Allocation of human capital and innovation at the frontier: Firm-level evidence on Germany and the Netherlands*

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Abstract

This paper examines how productivity effects of human capital and innovation vary at different points of the conditional productivity distribution. Our analysis draws upon two large unbalanced panels of 6,634 enterprises in Germany and 14,586 enterprises in the Netherlands over the period 2000-2008, considering 5 manufacturing and services industries that differ in the level of technological intensity. Industries in the Netherlands are characterized by a larger average proportion of high-skilled employees and industries in Germany by a more unequal distribution of human capital intensity. Except for low-technology manufacturing, average innovation performance is higher in all industries in Germany and the innovation performance distributions are more dispersed in the Netherlands. In both countries, we observe non-linearities in the productivity effects of investing in product innovation in the majority of industries. Frontier firms enjoy the highest returns to product innovation whereas the most negative returns to process innovation are observed in the best-performing enterprises of most industries. In both countries, we find that the returns to human capital increase with proximity to the technological frontier in industries with a low level of technological intensity. Strikingly, a negative complementarity effect between human capital and proximity to the technological frontier is observed in knowledge-intensive services, which is most pronounced for the Netherlands. Suggestive evidence for the latter points to a winner-takes-all interpretation of this finding.

JEL classification : C10, I20, O14, O30.
Keywords : Human capital, innovation, productivity, quantile regression.

1 Introduction

Over the past decade, concerns about the observed poor productivity performance in European countries, in particular compared to the US, have been expressed not only in academic circles but also among policy makers and politicians. Since the mid 1990s, the productivity gap between Europe and the US has risen

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dramatically: GDP per hour worked in the EU has decreased from 98.3 percent of the US level in 1995 to 90.0 percent in 2006. Numerous reports view Europe's unsatisfactory growth performance as a signal of its failure to transform into a knowledge-based economy (Kok, 2004; Sapir *et al.*, 2004; European Commission, 2008). Research into the policy drivers of a knowledge-based economy has taken many disparate routes, from theoretical modeling using an aggregate (macro) perspective to empirical explorations using firm-level (micro) data. Starting from the observation that neither micro evidence, nor meso evidence *per se* conclusively identifies the drivers that boost productivity, this paper takes an integrated micro-meso approach to examine the role of innovation and human capital in shaping the productivity distribution.

We first investigate firm-level heterogeneity in the productivity effects of the strategies to invest in innovation and human capital. Motivated by the increasing prominence of services in European countries and the central role played by knowledge-intensive services in the knowledge-based economies, we focus on high- versus low-technology manufacturing and service industries in Germany and the Netherlands. Given that (*i*) even within these industries, there is significant heterogeneity between firms and (*ii*) the returns to innovation and human capital are highly skewed, we use quantile regression techniques to study the relationship between innovative activity and human capital on the one hand and productivity on the other hand at different points of the conditional productivity distribution. In a subsequent, more descriptive step, we exploit the degree of heterogeneity in the returns to innovation and human capital to re-examine differences in the productivity distribution between industries.

There is a vast empirical literature on the effect of investments in R&D and innovation on productivity. On average, the private returns to R&D are strongly positive and somewhat higher than for ordinary capital (see Hall *et al.*, 2010 for a survey). On average, there are substantial positive impacts of product innovation on revenue productivity whilst the impact of process innovation is more ambiguous (see Hall, 2011 for a survey). Existing quantile regression analyses provide mixed evidence on the relationship between different aspects of R&D and innovation on the one hand and performance on the other hand (see e.g. include Coad and Rao, 2006; Coad and Rao, 2008; Ebersberger *et al.,* 2010; Falk, 2012; Goedhuys and Sleuwaegen, 2009; Hölzl, 2009; Kaiser, 2009; Love *et al.*, 2009; Mata and Wörter, 2013; Nahm, 2001; Segarra and Teruel, 2011 and Stam and Wennberg, 2009).[1]

Likewise, there is a vast empirical literature on the effects of human capital on productivity. On average, human capital returns are found to be significantly positive, particularly in recent studies on the impact of human capital on productivity (see e.g. Fox and Smeets, 2011 and Mason *et al.*, 2012).[2] Using a large panel of all Danish citizens over the period 1980-2001, Fox and Smeets (2011) construct detailed firm-level human capital measures and find that human capital inputs raise firm output considerably. Using cross-country industry-level data for 26 industries in 5 countries (France, Germany, the Netherlands UK and US) over the period 1979-2000, Mason *et al.* (2012) provide evidence of positive human capital returns, particularly when

[1] Estimating a dynamic structural model of the firm's demand for R&D using the Mannheim Innovation Panel, Peters *et al.* (2013) find that the long-run benefits of R&D are increasing with higher levels of productivity.

[2] Up to the first half of the nineties, macro evidence pointed to a positive relationship between human capital and output growth. However, this evidence was refuted by subsequent studies during the second half of the nineties (see Sianesi and van Reenen, 2003 and de la Fuente, 2011 for a survey). The latter finding is largely explained by methodological difficulties related to measuring skills and modeling the channels through which skills impact on economic performance. Starting with Krueger and Lindhal (2001), considerable progress has been made to tackle these methodological problems (see e.g. Cohen and Soto, 2007; de la Fuente and Doménech, 2001, 2006; Barro and Lee, 2010). As a results, the latter studies find again positive impacts of education on economic growth. Another set of recent studies, focusing on the quality of education rather than its quantity, show even larger productivity effects (e.g. Coulombe, 2004; Hanushek and Kimko, 2000; Hanushek and Wößmann, 2008, 2012).

using a composite human capital variable accounting for both certified skills (educational attainment) and uncertified skills acquired through on-the-job training and experience. To our knowledge, our study is the first to examine human capital returns at different points of the conditional productivity distribution.[3]

Our analysis draws upon specific elements of recent endogenous growth models confirming that economy-wide technological improvements occur through the channel of innovation in advanced economies. Benhabib and Spiegel (1994), Acemoglu *et al.* (2003, 2006) and Vandenbussche *et al.* (2006) share the underlying idea that technological improvements are the result of a combination of innovation and imitation. In particular, Acemoglu *et al.* (2003, 2006) show that innovation becomes more important than imitation as an economic entity approaches the technological frontier. Inspired by the argument of Nelson and Phelps (1966) that education facilitates the implementation of new technologies and adapting their framework to allow for the catch-up of technology to the technology of the leading country, Benhabib and Spiegel (1994) provide cross-country evidence that countries with higher education tend to close the technological gap faster than others and experience higher economic growth. Vandenbussche *et al.* (2006) go one step further and show that the contribution of human capital to productivity growth can be decomposed into a level effect and a composition effect. In line with Acemoglu (2006), they assume that unskilled labor is better suited to imitation whereas more intensive use of skilled labor is required for innovation. Taking into account endogenous labor allocation across these imitation and innovation activities, they argue that one needs to account for both an economy's distance to the technological frontier and the composition of its human capital, which they empirically confirm at the macro level.

In a broad sense, our study fits into the empirical literature advocating that growth-maximizing policies should depend on the distance to the technological frontier. So far, the role of distance to the technological frontier has predominantly been examined using industry-level data. Existing articles include Griffith *et al.* (2003, 2004) on R&D intensity in a panel of industries across 12 OECD countries, Aghion *et al.* (2004) on threat of entry in UK industries, Aghion *et al.* (2005) on product market competition in UK industries, Kneller and Stevens (2006) on human capital and R&D in a panel of industries across 12 OECD countries, Aghion *et al.* (2008) on the liberalization of product entry in India and Acemoglu *et al.* (2006) on openness to trade, entry costs and schooling level in a cross-country panel of about 100 non-OECD countries. In a more narrow sense, our study is most closely related to Vandenbussche *et al.* (2006), Inklaar *et al.* (2008) and Madsen *et al.* (2010). Using a panel dataset covering 19 OECD countries between 1960 and 2000, Vandenbussche *et al.* (2006) provide evidence of skilled labor having a higher growth-enhancing effect closer to the technological frontier. Using EUKLEMS industry data on multifactor productivity covering the period 1995-2004, Inklaar *et al.* (2008), however, do not find support for the argument that there are productivity externalities from employing university-educated workers for leaders in market services industries. Using a panel of 23 OECD countries and 32 developing countries covering the period 1970-2004, Madsen *et al.* (2010) show that R&D intensity, its interaction with distance to the frontier, educational attainment interacted with distance to the frontier and technological gap influence total factor growth positively and point to different effects for developed versus developing countries.

A detailed look at our data reveals three stylized facts about human capital, innovation and productivity in Germany and the Netherlands. *First*, irrespective of their level of technological intensity, industries in the

[3] Existing quantile regression studies have focused on changes in the returns of skills at different points of the *wages/earnings distribution* (see e.g. Arias *et al.*, 2001; Buchinsky, 1994; Buchinsky, 2001; Chevalier *et al.*, 2004; Choi and Jeong, 2007; Denny and O'Sullivan, 2007; Flabbi *et al.*, 2008; Harmon et al., 2003; Hartog *et al.*, 2001; Machado and Mata, 2001; Machado and Mata, 2005; Martins and Pereira, 2004; Mwabu-Schultz, 1996; Pereira and Martins, 2002 and Tobias, 2002).

Netherlands are characterized by a higher average share of employees possessing a college or university degree and industries in Germany by a more unequal distribution of human capital intensity. *Second*, average innovation performance –measured by the logarithm of real innovative sales per employee for product innovators– is higher in all industries, except for Low-technology manufacturing in Germany and the innovation performance distributions are more dispersed in all Dutch industries, except for Low-technology manufacturing. *Third*, average productivity is higher in all manufacturing industries in the Netherlands and productivity is more unequally distributed in all industries, except for High-technology manufacturing in Germany.

Allowing the productivity effects of human capital and innovation to vary at different points of the conditional productivity distribution, our two main findings are summarized as follows. *First*, we find increasing marginal returns to product innovation as we move up through the productivity distribution but negative marginal returns to process innovation for the best-performing enterprises in the majority of industries in both countries. Apparently, the best strategy for frontier firms is to focus on product rather than on process innovation. *Second*, the returns to human capital increase with proximity to the technological frontier in industries with a low level of technological intensity in both countries, thereby providing micro-evidence on the positive complementarity effect put forward by Vandenbussche *et al.* (2006). Strikingly, we find a negative complementarity effect between human capital and proximity to the technological frontier in knowledge-intensive services. The latter finding is most pronounced for the Netherlands.[4] We provide suggestive evidence in support of a winner-takes-all interpretation for the Netherlands. Investment in intangibles in knowledge-intensive services, making use of human capital intensely, might lead to a profitable breakthrough for one firm which could compensate the losses of many competitors.

We proceed as follows. Section 2 elucidates our empirical strategy. Section 3 discusses the data for Germany and the Netherlands. Section 4 presents some stylized facts. Section 5 reports the results. Section 6 concludes.

2 Econometric framework

Our empirical analysis consists of two parts. In the *first* part, we estimate the returns to human capital and innovation at the firm level. Our econometric framework is based on an augmented standard Cobb-Douglas production function approach. The logarithmic specification of the production function in intensity form is given by:

$$\begin{aligned} \ln\left(\frac{Q}{L}\right)_{it} &= \beta_0 + \beta_K \ln\left(\frac{K}{L}\right)_{it} + \beta_M \ln\left(\frac{M}{L}\right)_{it} + \beta_L \ln L_{it} \\ &\quad + \beta_{HC} HC_{it} + \beta_{CTF} CTF_{it-1} + \beta_{PD} PD_{it} + \beta_{PC} PC_{it} + \alpha Controls + u_{it} \end{aligned} \tag{1}$$

where Q_{it} is output of firm i in year t, and L, K and M denote the number of employees, physical capital and material, respectively. Although productivity is measured in intensity form, firm size ($\ln L$) is additionally included. It allows to test for the hypothesis of constant returns to scale which corresponds to $\beta_L = 0$. The production function is extended by including human capital (HC), the technological position of the firm (CTF), product innovation (PD) and process innovation (PC). We further account for the productivity impact of some additional control variables ($Controls$) that will be explained in more detail in Section 3.4. β_K and β_M measure the output elasticity of capital and material whilst β_{HC}, β_{PD} and β_{PC} capture the returns to human capital, product and process innovation respectively.

[4] The latter result no longer holds for Germany in regressions that also estimate individual fixed effects.

We estimate this production function at the country-industry level using four different estimation methods that differ in their degree of firm-level heterogeneity they account for. Standard least squares regression techniques (OLS) provide point estimates for the average productivity effect of the independent variables in a 'representative enterprise'. Unobserved heterogeneity among firms, however, may make it difficult to isolate the productivity effects of human capital and innovation as both variables are likely to correlate with unobserved firm characteristics such as managerial ability. As an additional source of heterogeneity, we therefore account for firm-specific effects in estimating the average returns to human capital and innovation by using the fixed effects (FE) estimator.

The exclusive focus on mean effects of OLS and FE may be misleading in our study since it seems unlikely that most firms obtain the 'average' return to human capital and innovation or even close to it. In order to obtain a more detailed picture of heterogeneous returns, we therefore use quantile regression (QR) techniques to model the conditional productivity distribution at various quantiles θ $(0 < \theta < 1)$, conditional on the explanatory variables. The use of quantile regression techniques provides two other major advantages. First, whilst the optimal properties of standard regression estimators are not robust to modest departures from normality, quantile regression results are characteristically robust to outliers and heavy-tailed distributions. In fact, the quantile regression solution is invariant to outliers of the dependent variable that tend to $\pm\infty$ (Buchinsky, 1994). Second, a quantile regression approach avoids the restrictive assumption that the error terms are identically distributed at all points of the conditional distribution.

The quantile regression model, first introduced in Koenker and Bassett's (1978) seminal contribution, can be written as:

$$y_{it} = x_{it}^{'}\beta_\theta + u_{\theta it} \qquad \text{with} \qquad Q_\theta\left(y_{it}|x_{it}\right) = x_{it}^{'}\beta_\theta \tag{2}$$

where y_{it} is the dependent variable, x_{it} a $(K \times 1)$-vector of regressors, β_θ the $(K \times 1)$-vector of parameters to be estimated and $u_{\theta it}$ the error term. $Q_\theta\left(y_{it}|x_{it}\right)$ denotes the θ^{th} conditional quantile of y_{it} given x_{it}. The θ^{th} conditional quantile function can be estimated by solving the following minimization problem:

$$\min_\beta \frac{1}{n}\left\{\sum_{i,t:y_{it}\geq x_{it}^{'}\beta} \theta|y_{it} - x_{it}^{'}\beta| + \sum_{i,t:y_{it}<x_{it}^{'}\beta} (1-\theta)\left|y_{it} - x_{it}^{'}\beta\right|\right\} = \min_\beta \frac{1}{n}\sum \rho_\theta u_{\theta it} \tag{3}$$

where $\rho_\theta u_{\theta it}$, known as the 'check function', is defined as

$$\rho_\theta u_{\theta it} = \begin{cases} \theta u_{\theta it} & \text{if} \quad u_{\theta it} \geq 0 \\ (\theta - 1)\, u_{\theta it} & \text{if} \quad u_{\theta it} < 0 \end{cases} \tag{4}$$

Eq. (3) is solved by linear programming methods. As one increases θ continuously from 0 to 1, one traces the entire conditional distribution of y, conditional on x (Buchinsky, 1994). In our study, the parameter estimate for the k^{th} exogenous variable, let's say human capital, is interpreted as the marginal change in productivity due to a marginal change in human capital conditional on being on the θ^{th} quantile of the distribution. This is also called the θ^{th} quantile return to human capital. We are particularly interested in how these returns change along the distribution.

The standard quantile regression method allows the impact of all explanatory variables to vary along the conditional productivity distribution. However, it does not account for other unobserved firm-specific variables α_i that might affect productivity. In order to take this type of heterogeneity into account when estimating the quantile returns to human capital and innovation, we use a fixed effects quantile regression ($FEQR$) estimator for panel data (Koenker, 2005):

$$y_{it} = x_{it}^{'}\beta_\theta + \alpha_i + \epsilon_{\theta it} \tag{5}$$

We employ a two-step estimation approach. In the first step, we estimate a standard fixed effects model and predict the firm-specific effects $\widehat{\alpha_i} = \overline{y_i} - \overline{x_i}'\widehat{\beta}_{FE}$. In the second step, we run a pooled quantile regression of $y_{it} - \widehat{\alpha_i}$ on all explanatory variables x_{it} in order to obtain quantile regression estimates for β_θ.

Based on our firm-level results, we examine in the *second* part of our empirical analysis whether heterogeneous productivity effects of human capital and innovation significantly change productivity distribution characteristics at the industry level. We follow an approach proposed by Machado and Mata (2000) and recently used by Mata and Wörter (2013) to investigate the effect of internal and external R&D strategies on the distribution of profits. Main attributes of the productivity distribution are the dispersion, skewness and kurtosis. Quantile-based definitions of these attributes are as follows (see Oja, 1981 and Ruppert, 1987):

$$\begin{aligned} dispersion &= (q_{0.75} - q_{0.25}) \,/\, (q_{0.75} + q_{0.25}) \\ skewness &= (q_{0.75} + q_{0.25} - 2q_{0.50}) \,/\, (q_{0.75} - q_{0.25}) \\ kurtosis &= (q_{0.90} - q_{0.10}) \,/\, (q_{0.75} - q_{0.25}) \end{aligned} \tag{6}$$

The dispersion is a ratio of the width of the distribution between the upper and lower quartiles over a measure of location. The skewness compares the difference between the upper quartile and median and the median and the lower quartile over the width of the distribution. This measure is zero for symmetric distributions. A negative value implies that the productivity distribution has longer tails on the left side but that the mass of the distribution is concentrated on the right. The kurtosis measures the weight of the tails by comparing the distance between the 0.10 and 0.90 quantiles with the distance between the upper and lower quartiles. A high kurtosis points to a productivity distribution where the dispersion of productivity results from extreme but infrequent productivity levels (extreme deviations) whereas a low kurtosis implies that the dispersion results from frequent modestly-sized deviations.

Inserting the equations for different quantiles into these definitions, we obtain a relationship between our explanatory variables and the distributional characteristics. In order to evaluate how changes in human capital and innovation *ceteris paribus* affect these distributional characteristics, we follow Mata and Wörter (2013) by using the estimated coefficients of these variables at the relevant quantiles. Standard errors of these non-linear combinations of parameter estimates are calculated using the Delta method (Wooldridge, 2002).[5]

3 Data description

To ensure that our results reflect underlying economic differences, we built two highly comparable microdata sets that span the period 1998-2008. Enterprises in manufacturing (European industry classification system NACE Rev. 1.1 15 to 37) and services (NACE 50 to 90) are included in the analysis. The population of interest consists of enterprises with at least ten employees. This section examines the German and Dutch microdata sets respectively. For both countries, price deflators for output, value added, intermediate inputs and capital are drawn from the EUKLEMS database (November 2009 release, March 2011 update) and unit labor costs are taken from the OECD database.

[5] Calculations are done in STATA using the *nlcom*-command.

3.1 Germany

We use the Mannheim Innovation Panel (MIP). The MIP is made up by representative innovation surveys which are collected by the Centre for European Economic Research (ZEW) in cooperation with the Fraunhofer Institute for Systems and Innovation Research (ISI) and the Institute for Applied Social Science (infas) on behalf of the German Federal Ministry of Education and Research (BMBF). Every fourth (before 2005) / second (after 2005) year, the MIP is the German contribution to the European-wide harmonized Community Innovation Surveys (CIS). In contrast to other European countries, the MIP is an *annual* panel that started in 1993 in manufacturing and was extended to services in 1995. It is based on a random stratified sample –industry, size and region serving as stratification criteria– that is refreshed every second year for dead and newly established firms respectively (see Rammer and Peters, 2013). In addition to the common harmonized innovation indicators, the German innovation surveys additionally ask firms about a host of other general firm characteristics such as sales, number of employees, the share of high-skilled employees, intermediate input costs (including energy costs and intermediate services) and the stock of tangible assets (physical capital).

3.2 The Netherlands

We use data that are sourced from different surveys collected by Statistics Netherlands, or "Centraal Bureau voor de Statistiek" (CBS). The innovation variables stem from five waves of the Dutch Community Innovation Surveys (CIS): CIS3 (1998-2000), CIS3.5 (2000-2002), CIS4 (2002-2004), CIS4.5 (2004-2006) and CIS5 (2006-2008). CIS enterprises are merged with data from the Production Surveys (PS).[6] The latter contains data on production value, factor inputs and factor costs.

The CIS and PS data are collected at the enterprise level. A combination of census and stratified random sampling is used for each wave of the CIS and PS. A census is used for the population of enterprises with at least fifty employees and a stratified random sampling is used for enterprises with fewer than fifty employees. The stratification variables are the industry and the number of employees of an enterprise. The same cut-off point of 50 employees is applied to each wave of the CIS and the PS.

The Social Statistics Database (SSB) forms the backbone to retrieve information on the skill composition of the workforce in the matched (CIS∩PS)-enterprises (Bakker, 2002). The SSB links administrative data for the entire population registered as living in the Netherlands with detailed demographic and socio-economic data from business and household surveys. The data are primarily obtained from the population register, tax registers, social security registers, education registers and various other registers and administrations. The SSB contains all the relevant information on persons, families, households, jobs, benefits and living quarters which can be matched with enterprise data through a unique personal identification number. Details on the measurement of the human capital variables are found in Section A.1 of Appendix A.

3.3 Main estimation samples

For estimation purposes, we use information from the aforementioned five waves of the CIS (Germany) and matched CIS samples (The Netherlands) in both countries. After some cleaning and trimming on nominal labor productivity levels and growth rates to eliminate outliers and anomalies, we end up with an unbalanced panel of 11,699 observations corresponding to 6,634 enterprises (61.4% in manufacturing and

[6] Approximately 26% of the CIS enterprises are matched with the corresponding PS enterprises in manufacturing. For services, the match increases to 33%.

