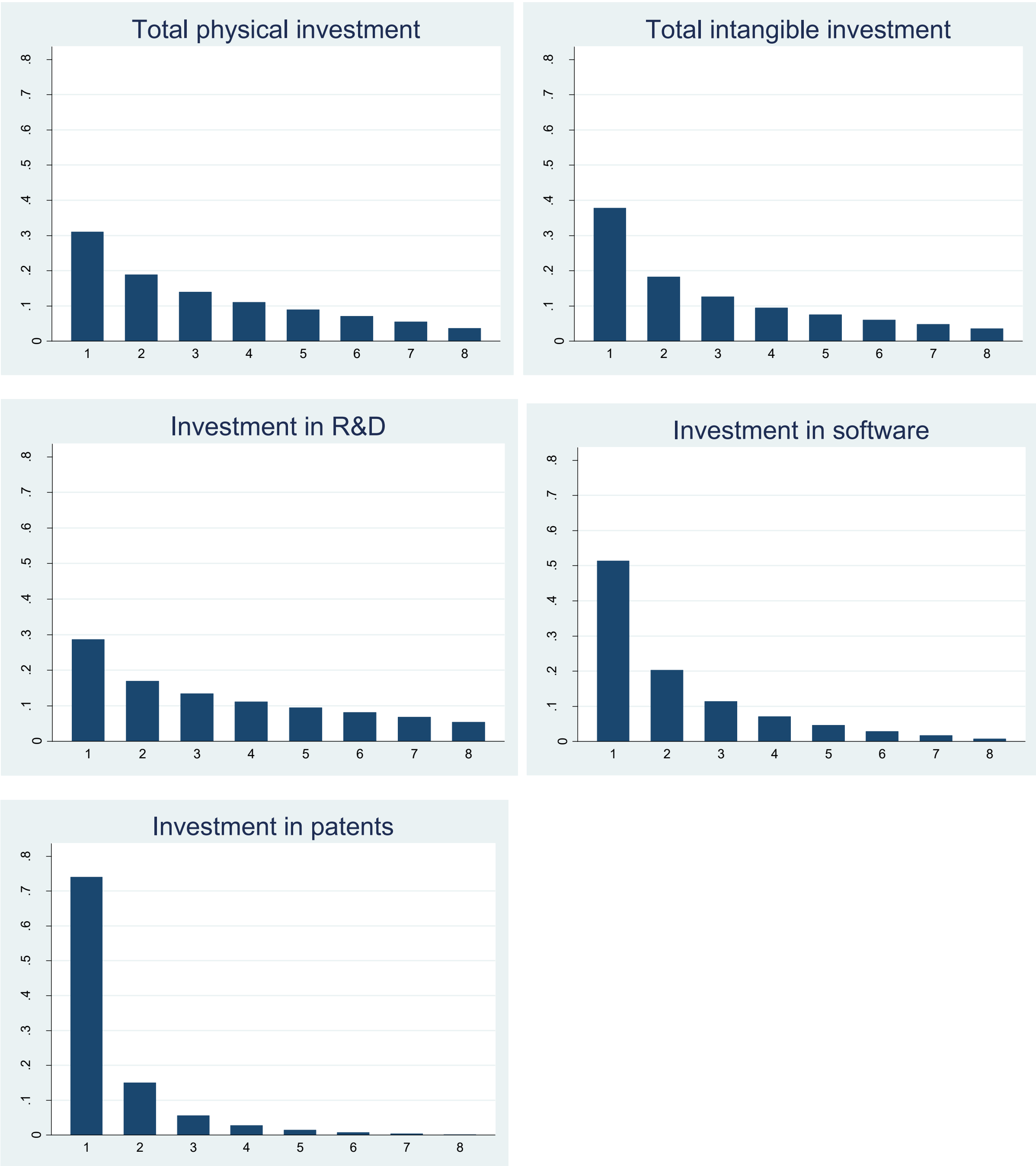
where the industry-level depreciation rate δ_{jt}^{θ} is constructed as above, and the industry-level growth rate r_{jt}^{θ} is constructed as the geometric mean of the annual growth rates of the different investment types (machinery, buildings, and intellectual capital) in the National Accounts over the period 1995-2008.

As a robustness check, we explore a similar method used in Dhyne et al. (2018). This method relies on the idea that due to the longer available history, the physical capital stock is measured more precisely than the intangible capital stock. We thus first construct the physical capital stock for each year using the PIM as described above. For the first year when intangible investment is observed, we impute the starting value for intangible capital as the physical capital stock in that year times the ratio of intangible to physical investment over the next four years. We then use this initial intangible capital stock to calculate the intangible capital stock for the subsequent years using the PIM.

[39] Dhyne et al. (2018) use a fixed rate of 31.5% for IT capital.

Appendix B: Robustness Checks

Figure B1. Share of a firm's cumulative 8-year investment which happened in the largest, 2nd, 3rd, …, lowest year



Source: German structural business surveys covering firms in the manufacturing sector with 20 or more persons employed. The calculations use a balanced sample of N=3,629 firms which are in both the cost structure survey and the investment survey over the whole period 2009-2016, own calculation. Survey weights are used.

Table B1: Production Functions, industry-specific, Value added spec, Wooldridge

	(1) Labour	(2) Phys. Capital	(3) R&D	(4) Software	(5) Patents
All high-intensity industries	*0.648**** *(0.004)*	*0.301**** *(0.019)*	*0.065**** *(0.010)*	*0.034**** *(0.004)*	*0.001* *(0.005)*
19/20: Coke/Chemical	0.601***	0.300***	0.062**	0.026**	-0.013
	(0.010)	(0.057)	(0.031)	(0.011)	(0.010)
21: Pharma	0.795***	0.105	0.156***	0.037	0.048*
	(0.026)	(0.099)	(0.053)	(0.024)	(0.028)
26: Data Processing Eq.	0.598***	0.309***	0.109***	0.002	-0.000
	(0.011)	(0.056)	(0.030)	(0.012)	(0.012)
27: Electrical Eq.	0.693***	0.180***	0.086***	0.057***	-0.009
	(0.009)	(0.039)	(0.025)	(0.011)	(0.011)
28: Engineering	0.697***	0.297***	0.051***	0.039***	0.009
	(0.006)	(0.027)	(0.016)	(0.006)	(0.007)
29: Motor Vehicles	0.634***	0.414***	0.079***	0.012	-0.003
	(0.011)	(0.065)	(0.026)	(0.014)	(0.015)
30: Other Vehicles	0.709***	0.092	-0.036	-0.004	-0.009
	(0.026)	(0.106)	(0.048)	(0.025)	(0.020)
All low-intensity industries	*0.706**** *(0.003)*	*0.239**** *(0.014)*	*0.044**** *(0.010)*	*0.030**** *(0.003)*	*0.011*** *(0.005)*
10-12: Food	0.608***	0.271***	-0.011	0.043***	0.022**
	(0.005)	(0.036)	(0.022)	(0.009)	(0.010)
13-15: Textiles	0.732***	0.433***	0.044*	0.026**	0.022
	(0.010)	(0.091)	(0.024)	(0.013)	(0.017)
16: Wood	0.779***	0.123**	0.001	0.025	-0.001
	(0.014)	(0.059)	(0.075)	(0.016)	(0.024)
17: Paper	0.688***	0.057	-0.008	0.010	0.032*
	(0.013)	(0.051)	(0.036)	(0.014)	(0.017)
18: Printing	0.736***	0.101*	-0.114	0.046***	0.034
	(0.015)	(0.054)	(0.121)	(0.016)	(0.029)
22: Rubber/Plastic	0.685***	0.337***	0.028	0.011	0.004
	(0.008)	(0.045)	(0.025)	(0.008)	(0.012)
23: Glass	0.673***	0.332***	0.015	0.031***	-0.011
	(0.010)	(0.059)	(0.041)	(0.012)	(0.016)
24: Basic Metals	0.703***	0.356***	0.036	0.003	0.009
	(0.010)	(0.062)	(0.029)	(0.010)	(0.015)
25: Fabricated Metal	0.749***	0.211***	0.042**	0.019***	0.009
Products	(0.006)	(0.023)	(0.018)	(0.006)	(0.009)
31-32: Furniture	0.703***	0.362***	0.094***	0.015	0.006
	(0.010)	(0.041)	(0.031)	(0.010)	(0.013)
33: Repairing	0.877***	0.074	0.029	0.018	0.005
	(0.009)	(0.048)	(0.037)	(0.013)	(0.019)