38.6% in services) over the period 2000-2008 in Germany (DE) and an unbalanced panel of 24,586 observations corresponding to 14,841 enterprises (38.5% in manufacturing and 61.5% in services) over the period 2000-2008 in the Netherlands (NL).[7] The estimation samples are further broken down into five industries according to the OECD (2001) classification: High-technology manufacturing (HT), Medium-technology manufacturing (MT), Low-technology manufacturing (LT), Knowledge-intensive services (KIS) and Other services (OS). Table A.6 in Appendix A provides details on the industry breakdown of manufacturing and services depending on their technological intensity.

Table 1 reports the number of observations and firms in the estimation sample by country, industry, size and year. Unsurprisingly, the German sample includes more larger enterprises (10.9% with more than 500 employees) than the Dutch sample (3.6%). With respect to industry composition, we find that the German sample includes more High-technology manufacturing firms but less Other services firms. That is, in DE (NL), 9.2% (2.7%) of the firms belong to High-technology manufacturing, 35.2% (22.6%) to Medium-technology manufacturing, 16.6% (10.5%) to Low-technology manufacturing, 24.1% (29.7%) to Knowledge-intensive services and 14.9% (34.8%) to Other services. In some robustness checks and to measure some variables (see Section 3.4), we use a more detailed industry classification (21 industries: 11 in manufacturing and 10 in services). Table B.1 in Appendix B presents the number of observations and the number of firms in the estimation sample by country and by 21-industry. Table B.2 in Appendix B gives the panel structure of the estimation sample. In DE (NL), 46% (38.2%) of the enterprises have at least two observations. For about 8% of the enterprises, we have at least four observations in the two countries.

<Insert Table 1 about here>

3.4 Dependent and explanatory variables

Our main dependent variable is the logarithm of real labor productivity (RLP). Nominal labor productivity is measured by sales per employee $\left(\frac{Q}{L}\right)$ where L is the number of employees in head counts.[8] EUKLEMS output price indicators (base year 2006) are used for deflation.

We explain the logarithm of real labor productivity by firm size ($\ln L_{it} = SIZE_{it}$) and the traditional input factors physical capital and material. Capital is measured as the logarithm of real physical capital per employee $\left(\ln\left(\frac{K}{L}\right)_{it} = CAP_{it}\right)$, where K is proxied by tangible assets in the German microdata set and by depreciation of fixed assets in the Dutch microdata set. It is deflated by using the industry-level gross fixed capital formation price index for all assets. Material is defined as the logarithm of real material costs per employee $\left(\ln\left(\frac{M}{L}\right)_{it} = MAT_{it}\right)$, where M is intermediate input costs including energy costs and intermediate services, deflated by the industry-level intermediate inputs price index. In order to investigate the role of human capital, we include the share of high-skilled labor (HC_{it}), where high-skilled employees are defined as having a college or university degree. Innovation is captured by two innovation outcome variables: product and process innovation. Product innovation is measured by the logarithm of real innovative sales per employee $\left(\ln\left(\frac{SSPD \times SALES}{L}\right)_{it} = PD_{it}\right)$. $SSPD_{it}$ refers to the share of total sales in year t accounted for by new or improved products and services introduced in $(t-2)$, $(t-1)$ and t. In addition, we make a corresponding distinction based on the share of sales due to products new to the firm only (firm novelties, $SSFN_{it}$) and

[7] In DE (NL), 2,506 (4,452) enterprises take part in at least two consecutive waves, 956 (1,860) in at least three consecutive waves, 390 (785) in at least four consecutive waves and 152 (348) in all five waves.

[8] L refers to the average number of employees in the German data set and to the number of employees in September of a given year in the Dutch data set.

the share of sales due to products new to the market (market novelties, $SSMN_{it}$). In contrast to product innovation, process innovation is measured by a binary indicator equaling one if an enterprise introduced any new or significantly improved production technology during the period under review, i.e. between $(t-2)$ and t (PC_{it}). In order to investigate whether distance to the technological frontier matters for firm-level productivity, we include the 1-year lagged value of closeness to the technological frontier ($CTF_{it-1} = L1.CTF$). Closeness to the technological frontier is measured as $CTF_{it} = 1 - DTF_{it} = 1 - \left(\frac{RLP_{Ft} - RLP_{it}}{RLP_{Ft}}\right) = \frac{RLP_{it}}{RLP_{Ft}}$, where RLP of the technological frontier firm F is proxied by the 95% percentile value of RLP at the NACE 3-digit industry level in both countries.[9] The definition of $L1.CTF$ implies that we capture persistence effects. Finally, our productivity estimates control for being part of a group (GP_{it}), being located in East Germany for *DE* ($EAST_{it}$) and time dummies (D_t). In the estimations, our main focus is on the effect of the human capital and the innovation variables.

Despite the same definitions, one important difference between the German and Dutch variables stems from the measurement of the human capital variable. For *DE*, the skill variable is directly taken from the survey information. For *NL*, this variable is mainly estimated using a matched employer-employee dataset (see Section A.1 in Appendix A). In addition to this measurement issue, there are inherent institutional differences between the two countries. In particular, the education system in *DE* is characterized by a dual system – integrating work-based and school-based learning– supportive for providing high-quality technical skills and for creating a high degree of specialization of skilled employees.

In addition to the main model specification, we perform various robustness checks in Section 5.3. The sensitivity analyses particularly refer to the measurement of the dependent variable and of human capital. We examine two alternative dependent variables. The first is total factor productivity (TFP) which is calculated as the residual of a panel estimation of a standard Cobb-Douglas production function at the industry level. We adopt the system generalized method of moments ($SYS\text{-}GMM$) estimator and use appropriate lags of the input factors as instruments. More specifically, we estimate a production function for each of the 35 NACE 2-digit industries in *DE* and each of the 149 NACE 3-digit industries in *NL* and and calculate TFP as $TFP_{it} = \ln(RLP)_{it} - \widehat{\gamma}_K \ln\left(\frac{K}{L}\right)_{it} - \widehat{\gamma}_M \ln\left(\frac{M}{L}\right)_{it} - \widehat{\gamma}_L \ln L_{it} - \sum_t \widehat{\gamma}_D D_t$.[10] The second is the one-year lead of real labor productivity growth ($RLPGR$), defined as labor productivity growth between year t and $(t+1)$.

Regarding human capital, HC_{it} is either replaced by (*i*) a binary variable equaling one if HC_{it} exceeds the median value of the share of high-skilled labor in industry j (21-industry classification) at time t or (*ii*) a more detailed decomposition of the workforce. This detailed decomposition is only feasible for *NL* and splits L into the number of low-skilled, low-medium-skilled, high-medium-skilled and high-skilled employees.[11] We furthermore investigate whether real labor productivity can be explained by different moments of the industry distribution of human capital intensity (where industries are defined according to the 21-industry classification). In particular, we consider the mean ($HCmean_{Jt}$), the standard deviation ($HCsd_{Jt}$), the skewness ($HCskew_{Jt}$) and the kurtosis ($HCkurt_{Jt}$) of industry-year distributions of human capital intensity.

[9] In *DE*, we consider the largest possible population of enterprises included in the MIP. In addition to the response sample, this also includes information from the non-response sample. In total, 84,454 observations from 19,351 enterprises were used for calculating annual CTF during the period 1998-2008. For details on the measurement of CTF in *NL*, we refer to Section A.2 of Appendix A.

[10] The number of observations for several 3-digit industries is insufficient to allow for estimations at a more detailed disaggregation level in *DE*.

[11] Details on the definition of the four skill types are provided in Section A.1 of Appendix A.

Table 2 shows descriptive statistics in the estimation samples for our key variables by country and by industry. Focusing on our dependent and primary explanatory variables, we observe considerable heterogeneity across countries and –within a country– across industries. Except for Other services, average RLP is higher for all industries in *NL*. In manufacturing, real labor productivity (both in levels and growth rates) varies much more across industries in *NL*, while the opposite is true for services. In both countries, average RLP decreases with the level of technological intensity in manufacturing. The same is true for services in DE whereas average RLP is the same in both service industries in *NL*. Over the period 2000-2008, real labor productivity grows at an average annual rate of 3.6% in DE and 5.3% in *NL*. Except for Low-technology manufacturing, average $RLPGR$ is significantly higher for all industries in *NL*. The relationship between average $RLPGR$ and technological intensity appears to be hump-shaped in German manufacturing whilst average $RLPGR$ increases with the level of technological intensity in Dutch manufacturing. Average $RLPGR$ is observed to be higher in Knowledge-intensive services compared to Other services in DE whereas no difference can be detected in *NL*.

The average share of high-skilled labor is 0.19 in DE and 0.26 in *NL*. A comparable difference in the average proportion of individuals (aged 15-64) with tertiary educational attainment over the period 2000-2008 is reported by Eurostat (2013), i.e. 0.20 in DE and 0.24 in *NL*, which suggests that measurement differences in our human capital variable between the two countries (see supra) do not give any obvious cause for concerns.[12] We observe considerable heterogeneity across industries. In both countries, high-technology enterprises in both manufacturing and services possess a significantly higher fraction of high-skilled labor compared to their low-technology counterparts.

In contrast to human capital, we find that the proportion of innovators, either defined in terms of product innovators or process innovators, and the share of innovative sales ($SSPD$) are on average higher in DE than in *NL*. 64% and 42% of the enterprises in the German and Dutch sample, respectively, report having process or product innovation. In DE (NL), the proportion of innovators ranges from 38% (29%) in Other services to 88% (66%) in High-technology manufacturing. The average share of sales due to products new to the market ($SSMN$) is slightly higher in *NL*, whereas the average share of sales due to products new to the firm only ($SSFN$) is much higher in *DE*. Comparing the different industries across countries reveals a clear pattern: the proportion of product and process innovators is higher in all German industries whilst the opposite is true for the proportion of enterprises having introduced market novelties in Low-technology manufacturing and Other services. Focusing on innovation performance, the share of innovative sales is higher in all German industries. Looking at the different types of product innovation, however, the numbers reveal that the share of sales due to market novelties is considerably higher in all Dutch industries, suggesting that innovations are more radical in *NL*.

<Insert Table 2 about here>

[12] Corroborative evidence on *NL* outperforming DE in terms of skill levels based on international test scores is given in Minne *et al.* (2007).

4 Distributions of human capital intensity, innovation and productivity: Some stylized facts

The productivity literature provides ample evidence that performance in terms of productivity is highly skewed across firms and that this heterogeneity is persistent over time (see Bartelsman and Doms, 2000 for a survey). This observation implies that persistent market dominance of firms is a pervasive fact in technologically advanced countries (e.g. Clements and Ohashi, 2005). The ubiquity of firm-level productivity variation and persistence in itself has spurred research into the underlying factors shaping the firm productivity distribution (see Syverson, 2011 for a survey). In this study, we are particularly interested in the role of human capital and innovation in boosting productivity, both across countries and across industries.

This section presents some stylized facts on human capital intensity, innovation and productivity in both countries which serve as the backbone of the econometric analysis. More specifically, we provide a detailed comparison of the distributions of human capital intensity, innovation and productivity across the two countries and across industries. When discussing the moments of these distributions, we take the standard normal distribution as the benchmark.

4.1 Human capital intensity distribution

Graph 1 presents the kernel density estimates of the distributions of human capital intensity by country and by industry. Table 3 reports the moments (mean, variance, skewness and kurtosis) of the corresponding distributions.[13] Focusing on cross-country differences, the average share of high-skilled employees is significantly higher in all Dutch industries. The difference varies between 4.6 and 10.1 percentage points in High- and Low-technology manufacturing respectively. This result is in line with OECD statistics on tertiary educational attainment levels in both countries. During the period 2000-2006 about 23-24% of the German population aged between 25-64 attained a tertiary degree. In *NL*, this proportion raised from 23.4 to 30.2% in the same period (OECD, 2009). We observe considerably higher dispersion in all German industries, suggesting more inequality in the distribution of human capital intensity in *DE*, as indicated by the coefficient of variation. In *DE*, the distribution of human capital intensity shows a right-skewed shape in all industries. In *NL*, we observe the same pattern, except for Knowledge-intensive services where the mass of the distribution of human capital intensity is concentrated on the right. The positive skewness is significantly larger in all German industries. In both countries, the distribution of human capital intensity appears to be heavy-tailed in Medium- and Low-technology manufacturing and Other services, as indicated by the positive excess kurtosis.[14] In those German industries, the positive excess kurtosis is much higher than in the Dutch counterparts, implying that more of the variance is due to extreme deviations. In line with expectations, High-technology manufacturing and Knowledge-intensive services are characterized by light-tailed distributions of human capital intensity.

Focusing on industry differences, the average share of high-skilled employees is the lowest in Low-technology manufacturing and the highest in Knowledge-intensive services followed by High-technology manufacturing. The coefficient of variation, however, shows that human capital intensity is less dispersed in High-technology manufacturing than in Knowledge-intensive services. The highest dispersion of human capital intensity

[13] When interpreting Graph 1 and Table 3, one should keep in mind that if all firms used human capital at the same intensity, the distribution of human capital intensity would degenerate at one mass point.

[14] In order to compare the distribution with a standard normal distribution which has a kurtosis (k) of $k = 3$, the excess kurtosis (k^e) is defined as $k^e = k - 3$.

among firms is observed in Other services. This industry distribution pattern holds for both countries. As already mentioned, the human capital intensity distribution is right-skewed in all industries, except for the Dutch Knowledge-intensive services. It is characterized by the highest positive skewness in Low-technology manufacturing in both countries whereas the distribution of human capital intensity in Knowledge-intensive services shows a light right-skewed shape in *DE* and even a left-skewed shape in *NL*. The distribution of human capital intensity is light-tailed in Knowledge-intensive services whilst most heavily tailed in Low-technology manufacturing in both countries.

<Insert Graph 1 and Table 3 about here>

4.2 Innovation performance distribution

While human capital intensity is consistently higher in the *NL* compared to *DE*, we observe the opposite pattern with respect to innovation performance. Graph 2 presents the kernel density estimates of the innovation performance distributions for product innovators by country and by industry. Table 4 completes this picture by reporting the related moments of the distributions. As mentioned above, innovation performance is measured by the logarithm of real innovative sales per employee for product innovators.

Interesting cross-country and cross-industry differences show up. Innovation performance is on average higher and at the same time less dispersed in all German industries, except for Low-technology manufacturing. The mass of the distribution is concentrated on the right in all German industries (left-skewed). The same holds for the Dutch counterparts, except for Medium-technology manufacturing. The left-skewness is more pronounced in High-technology manufacturing and Other services in *DE* and in Low-technology manufacturing and Knowledge-intensive services in *NL*. In contrast to the mean and dispersion, we find mixed results with respect to the kurtosis. Compared to a standard normal distribution, the innovation performance distribution is more peaked and has longer heavier tails in all German industries, except for Other services where we observe a platykurtic distribution. In *NL*, the distribution is likewise more peaked compared to a standard normal distribution in Medium- and Low-technology manufacturing and Knowledge-intensive services. This peakedness is less pronounced in Medium-technology manufacturing in *NL* but it is stronger than in *DE* in the latter two industries. In contrast, the excess kurtosis is negative in High-technology manufacturing in *NL*, indicating a relatively flat distribution.

Focusing on industry differences, we observe the same industry ranking in terms of average innovation performance in both countries. That is, average innovation performance is the highest in High-technology manufacturing and the lowest in Other services. At the same time, innovation performance is less dispersed in High-technology manufacturing and most widely dispersed in Other services in both countries. As already mentioned, the distribution is left-skewed in all German industries. The negative skewness is the highest in High-technology manufacturing and the lowest –almost symmetric– in Low-technology manufacturing. In *NL*, the innovation performance distribution is most skewed to the left in Knowledge-intensive services, followed by Low-technology manufacturing. In contrast, we observe a right-skewed shape in Medium-technology manufacturing. The kurtosis is the highest in High-technology manufacturing and the lowest in Other services in *DE* whilst the opposite holds in *NL*.

<Insert Graph 2 and Table 4 about here>

4.3 Labour productivity distribution

Table 5 reports the moments of the labor productivity distribution by country and by industry. The first part of the table presents the distributional characteristics for all enterprises, the second part distinguishes between high-skilled and low-skilled enterprises and the third part between enterprises with a high and low innovation performance.[15] The corresponding labor productivity differences are visualized in Graph 3.

Focusing on cross-country differences, average labor productivity is higher in all manufacturing industries in *NL* whilst the opposite is true for Other services. Labor productivity is less dispersed in all Dutch industries, except for High-technology manufacturing. We do not observe a clear pattern with respect to the skewness of the labor productivity distributions across countries. In Low-technology manufacturing and Knowledge-intensive services, the distribution is left-skewed in both countries and more pronounced so in *DE*. In High- and Medium-technology manufacturing, we likewise observe a left-skewed distribution in *DE* whilst it is skewed to the right in *NL*. In contrast, we find a right-skewed distribution in Other services in both countries, which is even more pronounced in *NL*. The figures further reveal that the labor productivity distributions consistently have sharper peaks and heavier tails than a standard normal distribution in all industries in both countries. Except for Medium-technology manufacturing, this positive excess kurtosis is higher in all Dutch industries.

Focusing on industry differences, we observe the lowest average labor productivity in Knowledge-intensive services in *DE* and in Other services in *NL*. In contrast, the highest average labor productivity is recorded in Other services in *DE* and in Medium-technology manufacturing in NL. While we do not observe a unified ranking of industries in terms of average productivity in both countries, we find one in terms of dispersion. The lowest dispersion is detected in High-technology manufacturing and the highest dispersion in Knowledge-intensive services in both countries. Both the coefficient of variation and the difference between the 0.90 and 0.10 quantiles lead to this conclusion. The latter indicates, e.g., that the 10% most productive firms in High-technology manufacturing are at least about 3.8 (*DE*) to 4.8 (*NL*) times more productive than the 10% least productive firms. The labor productivity distribution is most skewed to the left in High-technology manufacturing in *DE*. Among the left-skewed (right-skewed) distributions in *NL*, we observe the highest negative (positive) skewness in Low-technology (Medium-technology) manufacturing. The distribution is leptokurtic in all industries. The lowest positive excess kurtosis is detected in Knowledge-intensive services in both countries whilst the highest positive excess kurtosis is recorded in Medium-technology manufacturing in *DE* and High-technology manufacturing in *NL*.

How can these differences in labor productivity distributions across countries and industries be explained? As already pointed out, we are particularly interested in the role of human capital and innovation in shaping productivity. We therefore also differentiate between low- versus high-skilled and low- versus high-innovative enterprises.

Focusing on the first two moments of the labor productivity distribution in the low- and high-skilled groups, we confirm that average labor productivity is consistently higher in high-skilled enterprises, except for Other services in *DE*. Labor productivity is less dispersed in high-skilled enterprises in all German industries whilst this does not hold for Medium-technology manufacturing and Other services in *NL*.

[15] Enterprises with a share of high-skilled employees above the median are defined as high-skilled enterprises. Likewise, product innovators with real innovative sales per employee exceeding the median are defined as enterprises with a high innovation performance.

Distinguishing enterprises on the basis of their innovation performance, average labor productivity is consistently higher in all high-innovative enterprises in both countries. This is accompanied by a lower dispersion in these enterprises in *DE*, except for Low-technology manufacturing where no difference in dispersion can be detected. In *NL*, the pattern is more heterogeneous. Labor productivity is less dispersed in high-innovative enterprises in High-technology manufacturing and Knowledge-intensive services whilst the opposite is true in the other three industries.

<Insert Graph 3 and Table 5 about here>

So far, we looked at productivity distributions from a static point of view. When we shift our focus to the evolution of productivity distributions, a particular interesting feature is firm-level persistence. To get a first insight into the persistent market dominance of firms, we examine firm-level persistence in the closeness to the technological frontier in both countries. Table 6 reports transition probability rates of productivity across states over the period 2000-2008. The states are defined as the bottom four quintiles, the 80^{th}-95^{th} percentile and the frontier which captures the upper 5% of the distribution. We distinguish two samples: the population (which draws from the yearly Production Surveys in *NL*) and the estimation sample. For the former, we present one-year transition probability rates from period t to period $(t+1)$ and two-year transition probability rates from period t to period $(t+2)$. For the latter, we only report two-year transition probability rates since the CIS waves are on a biannual basis in *NL*. Overall, Table 6 reveals a relatively strong persistence in productivity as we observe the highest values on the diagonal for each of the six states. Focusing on the population, firm-level persistence appears to be slightly higher in *DE*. For example, comparing two-year transition probabilities, 61.3% of the frontier firms remain in their initial state in *DE* whilst this is only true for 52.6% of the frontier firms in *NL*. The observed persistence differences seem to disappear when focusing on the estimation sample, however. In both countries, frontier firms are fairly persistent: about 57% remain in their initial state.[16]

<Insert Table 6 about here>

Focusing on industry differences in the persistence of frontier firms and on yearly transition probability rates in the population, we observe the lowest persistence in High-technology manufacturing and the highest persistence in Knowledge-intensive services in *NL*: 60% of frontier firms remain in their initial state in the former and 75% in the latter.[17] In *DE*, we likewise find frontier firms to be least persistent in High-technology manufacturing (72%) but –in contrast to *NL*– frontier firms are most persistent in Low-technology manufacturing (81%), followed by Knowledge-intensive services (78%). We observe the same industry ranking in the estimation sample in *DE*, i.e. frontier firms appear to be least and most persistent in High- (53%) and Low-technology manufacturing (53%) respectively. In *NL*, this pattern changes. Frontier firms are least persistent in Knowledge-intensive services and most persistent in Other services in *NL*: 48% of frontier firms remain in their initial state in the former and 68% in the latter.

Summing up, this section illustrates considerable heterogeneity in productivity across the two countries, between different industries but also between enterprises within an industry. In the following section, we use econometric tools to investigate the role of human capital and innovation in shaping productivity distributions.

[16] In Table 6, CTF is based on real labor productivity. Transition rates where CTF is based on total factor productivity are fairly similar (see Table B.3 in Appendix B).

[17] Transition matrices for individual industries are not reported but available upon request.