Note: The Wooldridge estimations use energy input as the proxy variable. Standard errors in parentheses, clustered at the firm level, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Further controls are firm-level prices, dummies for missing intangible capital variables and missing firm-level prices, and year dummies. Survey weights are used. Source: German structural business surveys 2009-2015 covering firms in the manufacturing sector with 20 or more persons employed, own calculation.

Table B2: Production Functions, industry-specific, gross output specification, OLS

	(1) Materials	(2) Labour	(3) Phys. Capital	(4) R&D	(5) Software	(6) Patents
All high-intensity industries	*0.716****	*0.232****	*0.031****	*0.022****	*0.007****	*-0.000*
	(0.004)	*(0.006)*	*(0.002)*	*(0.002)*	*(0.001)*	*(0.001)*
19/20: Coke/Chemical	0.750***	0.180***	0.054***	0.014***	0.007**	0.002
	(0.013)	(0.015)	(0.007)	(0.004)	(0.003)	(0.003)
21: Pharma	0.737***	0.247***	0.021	0.017	0.003	0.003
	(0.016)	(0.025)	(0.015)	(0.012)	(0.007)	(0.006)
26: Data Processing Eq.	0.683***	0.244***	0.013	0.040***	0.011**	0.002
	(0.012)	(0.017)	(0.009)	(0.006)	(0.004)	(0.005)
27: Electrical Eq.	0.708***	0.255***	0.018***	0.022***	0.009***	-0.004
	(0.007)	(0.010)	(0.004)	(0.003)	(0.003)	(0.003)
28: Engineering	0.704***	0.247***	0.032***	0.018***	0.008***	-0.000
	(0.005)	(0.007)	(0.003)	(0.002)	(0.002)	(0.002)
29: Motor Vehicles	0.736***	0.227***	0.036***	0.023***	0.002	-0.004
	(0.019)	(0.025)	(0.007)	(0.004)	(0.004)	(0.004)
30: Other Vehicles	0.719***	0.260***	0.007	0.025***	0.007	-0.003
	(0.016)	(0.026)	(0.010)	(0.005)	(0.006)	(0.005)
All low-intensity industries	*0.719****	*0.237****	*0.035****	*0.014****	*0.008****	*0.003****
	(0.003)	*(0.004)*	*(0.002)*	*(0.001)*	*(0.001)*	*(0.001)*
10-12: Food	0.755***	0.190***	0.043***	0.002	0.019***	0.003
	(0.005)	(0.006)	(0.005)	(0.003)	(0.004)	(0.003)
13-15: Textiles	0.736***	0.267***	0.005	0.007*	0.004	0.009**
	(0.009)	(0.015)	(0.005)	(0.004)	(0.004)	(0.004)
16: Wood	0.756***	0.246***	0.009**	0.008	0.006*	-0.006
	(0.007)	(0.010)	(0.004)	(0.006)	(0.003)	(0.004)
17: Paper	0.745***	0.217***	0.046***	0.012**	0.010**	-0.003
	(0.021)	(0.025)	(0.008)	(0.005)	(0.004)	(0.004)
18: Printing	0.625***	0.338***	0.027***	0.018*	0.016***	0.013*
	(0.015)	(0.021)	(0.008)	(0.010)	(0.005)	(0.008)
22: Rubber/Plastic	0.713***	0.255***	0.032***	0.017***	0.002	0.002
	(0.009)	(0.014)	(0.005)	(0.003)	(0.002)	(0.003)
23: Glass	0.740***	0.224***	0.025***	0.018***	0.005	-0.001
	(0.007)	(0.008)	(0.005)	(0.004)	(0.004)	(0.003)
24: Basic Metals	0.783***	0.184***	0.026***	0.005	0.006***	-0.000
	(0.006)	(0.009)	(0.005)	(0.003)	(0.002)	(0.003)
25: Fabricated Metal Products	0.671***	0.282***	0.039***	0.013***	0.005**	-0.000
	(0.005)	(0.007)	(0.003)	(0.003)	(0.002)	(0.003)
31-32: Furniture	0.635***	0.299***	0.033***	0.041***	0.014***	0.000
	(0.008)	(0.011)	(0.006)	(0.004)	(0.003)	(0.004)
33: Repairing	0.626***	0.383***	0.012	0.027***	0.007*	-0.007
	(0.012)	(0.020)	(0.008)	(0.006)	(0.004)	(0.006)

Note: See Table B1.

Table B3: Production Functions, industry-specific, Value added specification, OLS

	(1) Labour	(2) Phys. Capital	(3) R&D	(4) Software	(5) Patents
All high-intensity industries	*0.826****	*0.117****	*0.073****	*0.031****	*0.008***
	(0.009)	*(0.005)*	*(0.004)*	*(0.003)*	*(0.003)*
19/20: Coke/Chemical	0.754***	0.198***	0.069***	0.022***	0.008
	(0.026)	(0.015)	(0.010)	(0.008)	(0.009)
21: Pharma	0.938***	0.078	0.078***	-0.004	0.043**
	(0.068)	(0.048)	(0.024)	(0.017)	(0.019)
26: Data Processing Eq.	0.779***	0.074***	0.114***	0.041***	0.012
	(0.024)	(0.015)	(0.015)	(0.011)	(0.010)
27: Electrical Eq.	0.852***	0.080***	0.074***	0.037***	-0.006
	(0.019)	(0.011)	(0.007)	(0.007)	(0.008)
28: Engineering	0.895***	0.077***	0.057***	0.034***	0.006
	(0.012)	(0.007)	(0.005)	(0.005)	(0.005)
29: Motor Vehicles	0.816***	0.142***	0.082***	0.023*	-0.003
	(0.042)	(0.025)	(0.011)	(0.012)	(0.014)
30: Other Vehicles	0.938***	0.060**	0.064***	0.028	-0.009
	(0.048)	(0.024)	(0.016)	(0.021)	(0.015)
All low-intensity industries	*0.855****	*0.128****	*0.049****	*0.037****	*0.015****
	(0.007)	*(0.004)*	*(0.004)*	*(0.003)*	*(0.003)*
10-12: Food	0.719***	0.242***	0.028***	0.074***	0.028***
	(0.013)	(0.009)	(0.010)	(0.007)	(0.008)
13-15: Textiles	0.926***	0.090***	0.031***	0.033***	0.034***
	(0.025)	(0.013)	(0.012)	(0.010)	(0.013)
16: Wood	0.963***	0.085***	0.002	0.025**	-0.010
	(0.025)	(0.014)	(0.019)	(0.011)	(0.016)
17: Paper	0.856***	0.179***	0.031**	0.033***	-0.004
	(0.029)	(0.018)	(0.015)	(0.009)	(0.013)
18: Printing	0.869***	0.110***	0.048**	0.032***	0.032*
	(0.025)	(0.014)	(0.023)	(0.010)	(0.018)
22: Rubber/Plastic	0.855***	0.145***	0.059***	0.011	0.004
	(0.017)	(0.012)	(0.009)	(0.007)	(0.007)
23: Glass	0.832***	0.149***	0.051***	0.029***	0.004
	(0.022)	(0.012)	(0.013)	(0.009)	(0.010)
24: Basic Metals	0.855***	0.147***	0.030***	0.025***	-0.019
	(0.024)	(0.017)	(0.011)	(0.008)	(0.014)
25: Fabricated Metal Products	0.911***	0.103***	0.039***	0.014***	0.003
	(0.012)	(0.007)	(0.007)	(0.005)	(0.006)
31-32: Furniture	0.841***	0.107***	0.087***	0.047***	0.002
	(0.019)	(0.011)	(0.010)	(0.007)	(0.009)
33: Repairing	0.938***	0.087***	0.056***	0.026***	-0.011
	(0.017)	(0.012)	(0.013)	(0.010)	(0.014)

Note: See Table B1.