5 Results

As a benchmark, we first present average returns to human capital and innovation in Section 5.1. Our main results are reported in Section 5.2, where we first examine firm-level heterogeneity in these returns and than exploit this degree of firm-level heterogeneity in order to describe how differences in human capital and innovation returns shape industry-specific productivity distributions. Section 5.3 presents the results of various robustness checks. We conclude with a discussion of the main results in Section 5.4.

5.1 Average returns to human capital and innovation

As a benchmark, we estimate average returns to human capital and innovation using Eq. (1). Tables 7 and 8 present OLS and FE results respectively. From Table 7, it follows that the average return to HC is significantly positive in both countries. However, an increase in the share of high-skilled employees, e.g. by 10 percentage points, raises productivity more strongly in *NL* (+4.9%) than in *DE* (+1.2%). Table 7 also reveals substantial heterogeneity in average HC returns across industries. In *DE*, we observe significantly positive average HC returns in Medium- and Low-technology manufacturing and Other services but surprisingly not in High-technology manufacturing and Knowledge-intensive services. Average HC returns are likewise significantly positive in all Dutch industries, except for High-technology manufacturing. In both countries, the average HC return decreases with the level of technological intensity of an industry. Except for Low-technology manufacturing, average HC returns are much higher in all Dutch industries. However, Table 8 shows that average HC returns become insignificant, except for Medium-technology manufacturing in *NL* when we account for unobserved firm-specific effects. A relatively low within-variation in the human capital variable might explain this finding.

<Insert Tables 7 and 8 about here>

The OLS estimates also point to significantly positive average returns to product innovation in all industries in both countries. The returns of a 1% increase in the product innovation performance range from 1.7% (Medium-technology manufacturing) to 7.7% (Other services) in *DE* and from 0.6% (Medium-technology manufacturing) to 5.5% (Other services) in *NL*. Except for Knowledge-intensive services, average returns to product innovation are higher in all German industries. Moreover, service enterprises yield on average a higher return in both countries. These significantly positive average returns to product innovation survive in all industries when we additionally account for firm-specific effects, except for High-technology manufacturing in *DE*. They shrink, however, to a range of about 0.7% to 2.9% in both countries.

From Table 7, it follows that average returns to process innovation are significantly negative in both countries and larger in absolute terms in services.[18] When accounting for unobserved firm-specific effects, the negative average returns to PC become generally smaller and they only survive in Other services in both countries and in Medium- and Low-technology manufacturing in *DE*.

[18] Admittedly, identifying the effect of process innovation is more difficult in empirical analyses. This is more likely to be the case in service industries since services are more often customized to specific demands and clearly structured production processes are lacking in many cases. Moreover, many enterprises perform product and process innovation simultaneously. But while the PD variable is continuous, our PC variable is a binary indicator and hence less informative than PD. These two reasons may partly explain the finding of a negative PC return.

5.2 Firm-level heterogeneity in returns to human capital and innovation and its impact on industry productivity distributions

To what extent do firm-level returns to human capital and innovation vary at different points of the conditional productivity distribution and how does this affect the characteristics of industry productivity distributions? We answer these two questions by first neglecting firm-fixed effects and using pooled quantile regressions (Section 5.2.1). In Section 5.2.2, we additionally account for firm-fixed effects in the quantile regressions.

5.2.1 Not accounting for firm-fixed effects

A. Firm-level heterogeneity in returns to human capital and innovation

Table 9 reports the results of pooled simultaneous-quantile regressions (QR) for the 10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th} percentiles of the productivity distribution.[19] Graphs 4, 5 and 6 display the estimated coefficients for our variables of interest (HC, PD and PC) across all quantiles, together with the 95% confidence intervals. For comparison, the OLS estimates and their 95% confidence intervals are presented as dotted horizontal lines. Clearly, OLS estimates – calculating 'the average effect for the average enterprise' – do not accurately describe the relationship between our main variables and productivity. Let us focus the discussion on our three main variables.

The upper part of Table 9 and Graph 4 reveal a heterogeneous pattern for the effect of human capital upon productivity at different quantiles. We observe heterogeneous productivity effects within an industry, and also discern cross-country and cross-industry differences. In *DE*, the estimates point to an inverted U-shaped influence of human capital along the conditional productivity distribution in High- and Low-technology manufacturing and Other services. This is particularly intriguing for High-technology manufacturing where we did not detect any significant *average* return. This can be explained by the fact that the 10% least-performing enterprises experience a significantly negative return to HC whereas enterprises along the 40^{th} and 80^{th} percentile of the distribution yield significantly positive returns. In Low-technology manufacturing and Other services, we observe a different pattern: enterprises yield positive but first increasing and than decreasing returns along the full conditional distribution. In Medium-technology manufacturing, we observe increasing marginal returns to human capital as we move from lower to upper quantiles. The coefficient for HC starts negative (but insignificant) at the bottom of the distribution and becomes significantly positive from the 40^{th} percentile onwards. On the contrary, we surprisingly observe diminishing rates of returns to human capital in Knowledge-intensive services. Productivity effects of human capital are significantly positive up to the 40^{th} percentile, become insignificantly positive between the 40^{th} and the 70^{th} percentiles and are significantly negative from the 70^{th} percentile onwards.

In contrast to *DE*, we do not find any such non-linearities in human capital returns in *NL*. We observe increasing rates of returns to human capital as we move up through the productivity distribution in Medium- and Low-technology manufacturing and Other services. In the former two industries, the increase tends to be steep whilst it is modest in the latter. Consistent with the German results, highly diminishing rates of returns to human capital are found in Knowledge-intensive services. From the 80^{th} percentile onwards, the estimated coefficient for human capital is significantly negative.

[19] We estimate pooled simultaneous-quantile regressions for $\theta \in \{0.05, 0.10, 0.20, 0.25, 0.30, 0.40, 0.50, 0.60, 0.70, 0.75, 0.80, 0.90, 0.95\}$. Table 9 shows results for some selected quantiles.

In a nutshell, the best-performing enterprises enjoy the highest rates of return to human capital in Medium-technology manufacturing in *DE* and in Medium- and Low-technology manufacturing and Other services in *NL*. This finding provides micro-economic support for the positive complementarity effect between human capital and proximity to the technological frontier as postulated by Vandenbussche *et al.* (2006). In sharp contrast, the top firms in Knowledge-intensive services seem to have the lowest (even negative) human capital returns in both countries, suggesting a negative aforementioned complementarity effect.

<Insert Table 9 and Graph 4 about here>

The middle part of Table 9 and Graph 5 highlight non-linearities in the returns to product innovation along the conditional productivity distribution in the majority of industries in both countries. In *DE*, we observe an increase in the rates of returns to product innovation as we move from the lower to the upper quantiles in Low-technology manufacturing. In all other industries, marginal returns to product innovation follow a U-shaped curve.

In *NL*, the U-shaped pattern is likewise observed in Low-technology manufacturing and both service industries. In contrast, a hump-shaped relationship is found in High-technology manufacturing with positive but insignificant returns below the 20^{th} and above the 80^{th} percentile. Product innovation returns appear to be very stable in Medium-technology manufacturing, although the estimated coefficient is not significantly different from zero from the 75^{th} percentile onwards.

Summing up, the best-performing enterprises enjoy the highest rates of return to product innovation in all industries in *DE* and in all but High- and Medium-technology manufacturing in *NL*, suggesting strong positive complementarity effects between product innovation and proximity to the frontier.

<Insert Graph 5 about here>

The main finding that follows from the lower part of Table 9 and Graph 6 is that the top firms in the majority of industries experience the most negative rates of returns to process innovation. This holds for Low-technology manufacturing and both service industries in *DE* and for all industries, except for High-technology manufacturing in *NL*. In addition, the results shed some light on the negative *average* returns to process innovation reported in Section 5.1. In all manufacturing industries in *DE* and in Low-technology manufacturing in *NL*, they are caused by (extreme) outliers whilst the productivity effect of investing in process innovation is insignificant for most enterprises along the productivity distribution.

<Insert Graph 6 about here>

B. Impact on industry productivity distribution

To gain insight into the importance of human capital and product and process innovation in shaping the characteristics of industry productivity distributions, we combine firm-level results from regressions at different quantiles of the productivity distribution to evaluate how changes in these three variables *ceteris paribus* affect the moments of industry productivity distributions.

The impact of human capital and both types of innovation upon the 2^{nd} through 4^{th} moment of the industry productivity distributions are reported in Table 10. In both countries, human capital is found to exert a significantly positive effect on the dispersion and the kurtosis of the productivity distribution in Medium- and Low-technology manufacturing whilst it leaves the skewness unchanged. Put differently, strategies to invest in human capital do not only increase the median return in these industries (see Table 9) but also widen the productivity distribution. This increased dispersion results from more extreme productivity outcomes at both right and left tails. In *DE*, we identify the same qualitative impact of product innovation on the productivity distribution in Medium-technology manufacturing and Other services. This means that (*i*) productivity is significantly more dispersed for firms in these industries that invest in product innovation and (*ii*) this increased variability results from an increased mass at both tails of the productivity distribution. The latter effect is much stronger for product innovation than for human capital. In *NL*, the same qualitative impact of process innovation on the productivity distribution –i.e. a positive influence on the dispersion and the kurtosis– is found in Medium- and Low-technology manufacturing.[20]

In addition, product innovation positively affects all three moments of the productivity distribution in Low-technology manufacturing in *DE* and Other services in *NL*. The finding that product innovation additionally alters the skewness of the distribution means that the increased dispersion results from more extreme productivity outcomes at both tails but that we observe an increase in the concentration of mass on the leftb.

On the contrary, human capital is found to exert a negative effect on the dispersion, skewness and kurtosis of the productivity distribution in Dutch Knowledge-intensive services.

<Insert Table 10 about here>

5.2.2 Accounting for firm-fixed effects

A. Restriction of estimation sample

To additionally account for unobserved firm heterogeneity in estimating human capital and innovation returns, we perform FE quantile regressions. For that purpose, we restrict the sample and only select firms with at least two observations. We end up with an unbalanced panel of 8,117 observations corresponding to 3,052 enterprises (61% in manufacturing and 39% in services) over the period 2000-2008 in *DE* and an unbalanced panel of 15,427 observations corresponding to 5,664 enterprises (42% in manufacturing and 58% in services) over the period 2000-2008 in *NL*.

To investigate the selectivity impact of this restricted estimation sample, we performed the same analysis as for the main estimation sample. The results of the first part, examining the average and quantile productivity effects of human capital and innovation at the firm level, are largely confirmed when moving to the restricted sample (see Table B.4 in Appendix B for the OLS and the FE results and Table B.5 in Appendix B for the standard QR estimates). Likewise, the results of the second part, evaluating the impact of human capital and innovation on the distributional characteristics of industry productivity, are mostly confirmed (see Table B.6 in Appendix B). In particular, results corroborate that human capital exerts a positive effect on the dispersion and kurtosis in Low-technology manufacturing in both countries and in Dutch Medium-technology manufacturing. In Germany, a similar pattern is also observed in Medium-technology manufacturing and Other services. Results for product innovation are fully confirmed in both countries. That is, product innovation positively affects the dispersion and kurtosis in Other services in both countries and in German Medium- and Low-technology manufacturing. In contrast, we do not find any distributional impact of process innovation anymore. This may be explained by the fact that the influence of process innovation was largely driven by some extreme outliers which may be dropped from the restricted sample.

[20] Mata and Wörter (2013) report a similar pattern for the impact of external innovation strategies on profits.

B. Firm-level heterogeneity in returns to human capital and innovation

Table 11 reports the results of estimating FE quantile regressions for the 10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th} percentiles of the productivity distribution. For the sake of parsimony, we only report the estimated coefficients for HC, $L1.CTF$, PD and PC. A visual representation is given in Graphs 7-9. For comparison, the standard FE estimates and their 95% confidence intervals are presented as dashed horizontal lines. Similar to the OLS estimates, it appears that standard FE estimates –making inferences about 'the average enterprise'– mask important aspects of the relationship between human capital and innovativeness on the one hand and productivity on the other hand.

The upper part of Table 11 and Graph 7 focus on the heterogeneous productivity effects of human capital. In *DE*, the shape of human capital returns in Medium- and Low-technology manufacturing and Other services is quite comparable to the one of the standard QR estimates. In sharp contrast, accounting for firm fixed effects leads to strongly increasing rates of returns to human capital as we move up through the productivity distribution in Knowledge-intensive services. The estimated coefficient is significantly positive from the 40^{th} percentile onwards.

Taking into account firm heterogeneity does not seem to affect the heterogeneous pattern in human capital returns in Medium-technology manufacturing and both service industries in *NL*. Similar to the standard QR results, we observe an increase in human capital returns as we move from the lower to the upper quantiles in Low-technology manufacturing but –contrary to the standard QR results– human capital returns appear to be significantly negative at each quantile. Contrary to the standard QR results, we observe positive but diminishing rates of returns to human capital in High-technology manufacturing.

Summing up, consistent with the standard QR results, we find evidence of a positive complementarity effect between human capital and proximity to the frontier in Medium-technology manufacturing in *DE* and in Medium- and Low-technology manufacturing and Other services in *NL*. Also consistent with the standard QR results, a negative complementarity effect between human capital and proximity to the frontier is found in Knowledge-intensive services in *NL*. In contrast to the standard QR results, the best-performing enterprises in Knowledge-intensive services seem to enjoy the highest rates of return to human capital in *DE*.

<Insert Table 11 and Graph 7 about here>

From the middle part of Table 11 and Graph 8, it follows that taking into account firm heterogeneity does not affect the shape of the returns to product innovation compared to the standard QR results in *NL*. In *DE*, we corroborate a U-shaped influence along the quantiles of the productivity distribution in all industries, except for Low-technology manufacturing. However, the U-shape has become wider and the returns to product innovation have become very stable for a broader range of quantiles. Contrary to the standard QR results, we do not find an increasing effect of product innovation along the quantiles in German Low-technology manufacturing anymore but a hump-shape when taking individual heterogeneity into account.

Consistent with the standard QR results, we observe non-linearities in the productivity effects of product innovation in Low-technology manufacturing and both service industries and stable product innovation returns in Medium-technology manufacturing in *NL*. In contrast to the standard QR results, we observe gradually increasing returns to product innovation in High-technology manufacturing in *NL*.

Summing up, consistent with the standard QR results, we confirm a positive complementarity effect between product innovation and proximity to the frontier in Medium-technology manufacturing and both service industries in *DE* and in all industries, except for Medium-technology manufacturing in *NL*.

<Insert Graph 8 about here>

The lower part of Table 11 and Graph 9 show that taking into account firm heterogeneity mainly influences the shape of returns to process innovation in *DE*. We only observe significantly estimated coefficients in Medium-technology manufacturing and Other services. More specifically, we find negative decreasing rates of returns to process innovation in Medium-technology manufacturing whilst an increasing shape is detected in Other services. For the latter, the estimated returns are significantly negative up to the 60^{th} percentile.

Consistent with the standard QR results, we observe decreasing rates of returns to process innovation in Knowledge-intensive services with the estimated coefficients being significantly negative from the 30^{th} percentile onwards in *NL*. Also consistent with the standard QR results, returns to process innovation follow a hump-shaped curve in Other services with significantly negatively estimated coefficients at each quantile in *NL*.

Summing up, we find negative complementarity effects between process innovation and proximity to the frontier in Medium-technology manufacturing in *DE* and in both service industries in *NL*. The latter is consistent with the standard QR results.

<Insert Graph 9 about here>

C. Impact on industry productivity distribution

Based on the FE quantile regression results, Table 12 reports the influence of human capital and product and process innovation upon various distributional characteristics. Taking into account unobserved firm heterogeneity significantly alters the impact of our variables of interest in *DE*. We do not observe any longer that human capital increases the productivity dispersion and kurtosis in German Medium- and Low-technology manufacturing. Instead, human capital even narrows the distribution in High-technology manufacturing. We already pointed out that the impact of product innovation has become very similar along different quantiles once we account for individual heterogeneity. As a result, we do not find a significant influence on the characteristics of industry productivity distributions anymore, except for Other services. Both product and process innovation affect the dispersion and the kurtosis in Other services negatively.

Similarly to *DE*, accounting for firm fixed effects changes the influence of our main variables on the distributional characteristics of productivity in *NL*. Consistent with the standard QR results, firms that invest in human capital in Medium-technology manufacturing are characterized by a wider productivity dispersion that is shaped by more infrequent productivity levels at both tails. We do not longer find a significant impact of human capital on the dispersion and the kurtosis in Low-technology manufacturing and Other services. Instead, human capital is found to widen the industry productivity distribution in Other services. Contrary to the standard QR results, the positive influence of product innovation on the dispersion and the kurtosis in High-technology manufacturing has disappeared but is now observed in Other services. Contrary to the standard QR results, we do not find any significant impact of process innovation on the distributional characteristics of productivity when taking into account individual heterogeneity.

<Insert Table 12 about here>

5.3 Robustness checks

To check the robustness of our results using the main estimation sample, we performed a large number of sensitivity checks.[21] The first set of robustness checks relates to our explanatory variables. Employing the logarithm of real labor productivity as the dependent variable, we examined in both countries the productivity effects of (*i*) different types of product innovation (i.e. market novelties versus firm novelties), (*ii*) human capital where human capital is measured by a binary variable equaling one if HC_{it} exceeds the median value of the share of high-skilled labor in industry j (21-industry classification), (*iii*) human capital when additionally controlling for different moments of industry-year distributions of human capital intensity (where industries are defined according to the 21-industry classification). In addition, we replaced the human capital variable and firm size in *NL* by a more detailed decomposition of the workforce, splitting the number of employees into the number of low-skilled, low-medium-skilled, high-medium-skilled and high-skilled employees.

In *DE*, our main results show a U-shaped pattern for product innovation returns along the conditional productivity distribution in all industries, except for Low-technology manufacturing where increasing returns are found. It turns out that these results are to a large extent driven by market novelties. In particular, we corroborate the results for this type of product innovation in all industries, except for High-technology manufacturing where the returns are steadily increasing when we move up through the productivity distribution. With respect to firm novelties, we still find evidence of U-shaped returns in Medium-technology manufacturing and Knowledge-intensive services. In contrast, decreasing returns to firm novelties are observed in High-technology manufacturing and Other services. In addition, the returns to market novelties are higher than the ones to firm novelties at nearly all quantiles in all industries in *DE*. In all industries, our results support evidence of positive complementarity effects between market novelties and proximity to the technological frontier. For firm novelties, this complementary effect only holds for Medium- and Low-technology manufacturing and Knowledge-intensive services. Firm-level heterogeneity in the returns to market novelties also significantly changes the distributional characteristics of productivity. We find a larger productivity dispersion in all industries –except for Other services– that primarily stems from more infrequent productivity levels at both tails.

In *NL*, we find increasing returns to market novelties in High- and Medium-technology manufacturing and in Knowledge-intensive services. Non-linearities in the productivity effects of investing in products new to the market are observed in Low-technology manufacturing and Other services. Consistent with *DE*, the best-performing enterprises enjoy the highest rates of returns to market novelties in all industries. Except for High-technology manufacturing, innovation of products new to the market appears to have a significantly positive impact on the dispersion and the kurtosis of the productivity distribution in all industries. We detect increasing returns to firm novelties in all industries, except for High-technology manufacturing. In the latter, the productivity effects of investing in products new to the firm follow a U-shaped pattern. In contrast to market novelties, we only find a positive complementarity effect between firm novelties and proximity to the technological frontier in Medium- and Low-technology manufacturing. Innovation of products new to the firm seems to exert a positive influence on the dispersion and skewness of the productivity distribution in all industries, except for High- and Medium-technology manufacturing.

In *NL*, the productivity effects of human capital are robust to the measurement of human capital and to the inclusion of additional covariates. In *DE*, we likewise confirm our main results with one exception. When measuring human capital by a binary variable, we do not find decreasing returns to human capital in

[21] Details on the results of these checks are available upon request.

Knowledge-intensive services any longer. Firms that are characterized by a human capital intensity above the industry-median consistently enjoy positive HC returns along all quantiles of the productivity distribution. These returns are increasing up to the median and then start to decrease.

The second set of robustness checks examines the sensitivity of our main results to using two alternative dependent variables in both countries: (i) total factor productivity and (ii) the one-year lead of real labor productivity growth. In *DE*, we fully confirm the results for the returns to product and process innovation when using TFP as the dependent variable. For human capital, however, evidence is mixed. We find increasing returns to human capital in High- and Medium-technology manufacturing but in none of the other industries. In *NL*, the results using TFP as the dependent variable are qualitatively similar to the main results.

In *DE*, the results for human capital are qualitatively confirmed in High- and Medium-technology manufacturing and Other services but not for the other two industries when using the one-year lead of real labor productivity growth as the dependent variable. Estimates for the returns to product innovation become insignificant for most quantiles in all German industries. In *NL*, the productivity effects of human capital are qualitatively confirmed in Medium-technology manufacturing and Knowledge-intensive services. In contrast, human capital returns lose significance in Low-technology manufacturing and Other services and become significantly negative from the 75^{th} percentile onwards in High-technology manufacturing. In contrast to the main results for *NL*, returns to product innovation only appear to be significant (and negative) from the 50^{th} percentile onwards in Low-technology manufacturing and returns to process innovation are significantly positive in the lower quantiles in all industries, except for Medium- and Low-technology manufacturing.