Table B4: Production Functions, quintile-specific estimates

Wooldridge, Value added specification

		Quintiles of intangible intensity:				
	Noninvestors	Lowest quintile	2nd quintile	3rd quintile	4th quintile	Highest quintile
Labour	0.727***	0.707***	0.693***	0.697***	0.653***	0.617***
	(0.004)	(0.006)	(0.011)	(0.010)	(0.008)	(0.006)
Physical Capital	0.215***	0.218***	0.337***	0.188***	0.406***	0.206***
	(0.020)	(0.033)	(0.037)	(0.030)	(0.033)	(0.027)
Intangible Capital		0.027***	0.044***	0.055***	0.134***	0.474***
		(0.008)	(0.012)	(0.014)	(0.019)	(0.028)
N Firms * Years	14,842	8,152	7,291	8,844	11,174	13,788

OLS, Gross output specification

		Quintiles of intangible intensity:				
	Noninvestors	Lowest quintile	2nd quintile	3rd quintile	4th quintile	Highest quintile
Intermediates	0.702***	0.709***	0.713***	0.728***	0.732***	0.715***
	(0.004)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)
Labour	0.275***	0.244***	0.229***	0.228***	0.203***	0.197***
	(0.007)	(0.007)	(0.009)	(0.008)	(0.008)	(0.007)
Physical Capital	0.028***	0.042***	0.051***	0.039***	0.037***	0.015***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Intangible Capital		0.004	0.005	0.004	0.026***	0.073***
		(0.003)	(0.005)	(0.005)	(0.005)	(0.005)
N Firms * Years	20,793	12,864	12,999	14,386	16,235	18,361

OLS, Value added specification

		Quintiles of intangible intensity:				
	Noninvestors	Lowest quintile	2nd quintile	3rd quintile	4th quintile	Highest quintile
Labour	0.906***	0.837***	0.836***	0.854***	0.820***	0.725***
	(0.009)	(0.012)	(0.016)	(0.016)	(0.018)	(0.014)
Physical Capital	0.127***	0.152***	0.158***	0.139***	0.133***	0.064***
	(0.005)	(0.007)	(0.008)	(0.007)	(0.009)	(0.007)
Intangible Capital		0.029***	0.035***	0.037***	0.082***	0.246***
		(0.006)	(0.012)	(0.011)	(0.013)	(0.010)
N Firms * Years	20,745	12,814	12,972	14,336	16,179	18,264

Note: "Noninvestors" are firms with a zero intangible capital stock. The sample of firms with positive intangible capital stock is further divided into quintiles of intangible intensity (intangible capital stock per FTE employee). Standard errors in parentheses, clustered at the firm level, * p < 0.1, ** p < 0.05, *** p < 0.01. Further controls are firm-level prices, dummies for missing intangible capital variables and missing firm-level prices, year dummies, and a dummy for East Germany. Survey weights are used. Source: German structural business surveys 2009-2015 covering firms in the manufacturing sector with 20 or more persons employed, own calculation.