5.4 Discussion

Focusing on the productivity effects of human capital, two main findings stand out. *First*, we observe increasing marginal human capital returns to the best-performing enterprises in industries with a low level of technological intensity in both countries. Having high-skilled employees makes it easier for frontier firms in these industries to excel. Put differently, we find a significantly positive complementarity between human capital and proximity to the frontier in these industries. *Second*, we observe diminishing (even negative) marginal human capital returns for the "stars" in Knowledge-intensive services, suggesting a significantly negative complementarity between human capital and proximity to the frontier.[22] Becoming a "superstar" seems to be extremely difficult if one is already quite successful. Apparently, high-skilled employees are hired for much more than they are worth. We put forward two interpretations. Firstly, the results simply reflect a misallocation of high-skilled employees. Secondly, winner-take-all behavior underlies this finding. Investment in intangibles in frontier firms of Knowledge-intensive services, using human capital intensely, might create a profitable breakthrough for one firm which could compensate the losses of many competitors. Suggestive evidence indicates that this interpretation might be more valid in *NL* as (i) more experimentation and radical innovation takes place in frontier firms in Knowledge-intensive services, (ii) the distribution of human capital intensity is more left-skewed in Knowledge-intensive services and (iii) the sharply decreasing human capital returns appear to be even stronger in the high-technology Knowledge-intensive services to which the telecommunication, computer and R&D services industries belong.

[22] This finding is less consistent across different estimates in *DE*, though (see FE quantile regression estimates and standard QR estimates using TFP as the dependent variable).

Focusing on the productivity effects of innovation, the main finding is that there are increasing marginal product innovation returns but negative marginal process innovation returns for the best-performing enterprises in the majority of industries in both countries. Hence, the best strategy for frontier enterprises is to focus on product rather than on process innovation. In addition, our results suggest that product innovation strategies are risky in Other services in both countries implying that these strategies might lead to a large number of successful projects but also to a large number of unsuccessful ones in that particular industry. In *DE*, the same result holds for Medium- and Low-technology manufacturing.

6 Conclusion

This study reconsiders the relationship between human capital and innovation on the one hand and productivity on the other hand. We examine firm-level heterogeneity in returns to human capital and product and process innovation across industries that differ in the level of technological intensity and across countries. In addition, we exploit the degree in this firm-level heterogeneity to evaluate the impact of human capital and product and process innovation upon the attributes of industry productivity distributions.

Irrespective of their level of technological intensity, industries in the Netherlands are characterized by a larger average proportion of employees possessing a college or university degree and industries in Germany by a more unequal distribution of human capital intensity. Average innovation performance –measured by the logarithm of real innovative sales per employee for product innovators– is higher in all industries in Germany, except for Low-technology manufacturing. The distribution of innovation performance appears to be wider in the Netherlands. Average productivity turns out to be higher in all manufacturing industries in the Netherlands. Productivity is more unequally distributed in all German industries, except for High-technology manufacturing.

In both countries, non-linearities in the productivity effects of investing in product innovation are found in the majority of industries. Frontier firms enjoy the highest returns to product innovation in most industries. Investing in product innovation significantly increases the spread of the productivity distribution and the probability of observations at both the right and left tails of the productivity distribution in Other services in both countries as well as in Medium- and Low-technology manufacturing in Germany. In sharp contrast, the most negative returns to process innovation are observed in the best-performing enterprises of most industries in both countries. Clearly, the best strategy for frontier firms is to focus on product rather than on process innovation.

In Germany, we observe non-linearities in the productivity effects of investing in human capital in High- and Low-technology manufacturing and in Other services whilst human capital returns follow an increasing linear curve as we move up through the productivity distribution in all industries in the Netherlands, except for Knowledge-intensive services. A positive complementarity effect between human capital and proximity to the technological frontier is found in industries with a low level of technological intensity whilst a negative complementarity effect is observed in Knowledge-intensive services in both countries. The latter result does no longer hold for Germany once individual unobserved heterogeneity is taken into account. Suggestive evidence for the Netherlands point to a winner-takes-all interpretation of this finding. Productivity is significantly more dispersed for enterprises that invest in human capital in Medium- and Low-technology manufacturing, which is caused by an increased mass of extreme (positive and negative) productivity outcomes in these industries.

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Table 1: Estimation sample by country, industry, size and year

Sample		GERMANY				THE NETHERLANDS			
		# obs.	%	**# firms**	%	**# obs.**	%	**# firms**	%
Industry	High-technology manufacturing (HT)	1,063	9.1	609	9.2	716	2.9	409	2.7
	Medium-technology manufacturing (MT)	4,213	36.0	2,336	35.2	6,091	24.8	3,362	22.6
	Low-technology manufacturing (LT)	1,910	16.3	1,103	16.6	2,665	10.8	1,555	10.5
	Knowledge-intensive services (KIS)	2,737	23.4	1,599	24.1	6,624	26.9	4,415	29.7
	Other services (OS)	1,776	15.2	987	14.9	8,490	34.5	5,167	34.8
Industry$^{a)}$	High-technology manufacturing (HT)	734	9.0	280	9.2	486	3.1	179	3.2
	Medium-technology manufacturing (MT)	2,977	36.7	1,100	36.0	4,275	27.7	1,543	27.2
	Low-technology manufacturing (LT)	1,287	15.9	480	15.7	1,753	11.4	635	11.2
	Knowledge-intensive services (KIS)	1,860	22.9	722	23.7	3,664	23.7	1,383	24.4
	Other services (OS)	1,259	15.5	470	15.4	5,249	34.1	1,924	34.0
Firm size	10-19	2,580	22.1	1,482	22.3	3,086	12.5	2,726	18.4
	20-49	2,659	22.7	1,487	22.4	6,333	25.7	4,797	19.5
	50-99	1,969	16.8	1,151	17.4	6,384	25.9	3,567	24.0
	100-249	2,075	17.7	1,170	17.6	5,910	24.0	2,482	16.7
	250-500	1,080	9.2	618	9.3	1,692	6.9	736	4.9
	500-999	652	5.6	360	5.4	726	2.9	314	2.1
	1000+	684	5.8	366	5.5	455	1.8	219	1.5
Year	2000	1,543	13.2	-		4,519	18.4	-	
	2002	2,246	19.2	-		5,365	21.8	-	
	2004	2,404	20.5	-		5,063	20.6	-	
	2006	2,486	21.2	-		4,533	18.4	-	
	2008	3,020	25.8	-		5,106	20.8	-	
Total		11,699	100.0	6,634	100.0	24,586	100.0	14,841	100.0

Note: a) Sample constrained to firms with at least 2 observations (DE: 3,052 firms, 8,117 observations; NL: 5,664 firms, 15,427 observations).

Table 2: Descriptive statistics by country and industry

		GERMANY						THE NETHERLANDS					
		MANUFACTURING			SERVICES		TOTAL	MANUFACTURING			SERVICES		TOTAL
	Unit	HT	MT	LT	KIS	OS		HT	MT	LT	KIS	OS	
$RLP^{a)}$	mill. € per emp.	0.160	0.176	0.182	0.125	0.200	0.167	0.178	0.224	0.249	0.139	0.139	0.173
$RLPGR$	%	0.031	0.043	0.037	0.038	0.022	0.036	0.074	0.048	0.035	0.058	0.057	0.053
TFP		-0.011	-0.018	-0.001	0.006	-0.018	-0.009	0.015	0.024	0.023	0.099	0.095	0.068
$TFPGR$	%	-0.527	0.082	-0.164	4.063	-0.641	0.831	-3.532	1.148	-1.300	0.125	1.184	0.486
$(median)$	%	(-0.059)	(-0.041)	(-0.010)	(-0.043)	(-0.036)	(-0.037)	(-0.193)	(-0.200)	(-0.200)	(-0.155)	(-0.110)	(-0.152)
$SIZE^{a)}$	head counts	692.4	1098.5	199.5	256.7	569.0	637.5	224.8	126.6	128.4	243.7	134.4	163.9
$(median)$	head counts	(60.0)	(94.0)	(70.0)	(31.0)	(49.0)	(61.0)	(68.0)	(64.0)	(64.0)	(70.0)	(70.0)	(68.0)
$CAP^{a)}$	mill. € per emp.	0.045	0.055	0.055	0.124	0.121	0.080	0.006	0.008	0.007	0.008	0.006	0.007
$MAT^{a)}$	mill. € per emp.	0.081	0.097	0.100	0.045	0.116	0.087	0.081	0.124	0.152	0.049	0.029	0.073
GP	[0/1]	0.426	0.441	0.326	0.289	0.318	0.367	0.735	0.690	0.587	0.537	0.687	0.638
$EAST$	[0/1]	0.365	0.314	0.329	0.407	0.365	0.351	-	-	-	-	-	-
$CTF^{b)}$	[0-1]	0.406	0.435	0.401	0.366	0.358	0.399	0.471	0.501	0.483	0.377	0.381	0.428
$CTF^{TFP\ c)}$	[$-\infty$,1]	-0.017	-0.036	-0.021	-0.025	-0.006	-0.025	0.012	0.025	0.016	0.093	0.071	0.058
HC	[0-1]	0.295	0.129	0.088	0.387	0.092	0.192	0.392	0.186	0.121	0.437	0.210	0.261
Innovation$^{d)}$	[0/1]	0.883	0.733	0.608	0.588	0.385	0.640	0.663	0.607	0.509	0.359	0.294	0.423
Product innovation$^{d)}$	[0/1]	0.772	0.571	0.418	0.422	0.220	0.476	0.570	0.505	0.407	0.281	0.209	0.334
$SSPD^{e)}$	[0-1]	0.373	0.265	0.245	0.340	0.190	0.288	0.291	0.247	0.209	0.244	0.212	0.236
Market novelties$^{d)}$	[0/1]	0.499	0.332	0.193	0.209	0.076	0.257	0.394	0.335	0.266	0.173	0.124	0.213
$SSMN^{e)}$	[0-1]	0.117	0.075	0.059	0.097	0.042	0.081	0.125	0.114	0.082	0.122	0.097	0.108
Firm novelties$^{d)}$	[0/1]	0.675	0.480	0.361	0.361	0.180	0.405	0.351	0.289	0.246	0.172	0.128	0.199
$SSFN^{e)}$	[0-1]	0.256	0.190	0.187	0.242	0.147	0.207	0.136	0.103	0.100	0.108	0.101	0.105
PC	[0/1]	0.489	0.451	0.371	0.338	0.231	0.382	0.405	0.386	0.364	0.205	0.176	0.263

Notes: Number of observations: 11,699 in DE and 24,586 in NL, except for TFP (10,921 in DE and 24,578 in NL) since TFP was estimated only for firms with at least two observations. All monetary values are in million Euro and in constant prices (base year 2006). a) Absolute (mean) values are reported. In the estimations, however, we use logarithmic values in order to account for the skewness of the distribution. b) CTF based on RLP. c) CTF based on TFP. d) Innovation, product innovation, market novelties and firm novelties are binary indicators. e) $SSPD$ is the share of sales in year t due to new products introduced in t, $(t-1)$ and $(t-2)$ for product innovators. In the estimations, however, we use the logarithm of real innovative sales per employee for product innovators $\big(PD = \ln\big(\frac{SSPD \times SALES}{L}\big)\big)$ as an explanatory variable. Analogue for market and firm novelties.

Table 3: Distribution of human capital intensity 2000-2008, by country and industry

	GERMANY						THE NETHERLANDS					
HC	**HT**	**MT**	**LT**	**KIS**	**OS**	**TOTAL**	**HT**	**MT**	**LT**	**KIS**	**OS**	**TOTAL**
Mean	0.328	0.157	0.101	0.425	0.119	0.216	0.429	0.214	0.147	0.481	0.182	0.290
Sd	0.186	0.129	0.109	0.306	0.154	0.220	0.182	0.155	0.093	0.282	0.154	0.240
Skewness	0.545	2.045	2.836	0.153	2.291	1.518	0.142	1.234	0.974	-0.409	1.156	0.854
Kurtosis	3.225	9.226	15.224	1.647	8.270	4.670	2.653	4.802	5.841	1.861	4.192	2.641
CV	0.567	0.819	1.075	0.720	1.293	1.018	0.425	0.726	0.633	0.587	0.850	0.828
p10	0.100	0.040	0.010	0.030	0.010	0.020	0.198	0.052	0.034	0.0001	0.022	0.038
p25	0.190	0.080	0.030	0.140	0.028	0.060	0.289	0.103	0.081	0.230	0.060	0.105
p50	0.320	0.120	0.071	0.410	0.060	0.133	0.421	0.175	0.135	0.558	0.140	0.210
p75	0.430	0.200	0.130	0.700	0.150	0.300	0.570	0.296	0.197	0.714	0.268	0.436
p90	0.600	0.320	0.220	0.880	0.313	0.560	0.648	0.419	0.267	0.800	0.396	0.689

Note: Human capital is measured as the share of high-skilled employees, defined as employees having a college or university degree.

Table 4: Innovation performance distribution 2000-2008, by country and industry

	GERMANY						THE NETHERLANDS					
PD	**HT**	**MT**	**LT**	**KIS**	**OS**	**TOTAL**	**HT**	**MT**	**LT**	**KIS**	**OS**	**TOTAL**
Mean	3.976	3.803	3.181	3.166	2.668	3.578	3.757	3.755	3.412	2.807	2.522	3.394
Sd	0.970	1.168	1.175	1.296	1.531	1.231	1.232	1.334	1.164	1.451	1.571	1.416
Skewness	-0.529	-0.421	-0.038	-0.266	-0.257	-0.444	-0.307	0.182	-0.458	-0.573	-0.107	-0.264
Kurtosis	3.978	3.338	3.188	3.314	2.420	3.356	2.797	3.251	3.308	3.457	3.559	3.732
CV	0.244	0.307	0.369	0.409	0.574	0.344	0.328	0.355	0.341	0.517	0.623	0.417
p10	2.742	2.190	1.684	1.471	0.136	1.975	2.041	2.075	1.832	0.962	0.720	1.615
p25	3.443	3.119	2.266	2.495	1.522	2.856	2.972	2.925	2.714	1.966	1.602	2.570
p50	4.047	3.818	3.197	3.239	2.961	3.668	3.865	3.681	3.540	2.923	2.466	3.455
p75	4.571	4.566	3.972	4.021	3.727	4.399	4.608	4.569	4.159	3.808	3.522	4.287
p90	5.147	5.298	4.561	4.849	4.489	5.054	5.334	5.593	4.751	4.619	4.483	5.056

Note: Innovation performance is measured as ln(real innovative sales per employee) for product innovators where real innovative sales are measured in thousand € (in constant prices of 2005).

Table 5: Labor productivity distribution 2000-2008, by country and industry

		GERMANY						THE NETHERLANDS					
Sample	**ln(RLP)**	**HT**	**MT**	**LT**	**KIS**	**OS**	**TOTAL**	**HT**	**MT**	**LT**	**KIS**	**OS**	**TOTAL**
Total	Mean	5.053	5.126	4.871	4.724	5.184	4.985	5.120	5.407	5.225	4.725	4.630	5.050
	Sd	0.587	0.712	0.877	1.135	1.104	0.881	0.630	0.710	0.797	0.975	0.794	0.883
	Skewness	-0.451	-0.054	-0.330	-0.334	0.940	-0.259	0.106	1.114	-0.123	-0.014	1.008	0.072
	Kurtosis	5.904	6.923	4.893	4.694	4.946	6.333	6.767	6.615	6.140	4.986	6.146	5.381
	CV	0.116	0.139	0.180	0.240	0.213	0.177	0.123	0.131	0.152	0.206	0.171	0.175
	p10	4.300	4.293	3.801	3.306	3.999	4.007	4.353	4.682	4.405	3.642	3.814	4.134
	p25	4.754	4.683	4.465	4.200	4.427	4.515	4.750	4.961	4.713	4.321	4.185	4.568
	p50	5.111	5.140	4.889	4.663	5.062	5.015	5.096	5.285	5.153	4.704	4.534	5.006
	p75	5.378	5.531	5.317	5.318	5.714	5.452	5.461	5.733	5.683	5.136	4.959	5.489
	p90	5.656	5.994	5.962	6.120	6.400	5.991	5.925	6.295	6.265	5.843	5.529	6.119
High HC[b)]	Mean	5.123	5.227	5.017	4.784	5.111	5.097	5.252	5.556	5.370	4.865	4.906	5.195
	Sd	0.529	0.702	0.844	0.729	0.999	0.750	0.570	0.772	0.775	0.745	0.872	0.886
	Skewness	-0.474	-0.216	-0.199	0.040	0.192	-0.116	0.388	1.093	-0.182	1.440	1.251	0.636
	Kurtosis	7.602	6.883	5.173	8.980	4.545	6.356	4.198	6.104	7.520	6.767	5.138	4.855
	CV	0.103	0.134	0.168	0.152	0.195	0.147	0.108	0.139	0.144	0.153	0.178	0.171
	p10	4.484	4.388	4.091	4.031	3.922	4.236	4.566	4.787	4.592	4.174	4.025	4.275
	p25	4.953	4.808	4.587	4.368	4.357	4.622	4.918	5.043	4.905	4.452	4.360	4.621
	p50	5.139	5.236	4.983	4.663	5.069	5.100	5.220	5.414	5.284	4.719	4.730	5.064
	p75	5.411	5.677	5.410	5.117	5.801	5.516	5.532	5.938	5.795	5.086	5.233	5.641
	p90	5.608	6.069	6.166	5.669	6.179	5.993	5.950	6.494	6.361	5.781	6.017	6.334
Low HC	Mean	4.892	5.000	4.664	4.644	5.264	7.415	4.907	5.201	4.938	4.549	4.452	4.886
	Sd	0.678	0.703	0.881	1.518	1.205	-0.143	0.664	0.551	0.762	1.181	0.683	0.849
	Skewness	-0.161	0.146	-0.470	-0.213	1.343	-0.143	0.118	0.461	-0.038	-0.204	0.410	-0.697
	Kurtosis	4.135	7.693	4.609	2.744	4.599	5.740	9.603	5.022	4.919	3.374	5.938	5.331
	CV	0.139	0.141	0.189	0.327	0.229	0.208	0.135	0.106	0.154	0.260	0.153	0.174
	p10	4.089	4.191	3.564	2.737	4.262	3.697	4.146	4.562	3.996	2.871	3.728	3.907
	p25	4.447	4.592	4.159	3.479	4.448	4.353	4.524	4.867	4.522	3.913	4.105	4.493
	p50	4.908	4.993	4.743	4.662	5.003	4.850	4.899	5.153	4.884	4.692	4.435	4.955
	p75	5.278	5.381	5.177	5.818	5.611	5.350	5.242	5.493	5.402	5.221	4.789	5.383
	p90	5.739	5.822	5.641	6.603	7.001	5.953	5.662	5.920	5.949	5.919	5.236	5.833
High PD[c)]	Mean	5.256	5.440	5.238	5.051	5.325	5.223	5.410	5.703	5.620	5.241	5.178	5.545
	Sd	0.409	0.525	0.679	0.750	0.707	1.148	0.574	0.745	0.641	0.753	0.832	0.718
	Skewness	0.639	0.642	0.783	0.832	1.453	1.266	0.569	1.200	0.394	0.944	1.082	0.985
	Kurtosis	6.019	6.020	3.808	3.851	7.774	4.766	3.010	5.261	2.765	4.371	4.140	4.872
	CV	0.078	0.097	0.130	0.149	0.133	0.220	0.106	0.131	0.114	0.144	0.161	0.129
	p10	4.807	4.820	4.566	4.265	4.657	4.034	4.750	4.941	4.813	4.464	4.357	4.772
	p25	5.032	5.100	4.772	4.472	4.766	4.427	4.939	5.163	5.102	4.716	4.585	5.043
	p50	5.178	5.386	5.135	4.975	5.300	5.007	5.301	5.528	5.542	5.082	5.003	5.425
	p75	5.466	5.787	5.571	5.343	5.801	5.636	5.853	6.160	6.084	5.548	5.605	5.950
	p90	5.724	6.117	6.234	6.177	6.062	6.732	6.239	6.632	6.482	6.175	6.249	6.463
Low PD	Mean	4.874	4.888	4.678	4.370	4.704	5.099	4.873	5.218	5.107	4.511	4.450	4.859
	Sd	0.507	0.579	0.609	0.739	0.638	1.023	0.556	0.513	0.547	0.799	0.700	0.711
	Skewness	-0.708	-0.086	-0.244	-0.181	0.414	0.798	0.204	0.605	-0.411	-0.935	0.693	-0.627
	Kurtosis	3.968	3.958	4.637	3.594	3.575	4.403	3.959	8.493	7.009	5.381	6.313	6.530
	CV	0.104	0.119	0.130	0.169	0.136	0.201	0.114	0.098	0.107	0.177	0.157	0.146
	p10	4.209	4.145	3.801	3.297	3.922	3.891	4.143	4.657	4.529	3.350	4.074	4.132
	p25	4.578	4.513	4.425	3.934	4.309	4.386	4.562	4.903	4.777	4.300	4.481	4.540
	p50	4.980	4.918	4.680	4.488	4.586	5.058	4.855	5.197	5.077	3.665	4.776	4.890
	p75	5.264	5.245	5.053	4.743	5.007	5.571	5.167	5.515	5.423	4.900	5.252	5.244
	p90	5.299	5.584	5.390	5.122	5.608	6.437	5.578	5.725	5.735	5.228	5.589	5.622

Notes: a) Labor productivity is measured as ln(real turnover per employee) where real turnover is measured in thousand € (in constant prices of 2005). b) High HC: high-skilled enterprises, defined as enterprises with a share of high-skilled employees above the median. c) High PD: high-innovative enterprises, defined as product innovators with real innovative sales per employee exceeding the median.

Table 6: Firm-level persistence in the closeness to the technological frontier, based on RLP (transition rates)

	GERMANY						THE NETHERLANDS					
	<q20	**q20 - <q40**	**q40 - <q60**	**q60 - <q80**	**q80 - <q95**	**≥q95**	**<q20**	**q20 - <q40**	**q40 - <q60**	**q60 - <q80**	**q80 - <q95**	**≥q95**
	Population$^{a)}$											
CTF_t	CTF_{t+1}											
<q20	**79.40**	15.08	3.50	1.25	0.60	0.17	**77.02**	14.24	4.98	2.44	1.01	0.32
q20 - <q40	14.83	**62.74**	16.87	4.23	1.13	0.19	13.81	**61.76**	16.46	5.39	2.18	0.39
q40 - <q60	2.85	18.11	**59.94**	16.04	2.64	0.41	3.27	17.57	**58.24**	16.98	3.42	0.52
q60 - <q80	1.11	4.04	16.98	**63.87**	12.98	1.01	1.75	4.91	17.51	**60.64**	14.04	1.15
q80 - <q95	0.64	1.65	3.94	19.45	**67.36**	6.96	0.96	2.23	5.23	19.28	**66.15**	6.15
≥q95 (frontier)	0.33	0.88	1.25	4.05	16.76	**76.72**	0.80	1.24	2.23	4.44	20.18	**71.11**
CTF_t	CTF_{t+2}											
<q20	**70.14**	20.21	5.84	2.53	0.97	0.31	**61.96**	20.27	9.69	5.00	2.20	0.88
q20 - <q40	19.28	**49.58**	22.15	6.78	1.80	0.41	19.96	**43.15**	22.02	9.35	4.59	0.93
q40 - <q60	4.62	22.46	**46.60**	21.35	4.31	0.65	6.70	24.73	**39.76**	21.64	6.05	1.12
q60 - <q80	2.20	7.04	21.59	**49.50**	17.88	1.79	3.44	9.29	24.26	**43.39**	17.60	2.02
q80 - <q95	1.18	2.69	6.61	26.21	**52.82**	10.48	2.18	4.27	8.84	26.91	**49.18**	8.63
≥q95 (frontier)	0.74	1.67	3.44	6.59	26.28	**61.28**	2.31	2.59	4.12	8.77	29.65	**52.56**
	Estimation sample$^{b)}$											
CTF_t	CTF_{t+2}											
<q20	**64.62**	24.34	6.52	2.89	1.38	0.25	**67.27**	18.93	8.16	2.96	1.88	0.79
q20 - <q40	21.34	**44.63**	22.80	8.66	2.20	0.37	20.95	**45.93**	20.46	8.35	3.76	0.56
q40 - <q60	5.49	23.27	**43.20**	21.84	5.73	0.48	5.19	23.24	**43.20**	22.08	5.47	0.82
q60 - <q80	2.24	7.73	22.82	**45.26**	19.95	2.00	2.57	9.16	24.84	**44.79**	16.75	1.88
q80 - <q95	1.53	3.05	6.10	26.78	**51.36**	11.19	1.35	3.60	8.46	29.34	**47.97**	9.27
≥q95 (frontier)	0.96	1.92	4.33	5.77	30.29	**56.73**	2.97	2.04	2.60	9.11	25.46	**57.81**

Notes: CTF is divided into six categories based on the annual 20^{th}, 40^{th}, 60^{th}, 80^{th} and 95^{th} percentiles of real labor productivity. a) DE: 61,741 observations, NL: 269,092 observations. b) DE: 11,699 observations, NL: 24,634 observations.

Table 7: Mean regression (OLS): Firm-level returns to human capital and innovation, by country and industry

	GERMANY						THE NETHERLANDS					
	MANUFACTURING			SERVICES		TOTAL	MANUFACTURING			SERVICES		TOTAL
	HT	MT	LT	KIS	OS		HT	MT	LT	KIS	OS	
HC	0.006	0.149***	0.423***	0.028	0.241**	0.124***	0.017	0.349***	0.417***	0.259***	0.677***	0.485***
	(0.055)	(0.057)	(0.093)	(0.039)	(0.105)	(0.025)	(0.067)	(0.036)	(0.105)	(0.028)	(0.035)	(0.023)
L1.CTF	1.036***	0.888***	1.009***	1.518***	1.415***	1.342***	0.652***	0.414***	0.344***	1.307***	1.316***	1.139***
	(0.088)	(0.048)	(0.083)	(0.070)	(0.069)	(0.030)	(0.077)	(0.032)	(0.044)	(0.043)	(0.034)	(0.020)
PD	0.019***	0.017***	0.028***	0.037***	0.077***	0.029***	0.015***	0.006***	0.019***	0.044***	0.055***	0.039***
	(0.005)	(0.002)	(0.005)	(0.004)	(0.007)	(0.002)	(0.005)	(0.002)	(0.004)	(0.003)	(0.003)	(0.001)
PC	-0.048**	-0.026**	-0.049**	-0.087***	-0.100***	-0.043***	-0.049*	-0.036*	-0.047***	-0.115***	-0.096***	-0.089***
	(0.022)	(0.013)	(0.022)	(0.023)	(0.033)	(0.009)	(0.027)	(0.008)	(0.018)	(0.017)	(0.014)	(0.007)
SIZE	0.034***	0.012**	-0.011	-0.083***	-0.037***	-0.013***	0.001	-0.010**	-0.003	-0.055***	-0.038***	-0.039***
	(0.010)	(0.005)	(0.010)	(0.010)	(0.011)	(0.004)	(0.013)	(0.005)	(0.011)	(0.006)	(0.006)	(0.003)
CAP	0.045***	0.055***	0.061***	0.085***	0.010	0.055***	0.118***	0.100***	0.114***	0.158***	0.091***	0.113***
	(0.009)	(0.007)	(0.010)	(0.007)	(0.009)	(0.003)	(0.018)	(0.006)	(0.013)	(0.007)	(0.006)	(0.004)
MAT	0.290***	0.318***	0.354***	0.206***	0.237***	0.231***	0.302***	0.442***	0.503***	0.144***	0.123***	0.185***
	(0.026)	(0.017)	(0.024)	(0.010)	(0.014)	(0.007)	(0.028)	(0.014)	(0.017)	(0.005)	(0.004)	(0.003)
GP	0.017	0.083***	0.097***	0.116***	0.061*	0.083***	0.082***	0.046***	0.068***	0.107***	0.100***	0.094***
	(0.026)	(0.014)	(0.027)	(0.028)	(0.033)	(0.010)	(0.029)	(0.009)	(0.016)	(0.014)	(0.010)	(0.006)
EAST	-0.075***	-0.140***	-0.128***	-0.127***	-0.117***	-0.112***	-	-	-	-	-	-
	(0.024)	(0.014)	(0.025)	(0.027)	(0.032)	(0.010)						
Const	-1.510***	-1.274***	-0.933***	-0.975***	-0.859***	-1.304***	-0.811***	-0.314***	-0.007	-0.820***	-1.095***	-1.095***
	(0.145)	(0.078)	(0.098)	(0.084)	(0.092)	(0.046)	(0.168)	(0.064)	(0.090)	(0.063)	(0.059)	(0.059)
Time dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry dummies	no	no	no	no	no	yes	no	no	no	no	no	yes
R^2	0.786	0.789	0.796	0.729	0.687	0.787	0.76	0.825	0.848	0.753	0.688	0.764
RMSE	0.304	0.299	0.369	0.484	0.469	0.375	0.303	0.261	0.329	0.449	0.374	0.389
# obs.	1,063	4,213	1,910	2,737	1,776	11,699	716	6,091	2,665	6,624	8,490	24,586

Notes: The dependent variable is ln(real labor productivity). Significance level of ***1%, **5%, *10%. Standard errors are heteroskedasticity consistent and clustered by enterprises.

Table 8: Mean regression (FE): Firm-level returns to human capital and innovation, by country and industry

	GERMANY						THE NETHERLANDS					
	MANUFACTURING			SERVICES		TOTAL	MANUFACTURING			SERVICES		TOTAL
	HT	MT	LT	KIS	OS		HT	MT	LT	KIS	OS	
HC	-0.082	-0.032	0.160	0.024	0.189	0.041	0.202	0.174***	-0.217	-0.022	0.038	0.053
	(0.121)	(0.085)	(0.135)	(0.062)	(0.199)	(0.042)	(0.181)	(0.057)	(0.153)	(0.049)	(0.068)	(0.035)
L1.CTF	0.537***	0.497***	0.256***	0.884***	0.680***	0.567***	0.190**	0.214***	0.223***	0.623***	0.545***	0.443***
	(0.116)	(0.052)	(0.057)	(0.144)	(0.121)	(0.046)	(0.082)	(0.036)	(0.081)	(0.064)	(0.054)	(0.026)
PD	0.007	0.017***	0.011***	0.029***	0.023***	0.020***	0.015**	0.008***	0.018***	0.023***	0.028***	0.022***
	(0.007)	(0.003)	(0.004)	(0.006)	(0.007)	(0.002)	(0.007)	(0.002)	(0.004)	(0.003)	(0.003)	(0.002)
PC	-0.010	-0.036***	-0.007	-0.012	-0.043*	-0.023***	-0.032	-0.002	-0.001	-0.018	-0.049***	-0.031***
	(0.024)	(0.012)	(0.015)	(0.020)	(0.026)	(0.009)	(0.037)	(0.008)	(0.017)	(0.014)	(0.012)	(0.007)
SIZE	-0.048	-0.148***	-0.343***	-0.216***	-0.264***	-0.184***	-0.135***	-0.165***	-0.251***	-0.336***	-0.228***	-0.294***
	(0.071)	(0.030)	(0.050)	(0.043)	(0.049)	(0.021)	(0.039)	(0.021)	(0.054)	(0.027)	(0.023)	(0.014)
CAP	0.054***	0.028***	0.033*	0.009	0.018*	0.020***	0.036	0.053***	0.049***	0.100***	0.075***	0.084***
	(0.017)	(0.011)	(0.018)	(0.006)	(0.011)	(0.004)	(0.031)	(0.010)	(0.013)	(0.011)	(0.010)	(0.006)
MAT	0.208***	0.156***	0.116***	0.053***	0.061***	0.087***	0.358***	0.447***	0.423***	0.117***	0.104***	0.147***
	(0.068)	(0.021)	(0.030)	(0.012)	(0.014)	(0.008)	(0.040)	(0.025)	(0.061)	(0.008)	(0.006)	(0.005)
GP	0.005	0.037*	0.010	-0.017	0.043	0.017	-0.026	0.003	0.058***	0.008	0.010	0.007
	(0.059)	(0.022)	(0.038)	(0.033)	(0.039)	(0.015)	(0.035)	(0.010)	(0.019)	(0.013)	(0.011)	(0.007)
EAST	-0.672***	-0.101	-0.345***	0.291**	-	-0.073	-	-	-	-	-	-
	(0.053)	(0.106)	(0.053)	(0.118)		(0.086)						
Time dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry dummies	no	no	no	no	no	yes	no	no	no	no	no	yes
ρ	0.855	0.894	0.962	0.916	0.920	0.916	0.818	0.823	0.872	0.888	0.836	0.876
R^2_{within}	0.347	0.378	0.288	0.324	0.332	0.284	0.670	0.715	0.545	0.677	0.418	0.525

Notes: The dependent variable is ln(real labor productivity). Significance level of ***1%, **5%, *10%. Standard errors are heteroskedasticity consistent. ρ denotes the fraction of the overall variance that is due to individual heterogeneity.

Table 9: Quantile regression (QR): Firm-level returns to human capital and innovation, by country and industry

		GERMANY						THE NETHERLANDS					
		HT	**MT**	**LT**	**KIS**	**OS**	**TOTAL**	**HT**	**MT**	**LT**	**KIS**	**OS**	**TOTAL**
HC	q10	-0.181**	-0.117	0.087	0.318***	0.126*	0.018	-0.014	0.152***	0.131*	0.582***	0.596***	0.316***
		(0.080)	(0.073)	(0.086)	(0.062)	(0.072)	(0.029)	(0.081)	(0.021)	(0.069)	(0.036)	(0.033)	(0.023)
	q25	0.017	0.047	0.221***	0.179***	0.131	0.109***	-0.006	0.207***	0.158***	0.498***	0.634***	0.384***
		(0.061)	(0.031)	(0.078)	(0.024)	(0.094)	(0.021)	(0.052)	(0.029)	(0.052)	(0.032)	(0.027)	(0.028)
	q50	0.114***	0.128***	0.397***	0.060	0.217**	0.160***	-0.012	0.293***	0.285***	0.191***	0.643***	0.420***
		(0.042)	(0.040)	(0.109)	(0.038)	(0.086)	(0.023)	(0.043)	(0.021)	(0.048)	(0.025)	(0.022)	(0.022)
	q75	0.134**	0.243***	0.638***	-0.096*	0.214**	0.164***	-0.038	0.388***	0.356***	-0.016	0.643**	0.436***
		(0.054)	(0.056)	(0.177)	(0.051)	(0.091)	(0.030)	(0.086)	(0.029)	(0.081)	(0.019)	(0.042)	(0.026)
	q90	0.068	0.348***	0.485**	-0.280***	0.001	0.140***	0.062	0.578***	0.591***	-0.184***	0.670***	0.497***
		(0.096)	(0.061)	(0.225)	(0.053)	(0.189)	(0.033)	(0.108)	(0.058)	(0.224)	(0.030)	(0.056)	(0.023)
L1.CTF	q10	0.793***	0.594***	0.553***	1.304***	0.802***	0.866***	0.154***	0.118***	0.121***	0.355***	0.872***	0.783***
		(0.072)	(0.043)	(0.041)	(0.121)	(0.101)	(0.030)	(0.020)	(0.024)	(0.021)	(0.067)	(0.049)	(0.020)
	q25	0.721***	0.541***	0.485***	1.276***	0.899***	0.900***	0.399***	0.201***	0.094***	0.988***	1.219***	0.903***
		(0.060)	(0.037)	(0.046)	(0.040)	(0.088)	(0.020)	(0.073)	(0.015)	(0.014)	(0.046)	(0.023)	(0.018)
	q50	0.673***	0.576***	0.534***	1.337***	1.136***	1.072***	0.500***	0.252***	0.121***	1.324***	1.311***	1.083***
		(0.056)	(0.043)	(0.050)	(0.056)	(0.055)	(0.025)	(0.064)	(0.016)	(0.016)	(0.039)	(0.025)	(0.014)
	q75	0.865***	0.689***	0.834***	1.566***	1.545***	1.334***	0.612***	0.277***	0.214***	1.508***	1.421***	1.244***
		(0.123)	(0.062)	(0.088)	(0.060)	(0.062)	(0.038)	(0.092)	(0.022)	(0.036)	(0.036)	(0.035)	(0.021)
	q90	1.336***	0.910***	1.299***	1.771***	1.536***	1.549***	0.865***	0.380***	0.429***	1.577***	1.526***	1.401***
		(0.087)	(0.068)	(0.116)	(0.074)	(0.088)	(0.050)	(0.125)	(0.025)	(0.061)	(0.059)	(0.048)	(0.023)
PD	q10	0.024***	0.014***	0.006**	0.034***	0.051***	0.019***	0.010	0.004***	0.007***	0.030***	0.043***	0.025***
		(0.005)	(0.002)	(0.003)	(0.006)	(0.006)	(0.001)	(0.006)	(0.001)	(0.002)	(0.004)	(0.004)	(0.001)
	q25	0.013***	0.010***	0.008***	0.035***	0.045***	0.017***	0.012***	0.003***	0.007***	0.029***	0.038***	0.027***
		(0.004)	(0.001)	(0.002)	(0.004)	(0.004)	(0.001)	(0.003)	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)
	q50	0.013***	0.009***	0.012***	0.024***	0.059***	0.016***	0.015**	0.004***	0.004*	0.028***	0.045***	0.028***
		(0.004)	(0.002)	(0.003)	(0.005)	(0.009)	(0.001)	(0.005)	(0.001)	(0.002)	(0.003)	(0.004)	(0.001)
	q75	0.018***	0.013***	0.026***	0.030***	0.085***	0.023***	0.020***	0.003	0.009**	0.033***	0.062***	0.034***
		(0.005)	(0.002)	(0.007)	(0.005)	(0.012)	(0.001)	(0.007)	(0.002)	(0.004)	(0.004)	(0.004)	(0.002)
	q90	0.012	0.021***	0.048***	0.048***	0.149***	0.035***	0.012	0.000	0.025***	0.062***	0.088***	0.044***
		(0.009)	(0.004)	(0.010)	(0.008)	(0.021)	(0.002)	(0.010)	(0.004)	(0.006)	(0.005)	(0.008)	(0.003)
PC	q10	-0.031	-0.016	0.002	-0.103**	-0.065	-0.014**	-0.042	-0.008	0.002	-0.075***	-0.082***	-0.063***
		(0.029)	(0.015)	(0.023)	(0.045)	(0.043)	(0.006)	(0.026)	(0.008)	(0.009)	(0.019)	(0.018)	(0.010)
	q25	-0.010	-0.008	-0.000	-0.058**	-0.039	-0.013***	-0.037	-0.012**	-0.005	-0.099***	-0.067***	-0.062***
		(0.021)	(0.009)	(0.018)	(0.024)	(0.040)	(0.005)	(0.026)	(0.005)	(0.009)	(0.018)	(0.015)	(0.006)
	q50	-0.015	-0.003	-0.021	-0.035	-0.077**	-0.024***	-0.053**	-0.022***	-0.001	-0.085***	-0.068***	-0.065***
		(0.017)	(0.010)	(0.015)	(0.029)	(0.037)	(0.006)	(0.024)	(0.006)	(0.009)	(0.016)	(0.017)	(0.009)
	q75	-0.044	-0.013	-0.048	-0.084**	-0.071	-0.032***	-0.051	-0.029***	-0.031	-0.096***	-0.068***	-0.077***
		(0.030)	(0.017)	(0.033)	(0.033)	(0.044)	(0.006)	(0.038)	(0.008)	(0.019)	(0.019)	(0.014)	(0.010)
	q90	-0.059	-0.036	-0.091**	-0.133***	-0.089*	-0.048***	-0.013	-0.035*	-0.086***	-0.139***	-0.115***	-0.090***
		(0.045)	(0.025)	(0.039)	(0.034)	(0.048)	(0.011)	(0.059)	(0.020)	(0.030)	(0.032)	(0.025)	(0.010)

Table 9 - Continued: Quantile regression (QR): Firm-level returns to human capital and innovation, by country and industry

		GERMANY						THE NETHERLANDS					
		HT	**MT**	**LT**	**KIS**	**OS**	**TOTAL**	**HT**	**MT**	**LT**	**KIS**	**OS**	**TOTAL**
SIZE	q10	0.023*	0.022***	0.018*	-0.069***	-0.039**	0.008*	0.003	-0.005	0.017***	-0.039***	-0.039***	-0.016***
		(0.014)	(0.005)	(0.010)	(0.013)	(0.015)	(0.004)	(0.012)	(0.004)	(0.006)	(0.007)	(0.006)	(0.003)
	q25	0.021***	0.016***	0.005	-0.081***	-0.038***	0.000	0.005	-0.003	0.000	-0.052***	-0.030***	-0.024***
		(0.007)	(0.003)	(0.004)	(0.007)	(0.012)	(0.003)	(0.008)	(0.003)	(0.004)	(0.005)	(0.005)	(0.002)
	q50	0.022***	0.005	0.004	-0.076***	-0.032***	-0.004	0.013**	-0.009**	-0.006	-0.047***	-0.035***	-0.034***
		(0.007)	(0.004)	(0.007)	(0.008)	(0.008)	(0.003)	(0.006)	(0.004)	(0.005)	(0.004)	(0.004)	(0.003)
	q75	0.036***	-0.002	-0.011	-0.065***	-0.041***	-0.010***	-0.005	-0.014***	-0.016***	-0.033***	-0.042***	-0.035***
		(0.012)	(0.005)	(0.012)	(0.012)	(0.011)	(0.004)	(0.021)	(0.004)	(0.005)	(0.004)	(0.004)	(0.003)
	q90	0.034*	-0.015**	-0.040**	-0.055***	-0.055***	-0.018***	-0.006	-0.018***	-0.020	-0.030***	-0.040***	-0.043***
		(0.018)	(0.007)	(0.016)	(0.017)	(0.013)	(0.005)	(0.026)	(0.006)	(0.015)	(0.009)	(0.007)	(0.004)
CAP	q10	0.016	0.027***	0.035***	0.047***	0.011	0.035***	0.030**	0.085***	0.070***	0.169***	0.141***	0.139***
		(0.013)	(0.006)	(0.011)	(0.012)	(0.008)	(0.005)	(0.013)	(0.004)	(0.007)	(0.007)	(0.008)	(0.005)
	q25	0.026***	0.035***	0.034***	0.079***	0.020***	0.045***	0.194***	0.055***	0.081***	0.106***	0.075***	0.124***
		(0.008)	(0.004)	(0.006)	(0.006)	(0.007)	(0.003)	(0.007)	(0.012)	(0.003)	(0.006)	(0.013)	(0.005)
	q50	0.045***	0.044***	0.043***	0.088***	0.020**	0.050***	0.107***	0.087***	0.088***	0.161***	0.082***	0.106***
		(0.008)	(0.005)	(0.008)	(0.007)	(0.008)	(0.003)	(0.013)	(0.004)	(0.005)	(0.006)	(0.005)	(0.004)
	q75	0.066***	0.058***	0.058***	0.101***	-0.000	0.047***	0.158***	0.092***	0.102***	0.131***	0.075***	0.090***
		(0.008)	(0.006)	(0.011)	(0.008)	(0.007)	(0.003)	(0.0159)	(0.005)	(0.011)	(0.007)	(0.005)	(0.004)
	q90	0.056***	0.074***	0.073***	0.085***	-0.013	0.045***	0.163***	0.106***	0.108***	0.129***	0.068***	0.077***
		(0.019)	(0.008)	(0.017)	(0.009)	(0.014)	(0.005)	(0.021)	(0.008)	(0.017)	(0.008)	(0.010)	(0.005)
MAT	q10	0.373***	0.460***	0.550***	0.269***	0.437***	0.384***	0.488***	0.621***	0.677***	0.240***	0.134***	0.260***
		(0.035)	(0.014)	(0.019)	(0.017)	(0.031)	(0.010)	(0.035)	(0.011)	(0.008)	(0.014)	(0.006)	(0.005)
	q25	0.380***	0.468***	0.551***	0.243***	0.411***	0.357***	0.452***	0.586***	0.673***	0.198***	0.108***	0.229***
		(0.022)	(0.013)	(0.015)	(0.010)	(0.025)	(0.006)	(0.027)	(0.007)	(0.006)	(0.009)	(0.003)	(0.004)
	q50	0.378***	0.442***	0.506***	0.222***	0.332***	0.301***	0.381***	0.544***	0.647***	0.150***	0.098***	0.197***
		(0.021)	(0.013)	(0.020)	(0.010)	(0.021)	(0.006)	(0.018)	(0.006)	(0.008)	(0.005)	(0.003)	(0.003)
	q75	0.324***	0.390***	0.410***	0.184***	0.237***	0.226***	0.324***	0.518***	0.591***	0.127***	0.113***	0.174***
		(0.039)	(0.016)	(0.023)	(0.010)	(0.012)	(0.010)	(0.029)	(0.010)	(0.010)	(0.003)	(0.004)	(0.004)
	q90	0.270***	0.315***	0.308***	0.185***	0.179***	0.179***	0.257***	0.453***	0.479***	0.1029***	0.145***	0.160***
		(0.036)	(0.015)	(0.020)	(0.010)	(0.011)	(0.008)	(0.025)	(0.010)	(0.017)	(0.005)	(0.005)	(0.003)

Notes: The dependent variable is ln(real labor productivity). Significance level of ***1%, **5%, *10%. Bootstrapped standard errors (20 replications). Quantile regressions additionally include *GP*, *EAST* (for *DE*) and time dummies. Number of observations: See Table 7. Results are based on pooled simultaneous-quantile regressions for $\theta \in \{0.05, 0.10, 0.20, 0.25, 0.30, 0.40, 0.50, 0.60, 0.70, 0.75, 0.80, 0.90, 0.95\}$. Results for other quantiles are available upon request.