Table B5. Production Functions, quintile-specific estimates by time period

Wooldridge, gross output specification

2009-2011 time period

	(1) Noninve stors	(2) Lowest quintile	(3) 2nd quintile	(4) 3rd quintile	(5) 4th quintile	(6) Highest quintile
Intermediates	0.707***	0.672***	0.750***	0.767***	0.723***	0.726***
	(0.005)	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)
Labour	0.240***	0.243***	0.230***	0.232***	0.222***	0.215***
	(0.003)	(0.005)	(0.008)	(0.007)	(0.006)	(0.004)
Physical Capital	0.088***	0.055**	0.108***	0.076***	0.117***	0.037**
	(0.013)	(0.022)	(0.023)	(0.018)	(0.021)	(0.017)
Intangible Capital		0.016***	0.017**	0.008	0.019	0.181***
		(0.005)	(0.008)	(0.009)	(0.012)	(0.020)
N Firms * Years	7,050	3,121	2,698	3,311	4,085	4,863

2012-2015 time period

	(1) Noninve stors	(2) Lowest quintile	(3) 2nd quintile	(4) 3rd quintile	(5) 4th quintile	(6) Highest quintile
Intermediates	0.685***	0.702***	0.693***	0.729***	0.733***	0.707***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)
Labour	0.284***	0.261***	0.242***	0.225***	0.197***	0.213***
	(0.003)	(0.004)	(0.006)	(0.006)	(0.004)	(0.004)
Physical Capital	0.081***	0.083***	0.144***	0.062***	0.180***	0.087***
	(0.013)	(0.018)	(0.022)	(0.017)	(0.017)	(0.016)
Intangible Capital		-0.003	0.017**	0.017**	0.057***	0.160***
		(0.005)	(0.007)	(0.008)	(0.010)	(0.016)
N Firms * Years	7,200	4,622	4,162	4,939	6,247	7,760

Note: “Noninvestors” are firms with a zero intangible capital stock. The sample of firms with positive intangible capital stock is further divided into quintiles of intangible intensity (intangible capital stock per FTE employee). Standard errors in parentheses, clustered at the firm level, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Further controls are firm-level prices, dummies for missing intangible capital variables and missing firm-level prices, year dummies, and a dummy for East Germany. Survey weights are used. Source: German structural business surveys 2009-2015 covering firms in the manufacturing sector with 20 or more persons employed, own calculation.

Table B6. Adjusting for double-counting of inputs

Gross output specification

	OLS Not adj.	OLS Adj.	WO Not adj.	WO Adj.
Intermediates	0.719***	0.719***	0.706***	0.702***
	(0.002)	(0.002)	(0.002)	(0.002)
Labour	0.241***	0.235***	0.236***	0.232***
	(0.003)	(0.003)	(0.001)	(0.001)
Physical Capital	0.035***	0.034***	0.095***	0.089***
	(0.001)	(0.001)	(0.005)	(0.004)
R&D	0.006***	0.017***	0.002	0.018***
	(0.001)	(0.001)	(0.003)	(0.003)
Software	0.007***	0.008***	0.007***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
Patents	0.001	0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
N Firms * Years	95,639	95,638	73,159	73,157
N Firms	22,439	22,439	22,428	22,428

Value added specification

	OLS Not adj.	OLS Adj.	WO Not adj.	WO Adj.
Labour	0.859***	0.843***	0.704***	0.690***
	(0.005)	(0.005)	(0.002)	(0.002)
Physical Capital	0.144***	0.138***	0.275***	0.256***
	(0.003)	(0.003)	(0.011)	(0.011)
R&D	0.021***	0.052***	0.007	0.047***
	(0.002)	(0.002)	(0.007)	(0.007)
Software	0.030***	0.032***	0.025***	0.026***
	(0.002)	(0.002)	(0.003)	(0.003)
Patents	0.008***	0.010***	0.005	0.005
	(0.002)	(0.002)	(0.003)	(0.003)
N Firms * Years	95,294	95,310	72,742	72,759
N Firms	22,428	22,428	22,417	22,417

Note: Standard errors in parentheses, clustered at the firm level, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Further controls are firm-level prices, dummies for missing intangible capital variables and missing firm-level prices, year dummies, and a dummy for East Germany. Survey weights are used. Source: German structural business surveys 2009-2015 covering firms in the manufacturing sector with 20 or more persons employed, own calculation.