Table 10: Impact of human capital, innovation, size, physical capital and material on *industry productivity distribution*, by country

		GERMANY						THE NETHERLANDS					
		HT	**MT**	**LT**	**KIS**	**OS**	**TOTAL**	**HT**	**MT**	**LT**	**KIS**	**OS**	**TOTAL**
HC	Dispersion	0.769	0.677***	0.485***	-3.289	0.242	0.201**	0.716	0.304***	0.385***	-1.064***	0.007	0.064**
		(0.680)	(0.173)	(0.162)	(2.897)	(0.388)	(0.097)	(2.075)	(0.062)	(0.154)	(0.085)	(0.041)	(0.032)
	Skewness	-0.656	0.165	0.158	0.134	-1.070	-0.881	0.646	0.049	-0.291	-0.196**	-0.945	-0.373
		(0.687)	(0.366)	(0.491)	(0.255)	(2.227)	(0.657)	(2.926)	(0.233)	(0.509)	(0.084)	(8.673)	(0.612)
	Kurtosis	-0.977	1.179**	1.371***	-0.136	1.522	2.881*	-1.511	4.037***	3.655***	-0.775***	145.3	15.55
		(1.113)	(0.594)	(0.498)	(0.374)	(2.786)	(1.737)	(6.553)	(0.686)	(1.458)	(0.086)	(879.6)	(7.978)
L1.CTF	Dispersion	0.091*	0.121***	0.265***	0.102***	0.264***	0.194***	0.211**	0.159***	0.390***	0.208***	0.077***	0.159***
		(0.051)	(0.032)	(0.051)	(0.026)	(0.044)	(0.012)	(0.095)	(0.038)	(0.075)	(0.019)	(0.013)	(0.010)
	Skewness	1.667**	0.522*	0.720***	0.584	0.265*	0.207***	0.049	-0.349	0.554***	-0.294***	0.093	-0.059
		(0.685)	(0.269)	(0.164)	(0.362)	(0.143)	(0.079)	(0.411)	(0.304)	(0.176)	(0.092)	(0.189)	(0.070)
	Kurtosis	14.797	10.138***	5.297***	10.606***	3.618***	5.571***	5.729**	7.021***	4.547***	4.710***	13.17***	6.402***
		(9.483)	(2.802v	(1.064)	(2.996)	(0.624)	(0.399)	(2.783)	(1.759)	(1.052)	(0.451)	(2.270)	(0.405)
PD	Dispersion	0.166	0.134**	0.526***	-0.079	0.309***	0.159***	0.252	0.089	0.161	0.059	0.238***	0.109***
		(0.141)	(0.054)	(0.147)	(0.082)	(0.072)	(0.039)	(0.196)	(0.313)	(0.206)	(0.052)	(0.044)	(0.026)
	Skewness	0.918	1.448	0.546*	-3.146	0.275	1.183***	0.029	-3.131	3.358	1.779	0.436**	0.824***
		(1.281)	(0.950)	(0.288)	(3.504)	(0.398)	(0.376)	(1.166)	(14.56)	(4.609)	(0.301)	(0.225)	(0.320)
	Kurtosis	7.045	11.204**	2.988**	-16.121	5.024***	8.545***	2.770	8.393	12.49	25.11	5.498***	10.23***
		(6.817)	(4.544)	(1.182)	(16.801)	(1.585)	(2.138)	(2.616)	(27.41)	(17.09)	(23.05)	(1.011)	(2.407)
PC	Dispersion	0.642	0.234	0.988	0.183	0.290	0.422***	0.161	0.434**	0.733**	-0.017	0.006	0.110**
		(0.638)	(0.507)	(0.719)	(0.200)	(0.422)	(0.133)	(0.467)	(0.182)	(0.407)	(0.885)	(0.084)	(0.047)
	Skewness	0.677	3.053	0.151	2.737	-1.392	-0.165	-1.305	-0.190	1.320	-7.179	-2.289	0.604
		(0.834)	(7.802)	(0.698)	(3.765)	(2.531)	(0.393)	(5.615)	(0.536)	(0.827)	(47.34)	(52.60)	(0.684)
	Kurtosis	2.613	10.251	1.851	9.078	4.805	3.212***	3.864	2.426*	3.195**	-64.11	258.9	10.01**
		(2.618)	(25.493)	(1.360)	(10.972)	(6.875)	(1.228)	(10.28)	(1.393)	(1.645)	(444.5)	(3850)	(4.551)
SIZE	Dispersion	0.254	-1.215	2.518	-0.110	0.041	1.051	42.02	0.615***	1.021*	-0.221***	0.167**	0.177***
		(0.157)	(0.789)	(3.918)	(0.102)	(0.158)	(0.675)	(4642)	(0.230)	(0.570)	(0.069)	(0.087)	(0.054)
	Skewness	0.969	-0.185	0.844	0.342	4.660	0.180	2.887	-0.133	0.293	0.458	0.115	-0.881
		(0.827)	(0.311)	(0.772)	(0.935)	(18.145)	(0.399)	(4.463)	(0.484)	(0.488)	(0.350)	(0.389)	(0.624)
	Kurtosis	3.948	-0.398	1.411	-7.682	29.020	0.961	0.388	2.138***	0.188	-3.651***	6.568**	5.659***
		(2.796)	(0.464)	(1.371)	(7.228)	(113.736)	(0.714)	(3.318)	(0.860)	(0.885)	(1.335)	(3.452)	(1.635)
CAP	Dispersion	0.431***	0.249***	0.263**	0.125***	-1.033	0.020	0.486***	0.062***	0.127***	-0.194***	-0.170***	-0.162***
		(0.117)	(0.045)	(0.111)	(0.041)	(0.690)	(0.039)	(0.088)	(0.023)	(0.048)	(0.026)	(0.034)	(0.018)
	Skewness	0.023	0.178	0.226	0.146	0.957	-3.698	-0.014	0.017	0.196	-0.051	-0.549*	-0.047
		(0.261)	(0.247)	(0.392)	(0.495)	(0.927)	(7.459)	(0.176)	(0.434)	(0.328)	(0.114)	(0.295)	(0.149)
	Kurtosis	1.807**	4.347***	4.468**	5.838***	0.102	44.227	1.872***	17.633***	7.753***	-4.737***	-6.749***	-6.217***
		(0.794)	(0.933)	(1.992)	(1.965)	(0.918)	(88.969)	(0.320)	(6.460)	(3.032)	(0.709)	(1.365)	(0.691)
MAT	Dispersion	-0.080*	-0.091***	-0.147***	-0.138***	-0.268***	-0.225***	-0.165***	-0.061***	-0.065***	-0.218***	0.023	-0.136***
		(0.047)	(0.013)	(0.021)	(0.029)	(0.023)	(0.019)	(0.051)	(0.008)	(0.007)	(0.021)	(0.021)	(0.010)
	Skewness	0.912*	0.335*	0.362***	0.294	0.091	0.134**	-0.107	-0.225**	0.371***	-0.363***	5.097	-0.282***
		(0.514)	(0.181)	(0.131)	(0.274)	(0.157)	(0.054)	(0.180)	(0.105)	(0.101)	(0.095)	(4.841)	(0.072)
	Kurtosis	-11.466*	-9.976***	-6.061***	-7.725***	-3.549***	-4.293***	-5.839***	-15.849***	-14.021***	-4.827***	55.29	-7.679***
		(6.414)	(1.455)	(0.845)	(1.559)	(0.298)	(0.317)	(1.806)	(1.952)	(1.506)	(0.491)	(150.81)	(0.593)

Notes: Significance level of ***1%, **5%, *10%. Tests are based on estimation results in Table 9.

Table 11: FE quantile regression (FEQR): Firm-level returns to human capital and innovation, by country and industry

		GERMANY						THE NETHERLANDS					
		HT	**MT**	**LT**	**KIS**	**OS**	**TOTAL**	**HT**	**MT**	**LT**	**KIS**	**OS**	**TOTAL**
HC	q10	-0.194***	-0.118***	0.141	0.009	0.161	-0.038	0.240***	0.057*	-0.303**	0.018	-0.048	0.001
		(0.052)	(0.038)	(0.117)	(0.026)	(0.120)	(0.023)	(0.061)	(0.031)	(0.075)	(0.023)	(0.034)	(0.024)
	q25	-0.129***	-0.096**	0.178***	0.010	0.212***	0.003	0.201***	0.144***	-0.190***	-0.013*	0.013	0.028**
		(0.037)	(0.039)	(0.062)	(0.018)	(0.053)	(0.015)	(0.046)	(0.020)	(0.036)	(0.014)	(0.020)	(0.014)
	q50	-0.083***	-0.033**	0.156***	0.032***	0.188***	0.038***	0.198***	0.158***	-0.176***	-0.023**	0.041***	0.056***
		(0.017)	(0.017)	(0.023)	(0.011)	(0.026)	(0.012)	(0.032)	(0.02)	(0.033)	(0.010)	(0.014)	(0.011)
	q75	-0.022	-0.001	0.142**	0.058***	0.160***	0.093***	0.167***	0.217***	-0.151***	-0.035**	0.065***	0.083***
		(0.039)	(0.037)	(0.057)	(0.015)	(0.060)	(0.014)	(0.044)	(0.017)	(0.038)	(0.015)	(0.017)	(0.012)
	q90	0.058	0.135**	0.200	0.064***	0.142	0.136***	0.144	0.298***	-0.118**	-0.060**	0.094***	0.119***
		(0.067)	(0.068)	(0.122)	(0.025)	(0.144)	(0.026)	(0.103)	(0.029)	(0.057)	(0.026)	(0.031)	(0.022)
L1.CTF	q10	0.496***	0.491***	0.266***	0.789***	0.586***	0.525***	0.227***	0.183***	0.185***	0.590***	0.513***	0.403***
		(0.064)	(0.031)	(0.035)	(0.039)	(0.046)	(0.023)	(0.034)	(0.011)	(0.015)	(0.022)	(0.017)	(0.010)
	q25	0.513***	0.482***	0.252***	0.819***	0.606***	0.532***	0.218***	0.188***	0.188***	0.599***	0.507***	0.410***
		(0.033)	(0.018)	(0.021)	(0.028)	(0.039)	(0.013)	(0.036)	(0.009)	(0.012)	(0.022)	(0.020)	(0.008)
	q50	0.523***	0.474***	0.257***	0.869***	0.657***	0.539***	0.182***	0.204***	0.202***	0.625***	0.539***	0.436***
		(0.025)	(0.014)	(0.014)	(0.013)	(0.015)	(0.009)	(0.033)	(0.008)	(0.012)	(0.017)	(0.010)	(0.006)
	q75	0.496***	0.462***	0.239***	0.853***	0.652***	0.539***	0.150***	0.219***	0.193***	0.662***	0.580***	0.479***
		(0.038)	(0.020)	(0.025)	(0.024)	(0.027)	(0.011)	(0.044)	(0.011)	(0.014)	(0.031)	(0.015)	(0.008)
	q90	0.554***	0.477***	0.226***	0.883***	0.718***	0.562***	0.164**	0.237***	0.202***	0.666***	0.621***	0.496***
		(0.050)	(0.026)	(0.035)	(0.043)	(0.074)	(0.020)	(0.068)	(0.016)	(0.022)	(0.036)	(0.024)	(0.011)
PD	q10	0.005	0.015***	0.008**	0.030***	0.028***	0.019***	0.006	0.008***	0.019***	0.023***	0.031***	0.021***
		(0.004)	(0.002)	(0.003)	(0.003)	(0.004)	(0.001)	(0.005)	(0.002)	(0.003)	(0.002)	(0.003)	(0.001)
	q25	0.006**	0.016***	0.010***	0.027***	0.023***	0.019***	0.011***	0.006***	0.014***	0.020***	0.025***	0.019***
		(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)	(0.004)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
	q50	0.007***	0.016***	0.010***	0.027***	0.023***	0.018***	0.013***	0.007***	0.014***	0.021***	0.025***	0.019***
		(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	q75	0.004	0.017***	0.011***	0.027***	0.016***	0.018***	0.018***	0.006***	0.014***	0.022***	0.025***	0.020***
		(0.003)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.004)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
	q90	-0.000	0.020***	0.011***	0.028***	0.019**	0.020***	0.021***	0.005***	0.016***	0.028***	0.026***	0.022***
		(0.005)	(0.002)	(0.003)	(0.003)	(0.008)	(0.002)	(0.006)	(0.001)	(0.003)	(0.004)	(0.003)	(0.001)
PC	q10	-0.015	-0.023**	0.011	-0.012	-0.087***	-0.015**	-0.024	0.009	-0.003	-0.005	-0.066**	-0.029***
		(0.024)	(0.011)	(0.013)	(0.018)	(0.028)	(0.008)	(0.028)	(0.008)	(0.012)	(0.014)	(0.017)	(0.007)
	q25	-0.016	-0.031***	0.001	-0.004	-0.046***	-0.020***	-0.025	0.001	-0.001	-0.011	-0.042***	-0.023***
		(0.012)	(0.006)	(0.009)	(0.010)	(0.015)	(0.004)	(0.022)	(0.005)	(0.006)	(0.009)	(0.010)	(0.004)
	q50	-0.009	-0.031***	-0.003	-0.008	-0.034***	-0.019***	-0.018	0.000	-0.002	-0.021***	-0.036***	-0.023***
		(0.008)	(0.005)	(0.007)	(0.007)	(0.010)	(0.003)	(0.014)	(0.003)	(0.006)	(0.008)	(0.005)	(0.003)
	q75	-0.004	-0.034***	-0.009	-0.012	-0.008	-0.017***	-0.038*	-0.001	-0.007	-0.023**	-0.043***	-0.029***
		(0.015)	(0.006)	(0.010)	(0.009)	(0.013)	(0.005)	(0.020)	(0.005)	(0.007)	(0.010)	(0.007)	(0.004)
	q90	-0.008	-0.032***	-0.017	-0.014	0.004	-0.024***	-0.004	-0.004	-0.017	-0.031*	-0.043***	-0.031***
		(0.019)	(0.012)	(0.015)	(0.016)	(0.025)	(0.009)	(0.033)	(0.007)	(0.011)	(0.016)	(0.013)	(0.007)

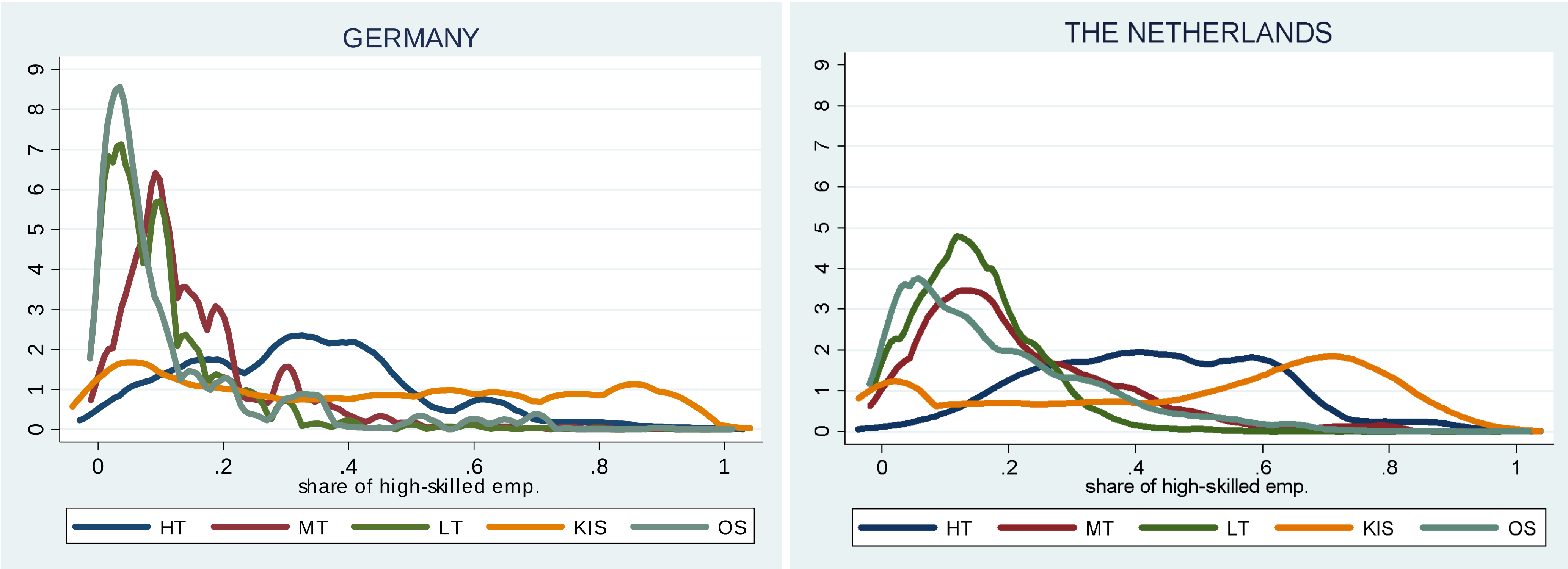
Notes: Sample: firms with 2 or more observations (DE: 8,117; NL: 15,427 observations). The dependent variable is ln(real labor productivity). Included but not reported are *SIZE*, *CAP*, *MAT*, *GP*, *EAST* (for DE), time dummies and industry dummies (only for the total sample).

Table 12: Impact of human capital and innovation on *industry productivity distribution*, by country

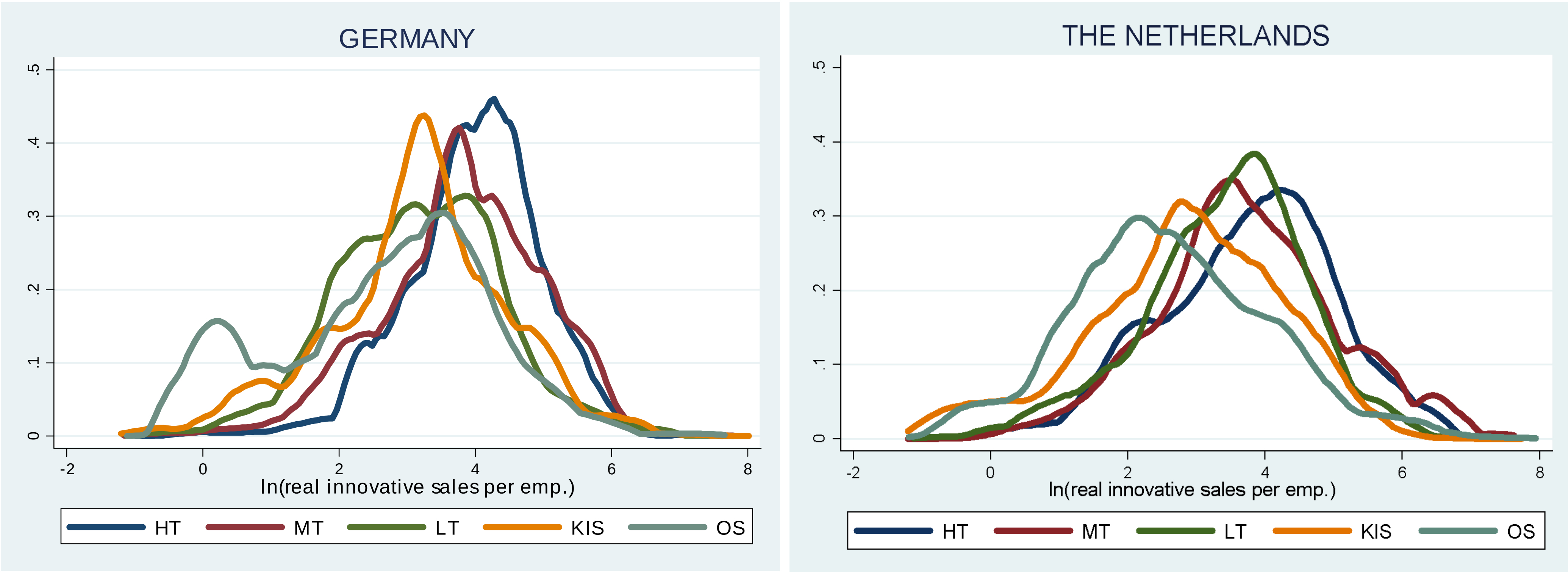
		GERMANY						THE NETHERLANDS					
		HT	**MT**	**LT**	**KIS**	**OS**	**TOTAL**	**HT**	**MT**	**LT**	**KIS**	**OS**	**TOTAL**
HC	Dispersion	-0.712*	-0.986	-0.114	0.705	-0.141	0.930***	-0.094	0.203***	-0.113	0.447	0.668*	0.497***
		(0.417)	(0.754)	(0.220)	(0.437)	(0.192)	(0.287)	(0.135)	(0.031)	(0.122)	(0.432)	(0.395)	(0.173)
	Skewness	0.137	-0.335	-0.221	0.089	0.078	0.226	0.815	0.616*	0.305	0.085	-0.074	-0.018
		(0.460)	(0.483)	(2.150)	(0.452)	(1.397)	(0.209)	(1.997)	(0.356)	(1.341)	(0.766)	(0.470)	(0.247)
	Kurtosis	-1.259	0.170	-9.376	1.532	-5.783	1.097**	-11.13	4.844***	-10.92	1.962	0.868	2.168***
		(1.024)	(0.843)	(18.453)	(1.074)	(7.997)	(0.458)	(16.91)	(1.567)	(11.86)	(2.321)	(1.060)	(0.893)
L1.CTF	Dispersion	-0.017	-0.022	-0.028	0.020	0.037	0.007	-0.185	0.076***	0.011	0.050**	0.067***	0.079***
		(0.039)	(0.024)	(0.058)	(0.018)	(0.031)	(0.012)	(0.126)	(0.025)	(0.045)	(0.024)	(0.018)	(0.011)
	Skewness	2.207	0.158	1.719	-1.972	-1.202	-0.887	-0.039	-0.026	-5.223	0.166	0.116	0.234
		(5.237)	(1.229)	(3.807)	(1.966)	(1.075)	(2.160)	(0.726)	(0.412)	(21.65)	(0.525)	(0.284)	(0.153)
	Kurtosis	-60.875	-47.057	-36.311	49.843	28.265	150.865	-6.097	12.90***	94.66	19.32**	15.08***	12.37***
		(138.899)	(51.303)	(76.384)	(45.389)	(23.153)	(260.788)	(4.407)	(4.220)	(369.5)	(9.248)	(3.967)	(1.724)
PD	Dispersion	-0.216	0.016	0.049	0.007	-0.159*	-0.019	0.266*	-0.039	0.008	0.048	-0.008	0.032
		(0.341)	(0.040)	(0.103)	(0.043)	(0.083)	(0.026)	(0.157)	(0.083)	(0.055)	(0.052)	(0.036)	(0.025)
	Skewness	1.732	0.076	0.603	2.275	1.197	-1.129	0.451	2.925	-1.878	0.098	1.260	0.430
		(2.816)	(2.909)	(2.393)	(16.904)	(0.882)	(2.366)	(0.715)	(6.666)	(15.53)	(1.250)	(7.386)	(0.836)
	Kurtosis	-2.139	65.559	17.797	151.569	-7.438*	-54.629	3.513*	-25.41	153.3	24.97	-138.9	33.73
		(5.091)	(163.218)	(37.428)	(924.778)	(4.361)	(71.780)	(2.181)	(54.83)	(1056)	(27.19)	(612.1)	(26.58)
PC	Dispersion	-0.571	0.044	1.326	0.506	-0.712*	-0.090	0.199	33.88	0.857	0.373	0.019	0.132
		(1.112)	(0.117)	(2.853)	(0.900)	(0.394)	(0.142)	(0.359)	(3990)	(1.329)	(0.327)	(0.121)	(0.095)
	Skewness	-0.247	0.748	0.129	0.093	0.414	0.434	2.158	0.482	0.564	-0.659	7.371	0.861
		(1.544)	(3.272)	(1.217)	(1.352)	(0.552)	(1.798)	(4.298)	(3.091)	(1.662)	(1.081)	(48.60)	(0.990)
	Kurtosis	-2.077	19.577	0.499	3.214	-2.197*	-12.097	2.237	-2.013	3.104	2.850	66.58	8.759
		(3.970)	(51.442)	(2.147)	(5.439)	(1.296)	(18.721)	(5.117)	(7.332)	(4.217)	(2.601)	(414.7)	(6.388)

Notes: Significance level of ***1%, **5%, *10%. Tests are based on *FE* quantile regression estimation results in Table 11.

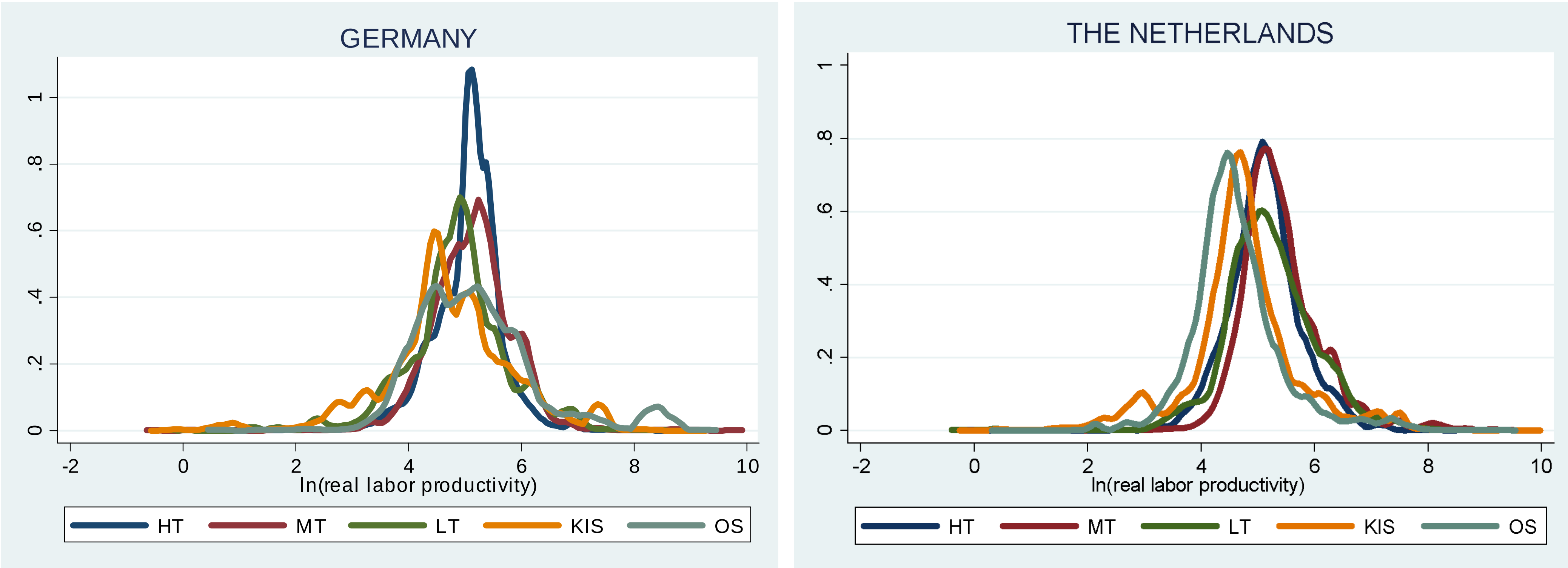
Graph 1: Distribution of human capital intensity, by country and industry



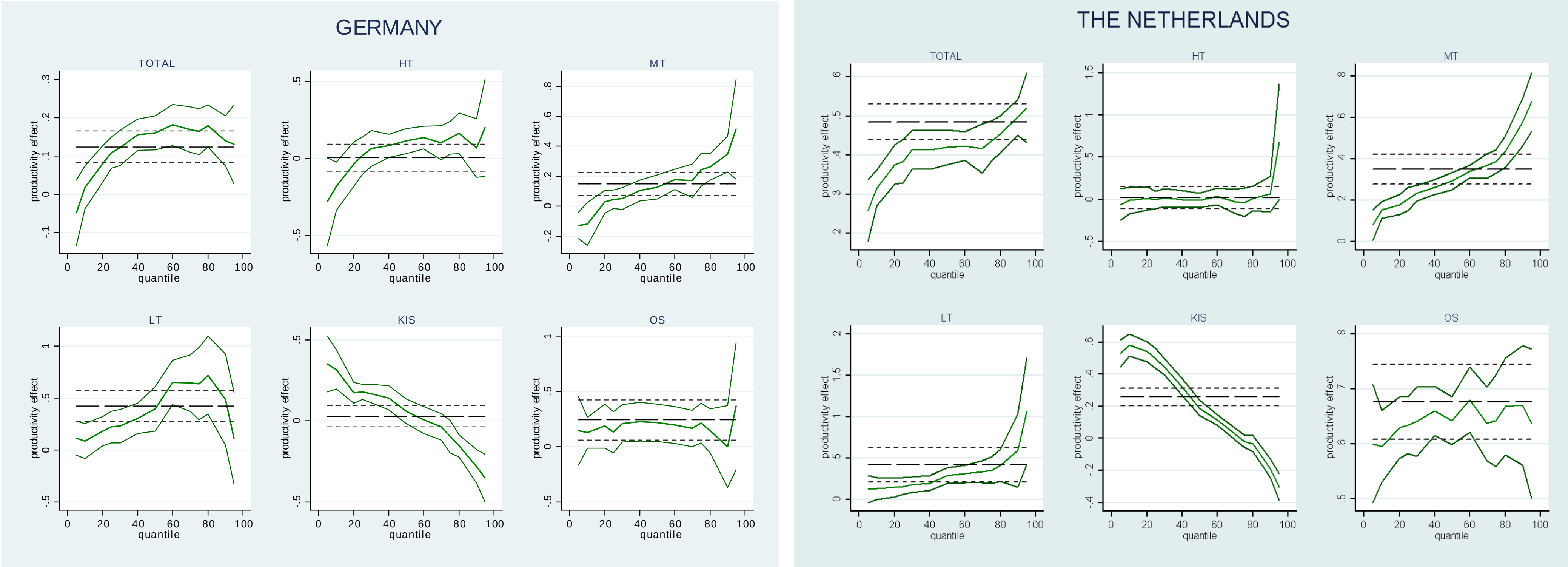
Graph 2: Innovation performance distribution, by country and industry



Graph 3: Productivity distribution, by country and industry

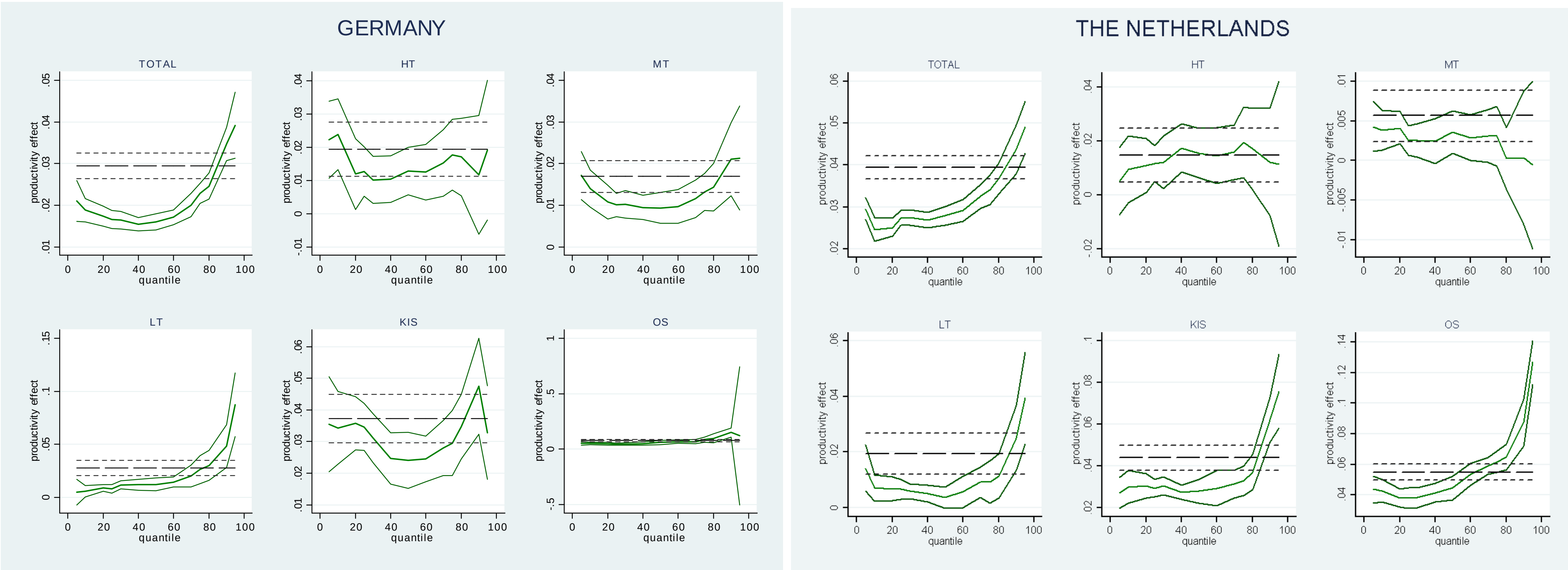


Graph 4: Average and quantile impact of human capital on productivity, by country and industry



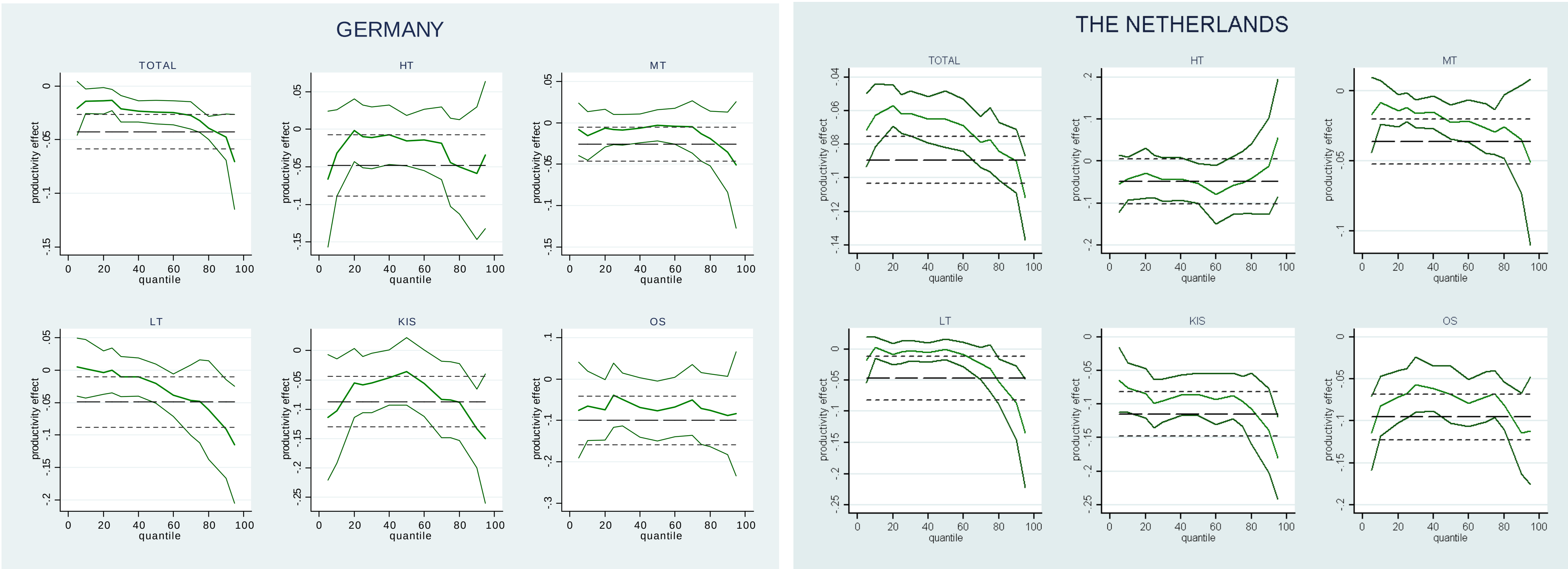
Note: Solid lines present coefficient estimates and 95% confidence intervals of quantile regressions. For comparison, dashed lines mark coefficient estimates and 95% confidence intervals of the OLS regression.

Graph 5: Average and quantile impact of product innovation on productivity, by country and industry



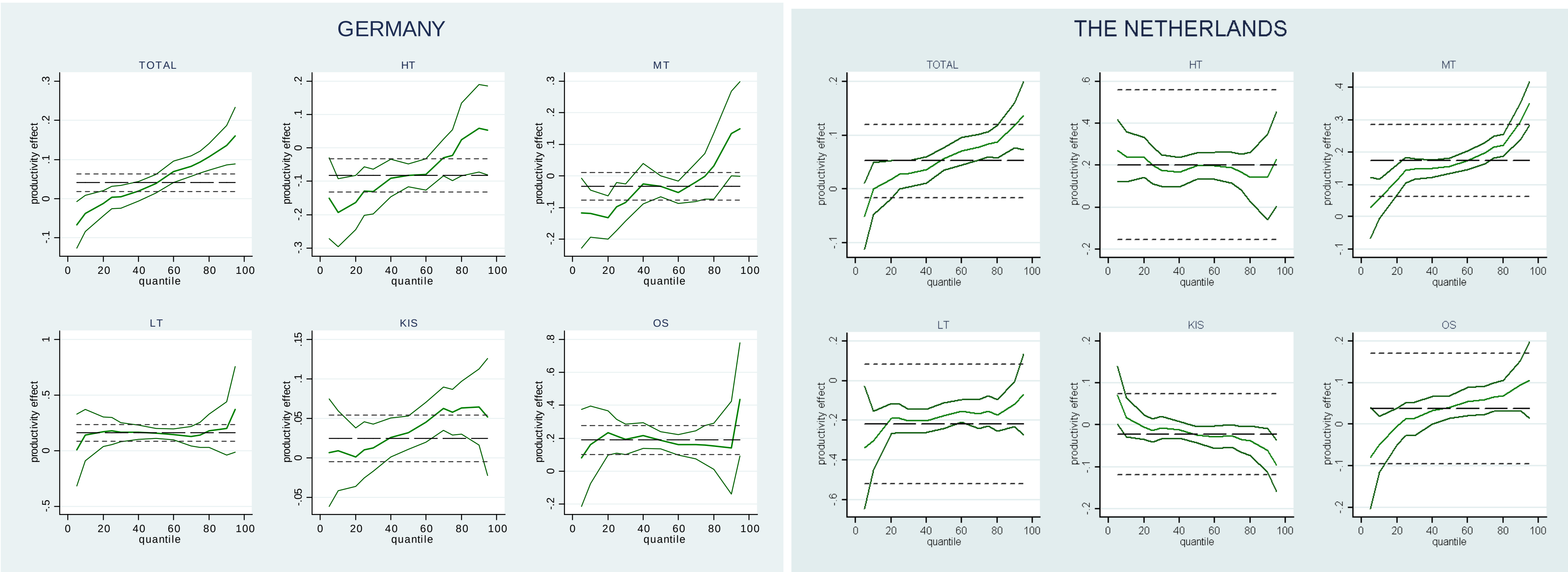
Note: Solid lines present coefficient estimates and 95% confidence intervals of quantile regressions. For comparison, dashed lines mark coefficient estimates and 95% confidence intervals of the OLS regression.

Graph 6: Average and quantile impact of process innovation on productivity, by country and industry



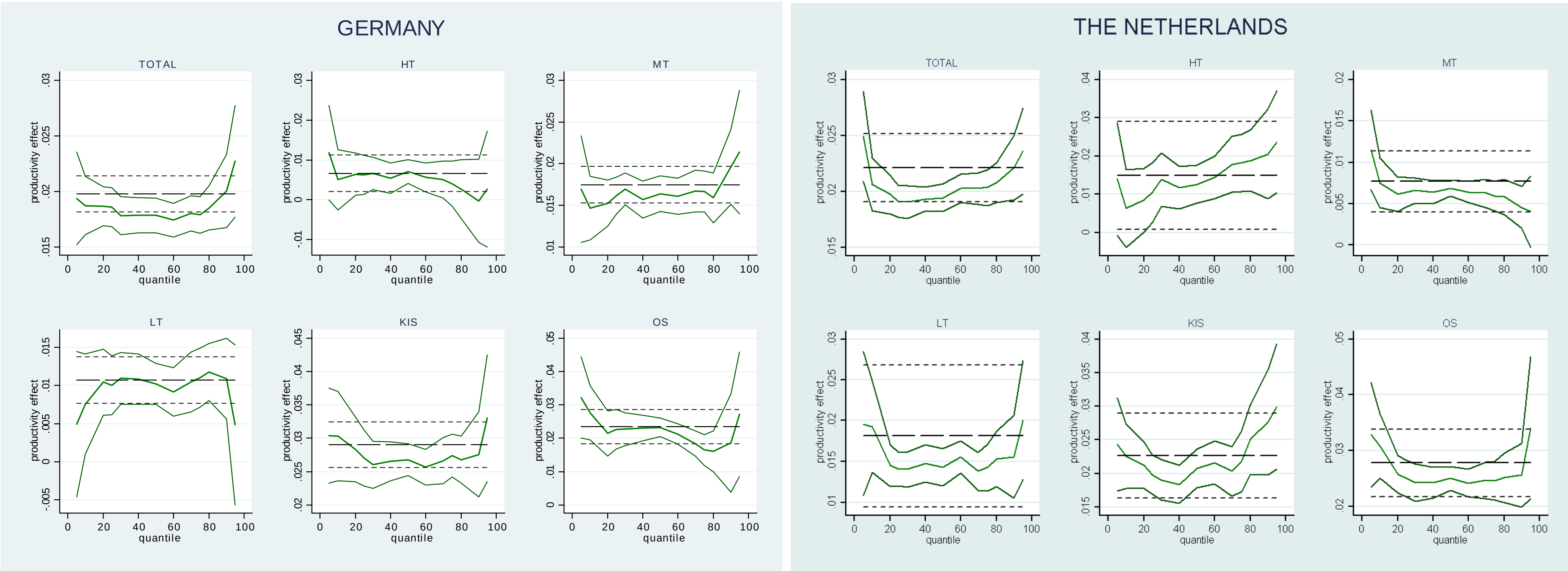
Note: Solid lines present coefficient estimates and 95% confidence intervals of quantile regressions. For comparison, dashed lines mark coefficient estimates and 95% confidence intervals of the *OLS* regression.