Table B7. Including temporary agency workers

Gross output specification

	OLS Without temp.	OLS With temp.	WO Without temp.	WO With temp.
Intermediates	0.719***	0.705***	0.702***	0.692***
	(0.002)	(0.002)	(0.002)	(0.002)
Labour	0.235***	0.251***	0.232***	0.247***
	(0.003)	(0.003)	(0.001)	(0.001)
Physical Capital	0.034***	0.034***	0.089***	0.089***
	(0.001)	(0.001)	(0.004)	(0.005)
R&D	0.017***	0.016***	0.018***	0.017***
	(0.001)	(0.001)	(0.003)	(0.003)
Software	0.008***	0.008***	0.007***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
Patents	0.001	0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
N Firms * Years	95,638	95,638	73,157	73,157
N Firms	22,439	22,439	22,428	22,428

Value added specification

	OLS Without temp.	OLS With temp.	WO Without temp.	WO With temp.
Labour	0.843***	0.848***	0.690***	0.696***
	(0.005)	(0.005)	(0.002)	(0.002)
Physical Capital	0.138***	0.132***	0.256***	0.245***
	(0.003)	(0.003)	(0.011)	(0.011)
R&D	0.052***	0.050***	0.047***	0.045***
	(0.002)	(0.002)	(0.007)	(0.007)
Software	0.032***	0.031***	0.026***	0.025***
	(0.002)	(0.002)	(0.003)	(0.003)
Patents	0.010***	0.010***	0.005	0.005*
	(0.002)	(0.002)	(0.003)	(0.003)
N Firms * Years	95,310	95,358	72,759	72,816
N Firms	22,428	22,430	22,417	22,419

Note: Standard errors in parentheses, clustered at the firm level, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Further controls are firm-level prices, dummies for missing intangible capital variables and missing firm-level prices, year dummies, and a dummy for East Germany. Survey weights are used. Source: German structural business surveys 2009-2015 covering firms in the manufacturing sector with 20 or more persons employed, own calculation.

Table B8. Controlling for firm-level prices

Gross output specification

	OLS Log rev.	OLS Log rev.	WO Log rev.	WO Log rev.
Intermediates	0.717***	0.719***	0.704***	0.702***
	(0.002)	(0.002)	(0.002)	(0.002)
Labour	0.236***	0.235***	0.234***	0.232***
	(0.003)	(0.003)	(0.001)	(0.001)
Physical Capital	0.034***	0.034***	0.090***	0.089***
	(0.001)	(0.001)	(0.004)	(0.004)
R&D	0.016***	0.017***	0.018***	0.018***
	(0.001)	(0.001)	(0.003)	(0.003)
Software	0.008***	0.008***	0.007***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
Patents	0.001	0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
firmprice		0.008***		0.008
		(0.001)		(0.009)
N Firms * Years	95,638	95,638	73,157	73,157
N Firms	22,439	22,439	22,428	22,428

Value added specification

	OLS Log VA	OLS Log VA	WO Log VA	WO Log VA
Labour	0.844***	0.843***	0.692***	0.690***
	(0.005)	(0.005)	(0.002)	(0.002)
Physical Capital	0.136***	0.138***	0.255***	0.256***
	(0.003)	(0.003)	(0.011)	(0.011)
R&D	0.053***	0.052***	0.048***	0.047***
	(0.002)	(0.002)	(0.007)	(0.007)
Software	0.032***	0.032***	0.026***	0.026***
	(0.002)	(0.002)	(0.003)	(0.003)
Patents	0.010***	0.010***	0.005	0.005
	(0.002)	(0.002)	(0.003)	(0.003)
firmprice		0.019***		0.015
		(0.003)		(0.021)
N Firms * Years	95,310	95,310	72,759	72,759
N Firms	22,428	22,428	22,417	22,417

Note: Standard errors in parentheses, clustered at the firm level, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Further controls are firm-level prices, dummies for missing intangible capital variables and missing firm-level prices, year dummies, and a dummy for East Germany. Survey weights are used. Source: German structural business surveys 2009-2015 covering firms in the manufacturing sector with 20 or more persons employed, own calculation.

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