Graph 7: FE: Average and quantile impact of human capital on productivity, by country and industry



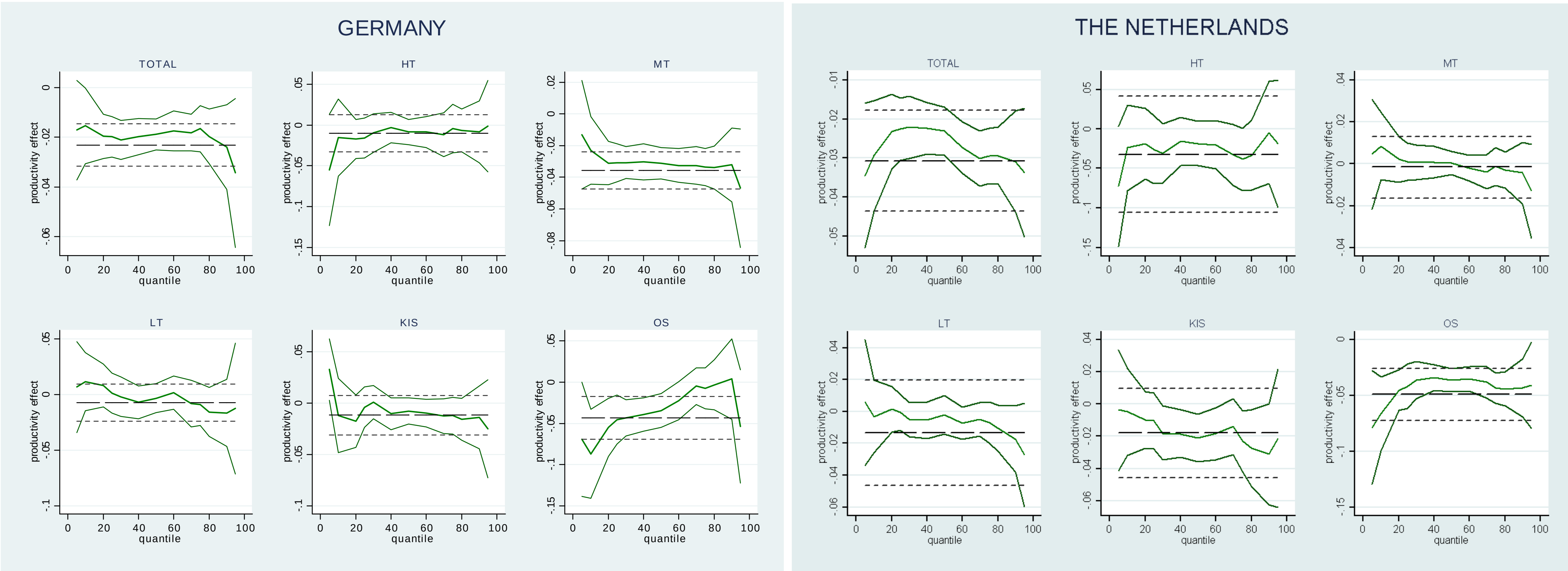
Note: Solid lines present coefficient estimates and 95% confidence intervals of quantile regressions. For comparison, dashed lines mark coefficient estimates and 95% confidence intervals of the FE regression.

Graph 8: *FE*: Average and quantile impact of product innovation on productivity, by country and industry



Note: Solid lines present coefficient estimates and 95% confidence intervals of quantile regressions. For comparison, dashed lines mark coefficient estimates and 95% confidence intervals of the *FE* regression.

Graph 9: FE: Average and quantile impact of process innovation on productivity, by country and industry



Note: Solid lines present coefficient estimates and 95% confidence intervals of quantile regressions. For comparison, dashed lines mark coefficient estimates and 95% confidence intervals of the FE regression.

Appendix A : Measurement details

A.1 Measurement of the human capital variable in the Dutch data

In order to define the education type of employees in the matched (CIS∩PS)-enterprises, we built a matched employer-employee microdata set by merging our enterprise data with the Social Statistics Database (SSB). The population of interest consists of individuals aged 15-65 covering the period 1999-2008.[1] Table A.1 reports the number of employees (N), the number of enterprises, and the median number of employees per enterprise for each year in manufacturing and services in the matched employer-employee data.

Table A.1: Panel structure of matched employer-employee microdata set - 1999-2008

	MANUFACTURING				SERVICES			
Year	# emp.	% emp. in Educ.	# firms	$\frac{\text{\# emp.}}{\text{firm}}^{a)}$	# employ.	% emp. in Educ.	# firms	$\frac{\text{\# emp.}}{\text{firm}}^{a)}$
1999	768,844	19.2	9,452	30	1,749,492	30.5	14,320	29
2000	759,266	20.1	9,284	31	1,796,189	32.0	14,192	31
2001	745,032	20.4	9,244	31	1,760,933	32.4	14,382	32
2002	705,867	21.1	9,048	30	1,729,602	33.3	14,417	32
2003	677,188	22.6	8,842	30	1,669,277	34.8	14,236	31
2004	648,995	24.3	8,675	29	1,667,713	36.6	14,086	31
2005	626,966	26.2	8,429	29	1,664,649	39.3	13,766	31
2006	623,756	29.2	8,074	30	1,686,114	42.8	13,253	32
2007	614,249	31.4	7,875	31	1,720,888	45.4	12,987	32
2008	611,725	33.8	7,496	31	1,722,096	47.5	12,194	33

Note: a) Median value.

The education type of each employee is determined in two stages. In the *first* stage, the matched employer-employee microdata set is linked to the Education database which provides the highest level of education attained by an individual. The education type is based on a 2-digit SOI-code (Dutch education classification: **S**tandaard **O**nderwijs**i**ndeling) and is converted to the ISCED classification (**I**nternational **S**tandard **C**lassification of **Ed**ucation). Table A.2 provides details on the Dutch education system and on the mapping between the SOI and the ISCED classifications.

[1] We select the period 1999-2008 since this period is covered in the Education database (see supra).

Table A.2: The Dutch education system

Dutch education system	**SOI code**	**ISCED code**	**3-skill type**	**4-skill type**
Pre-primary education, age 4-5		0		
Primary education, age 6-12	20	1	LS	LS
Lower secondary education, age 13-16: - vocational: MBO (level 1), VMBO (grade 3-4) - general: VMBO (grade 1-2), HAVO/VWO (grade 1-3), MAVO (grade 1-4)	31-33	2	LS	LS
Higher secondary education, age 17-18: - vocational: MBO (level 2-4) - general: HAVO/VWO (grade 4-6)	41-42	3	MS	LMS
Post-secondary, non-tertiary education, age > 19: - MBO (level 4) - 1-year HBO	43	4	MS	HMS
Tertiary education, type B: 2-3 year HBO	51-52	$5B$	HS	HMS
Tertiary education, type A:				
- 4-6 year HBO	53	$5A$	HS	HS
- WO and HBO Bachelor, WO Master	60	$5A$	HS	HS
Advanced research qualification: AIO, OIO, WO-Ph.D.		6		

On the basis of the ISCED-codes, we characterize two decompositions of the workforce which are reported in the last two columns of Table A.2. Following Antenbrink *et al.* (2005), the first decomposition splits the workforce into three skill types (low-skilled (LS), medium-skilled (MS) and high-skilled (HS)). In line with O'Mahony *et al.* (2008), the second decomposition further refines the middle type into low-medium-skilled (LMS) and high-medium-skilled (HMS) types. The third and seventh columns in Table A.1 report the fraction of employees that are observed in the Education database in manufacturing and services respectively. The fraction lies in the [19.2%-33.8%]-range for manufacturing and in the [30.5%-47.5%]-range for services.

In the *second* stage, we determine the skill type of employees who are not observed in the Education database. For that purpose, we estimate a reverse Mincer equation. More specifically, we estimate an ordered probit model to predict each individual's skill type (LS, MS, HS) based on individual and firm characteristics in the matched employer-employee microdata for each year during the period 1999-2008. The ordered probit model is built around a latent regression equation:

$$Skill^*_{j(i)} = \mathbf{x}_j\boldsymbol{\alpha} + \mathbf{z}_i\boldsymbol{\beta} + \epsilon_j \tag{A.1}$$

where $Skill^*_{j(i)}$ is the skill type of individual i working in enterprise j, $\mathbf{x}_j$ a vector of the individual's family background and labor market characteristics, $\mathbf{z}_i$ a vector of enterprise characteristics and ϵ_j a normally distributed error term. We do not observe the latent variable $Skill^*_{j(i)}$. However, the observed skill type can be modeled in the following way:

$$Skill_{j(i)} = l \quad \text{if} \quad c_{l-1} \leq Skill^*_{j(i)} < c_l \tag{A.2}$$

where $l = 1, 2, 3$ are the three skill types and c_l are the cut-off levels in the ordered probit model. To predict skill outcomes, we use the following explanatory variables: age, age squared, tenure, tenure squared, ln(yearly gross wage), ln(yearly working hours), 11 province dummies capturing the location of the individual[2], sex dummy (0 = female, 1 = male), marital status dummy (0 = married/widowed/divorced/registered partnership, 1 = married), birth country dummy (0 = other than the Netherlands (NL), 1 = NL), birth country father dummy (0 = other than NL, 1 = NL), birth country mother dummy (0 = other than NL, 1 = NL), 6 size class dummies[3] and 20 industry dummies[4]. The estimation sample is restricted to individuals aged 15-65 with wage and working time values within the [p1-p99]-range.

Table A.3 presents the yearly skill composition of the workforce in manufacturing and services. The first percentage in each column refers to the proportion of respectively low-skilled, medium-skilled and high-skilled employees based on the Education Database, i.e. the education (and hence skill) type for these individuals is observed. The second percentage in each column –put in square brackets– corresponds to the skill composition based on predicted skill outcomes.[5] The match between the observed and the predicted skill type for individuals in the Education Database lies in the [58%-65%]-range in both manufacturing and services.[6] Focusing on the skill composition in square brackets, we observe a slight decrease in the proportion of low-skilled employees and a considerable decrease in the proportion of medium-skilled employees over time in both manufacturing and services which translates into a significant increase in the proportion of high-skilled employees over time. The latter appears to be more pronounced in manufacturing.

Table A.3: Skill composition of the workforce in matched employer-employee microdata set - 1999-2008

	MANUFACTURING			**SERVICES**		
Year	% LS	% MS	% HS	% LS	% MS	% HS
1999	25.0 [21.7]	43.1 [59.9]	31.8 [18.4]	22.0 [16.3]	46.1 [55.8]	32.0 [28.1]
2000	25.4 [21.7]	41.7 [58.5]	32.9 [19.8]	23.4 [16.9]	44.5 [53.8]	32.1 [29.3]
2001	24.3 [21.5]	41.3 [58.0]	34.3 [20.5]	22.6 [16.3]	44.3 [53.2]	33.1 [30.5]
2002	24.2 [21.7]	40.0 [56.1]	35.8 [22.2]	22.8 [16.7]	42.9 [51.3]	34.2 [32.0]
2003	25.7 [23.1]	37.9 [52.2]	36.4 [24.7]	25.4 [17.7]	40.5 [48.6]	34.1 [33.6]
2004	26.0 [25.2]	37.4 [49.1]	36.6 [25.7]	26.4 [18.2]	40.0 [47.5]	33.5 [34.3]
2005	25.9 [24.3]	37.7 [49.4]	36.5 [26.3]	26.2 [17.5]	40.6 [47.2]	33.2 [35.2]
2006	24.8 [23.0]	37.4 [48.8]	37.8 [28.2]	27.0 [18.9]	40.6 [46.7]	32.4 [34.4]
2007	26.0 [24.0]	37.8 [49.1]	36.2 [26.9]	27.9 [19.8]	40.7 [47.0]	31.3 [33.1]
2008	25.9 [24.1]	38.2 [49.4]	35.8 [26.4]	27.9 [20.1]	41.2 [47.8]	31.0 [32.1]
TOTAL[a)]	25.5 [23.0]	38.0 [50.8]	36.0 [25.2]	25.8 [17.6]	40.9 [48.2]	32.7 [32.6]

Note: a) Median value.

[2] The 12 provinces are Groningen (reference), Friesland, Drenthe, Overijssel, Flevoland, Gelderland, Utrecht, Noord-Holland, Zuid-Holland, Zeeland, Noord-Brabant and Limburg.

[3] The 7 size classes are defined as follows: size class = 1 if the number of employees (L) < 10 (reference), size class = 2 if $L \in [10, 20[$, size class = 3 if $L \in [20, 50[$, size class = 4 if $L \in [50, 100[$, size class = 5 if $L \in [100, 200[$, size class = 6 if $L \in [200, 500[$ and size class = 7 if $L \geq 500$.

[4] The 11 manufacturing industries are food, textiles, wood, chemicals, plastics, glass, metal, machinery, electrical engineering, vehicles, furniture/recycling and the 10 services industries are wholesale, transport, telecommunication, computer, technical services, consultancy, other business related services, renting, retail and R&D services.

[5] Evidently, we take the *observed* skill type for individuals in the Education Database. The predicted skill type is used for the remaining individuals.

[6] Details on the ordered probit estimates are not reported but available upon request.

We applied the same procedure to determine the skill type for each employee in the matched employer-employee microdata set based on the 4-skill type decomposition (see supra).[7]

As noted above, we performed the ordered probit regressions on a *yearly* basis. To investigate the stability of an individual's (observed or predicted) skill type over the considered period (1999-2008), we compared the skill type of an individual in the first year of observation to her skill type in the last year of observation. Focusing on manufacturing, our unbalanced panel consists of $1,470,982$ individuals over the period 1999-2008. The skill type is observed for 31.1% of the individuals. Considering the subsample of individuals for which the skill type is observed, 34.8% of the individuals belong to the low-skilled type, 38.1% to the medium-skilled type and 27.1% to the high-skilled type. Considering the total sample of individuals (for which the skill type is either observed or predicted), the corresponding shares are 24.3%, 51.9% and 23.9%. The number of observations per individual is 2 for the first quartile of individuals, 3 for the second quartile and 8 for the third quartile.[8] Restricting the sample to individuals having at least two observations, we observe that the skill type is unchanged for 69.1% of the individuals whereas 14.6% of the individuals experience skill upgrading and 16.4% skill downgrading. Focusing on services, our unbalanced panel consists of $4,865,343$ individuals over the period 1999-2008. The skill type is observed for 42.2% of the individuals. Considering the subsample of individuals for which the skill type is observed, 41.4% of the individuals are low-skilled, 38.7% medium-skilled and 19.9% high-skilled. Considering the total sample of individuals, the corresponding shares are 26.1%, 49.0% and 24.9%. The number of observations per individual is 1 for the first quartile of individuals, 3 for the second quartile and 5 for the third quartile.[9] Restricting the sample to individuals having at least two observations, we observe that the skill type is unchanged for 66.6% of the individuals whereas 23.2% of the individuals experience skill upgrading and 10.2% skill downgrading. Since no clear pattern can be discerned in the skill type of the skill-downgrading category in both manufacturing and services, we decided to leave the skill type of these individuals unchanged.

Finally, we determine the share of each skill type for each matched (CIS∩PS)-enterprise by aggregating to the enterprise level.[10] Table A.4 reports the means, standard deviations and quartile values of the skill types –defined as shares lying in the $[0, 1]$-range– in manufacturing and services. We further break down manufacturing and services into five industries according to the OECD (2001) classification: High-technology manufacturing (HT), Medium-technology manufacturing (MT), Low-technology manufacturing (LT), Knowledge-intensive services (KIS) and Other services (OS).

[7] Details are not provided but available upon request.

[8] Putting the number of individuals between brackets and the number of observations between square brackets, the structure of the manufacturing data is given by: (333,076) [1], (242,420) [2], (163,997) [3], (103,604) [4], (83,037) [5], (71,751) [6], (75,460) [7], (71,246) [8], (86,136) [9], (240,255) [10]. The total number of observations is 6,845,976.

[9] Putting the number of individuals between brackets and the number of observations between square brackets, the structure of the services data is given by: (1,300,050) [1], (1,015,217) [2], (677,490) [3], (476,719) [4], (335,782) [5], (247,174) [6], (205,536) [7], (174,679) [8], (172,800) [9], (259,896) [10]. The total number of observations is 17,422,128.

[10] Information on the skill decomposition of the workforce is missing for about 5% of the matched (CIS∩PS)-enterprises.

Table A.4: Skill composition of the workforce in enterprise data set - 1999-2008

Variables	Mean	Sd.	Q_1	Q_2	Q_3	N
MANUFACTURING						
LS	0.266	0.141	0.160	0.250	0.354	22 614
MS	0.557	0.128	0.476	0.556	0.641	22 883
HS	0.180	0.153	0.069	0.140	0.254	23 225
HT						
LS	0.139	0.089	0.071	0.118	0.190	1 549
MS	0.480	0.158	0.387	0.489	0.583	1 619
HS	0.387	0.205	0.237	0.362	0.522	1 644
MT						
LS	0.258	0.135	0.156	0.241	0.344	14 557
MS	0.560	0.122	0.480	0.557	0.639	14 738
HS	0.184	0.145	0.077	0.149	0.264	14 961
LT						
LS	0.313	0.142	0.210	0.293	0.402	6 508
MS	0.570	0.127	0.486	0.569	0.658	6 526
HS	0.119	0.099	0.044	0.100	0.170	6 620
SERVICES						
LS	0.170	0.122	0.074	0.149	0.240	30 787
MS	0.518	0.186	0.385	0.545	0.656	33 766
HS	0.317	0.256	0.101	0.250	0.510	35 417
KIS						
LS	0.141	0.130	0.041	0.094	0.214	12 319
MS	0.418	0.193	0.258	0.397	0.571	14 713
HS	0.439	0.290	0.152	0.493	0.692	15 901
OS						
LS	0.189	0.113	0.107	0.173	0.250	18 468
MS	0.596	0.137	0.506	0.602	0.692	19 053
HS	0.217	0.167	0.082	0.186	0.320	19 516

From Table A.4, it follows that the median proportion of high-skilled employees (HS) is about 14% in manufacturing. We observe considerable heterogeneity across industries: the median HS ranges from 10% in Low-technology manufacturing industries to 36.2% in High-technology manufacturing industries. The median HS amounts to 25% in services, ranging from 18.6% in Other services to 49.3% in Knowledge-intensive services.

A.2 Measurement of closeness to the technological frontier variable in the Dutch data

A.2.1 Closeness-to-frontier variable based on real labor productivity

In order to define our main closeness-to-the-technological-frontier variable which is based on real labor productivity (CTF_{it-1}), we consider the largest possible population of enterprises from the Production Surveys. After some cleaning and trimming on nominal labor productivity levels and growth rates to eliminate outliers and anomalies, we have an unbalanced panel of $381,546$ observations corresponding to $130,893$ enterprises (35% in manufacturing and 65% in services) over the period 1998-2008. 1.7% of the enterprises belong to High-technology manufacturing, 12.3% to Medium-technology manufacturing, 13.8% to Low-technology manufacturing, 31.2% to Knowledge-intensive services and 41.1% to Other services.

Table A.5: Panel structure of PS sample - 1998-2008

# consecutive years	# firms
≥ 2	$74,378$
≥ 3	$32,114$
≥ 4	$22,714$
≥ 5	$17,310$
≥ 6	$12,990$

A.2.2 Closeness-to-frontier variable based on total factor productivity

In the robustness check using total factor productivity (TFP) as the dependent variable, we include as a covariate the one-year lagged value of the closeness-to-the-technological-frontier variable which is based on estimates of total factor productivity $\left(CTF_{it-1}^{TFP}\right)$. We measure the latter as CTF_{it}^{TFP} as $1-DTF_{it}^{TFP} = 1-\left(\frac{\widehat{TFP}_{Ft}-\widehat{TFP}_{it}}{\widehat{TFP}_{Ft}}\right) = \frac{\widehat{TFP}_{it}}{\widehat{TFP}_{Ft}}$ where $\widehat{TFP}$ of the technological frontier firm F is proxied by the 95% percentile value of $\widehat{TFP}$ at the NACE 3-digit industry level. The data that are used to estimate TFP of the technological frontier F stem from the largest possible population of enterprises from the Production Surveys. After some cleaning and trimming on nominal labor productivity levels and growth rates to eliminate outliers and anomalies and restricting the population to enterprises having at least two consecutive years, our estimation sample consists of 292,770 observations corresponding to 74,378 enterprises (40.5% in manufacturing and 59.5% in services) spanning the period 1998-2008. 2.1% of the enterprises belong to High-technology manufacturing, 16.8% to Medium-technology manufacturing, 19.6% to Low-technology manufacturing, 22% to Knowledge-intensive services and 39.4% to Other services.

A.3 Breakdown of manufacturing and services according to technological intensity

Table A.6: Breakdown of manufacturing and services according to technological intensity

	NACE Rev. 1.1 codes
MANUFACTURING	
High-technology manufacturing (HT)	**24.4** Pharmaceuticals, medicinal chemicals and botanical products **30** Office machinery and computers **32** Radio, television and communication equipment and apparatus **33** Medical, precision and optical instruments, watches and clocks **35.3** Aircraft and spacecraft
Medium-technology manufacturing (MT)	**23** Coke, refined petroleum products and nuclear fuel **24** Chemicals and chemical products, **excluding 24.4** **25 to 28** Rubber and plastic products; basic metals and fabricated metal products; other non-metallic mineral products **29** Machinery and equipment n.e.c. **31** Electrical machinery and apparatus n.e.c. **34** Motor vehicles, trailers and semi-trailers **35** Other transport equipment, **excluding 35.3**
Low-technology manufacturing (LT)	**15 to 22** Food products, beverages and tobacco; textiles and textile products; leather and leather products; wood and wood products; pulp, paper and paper products, publishing and printing **36 to 37** Manufacturing n.e.c.
SERVICES	
Knowledge-intensive services (KIS)	**61** Water transport **62** Air transport **64** Post and telecommunications **65 to 67** Financial intermediation **70 to 74** Real estate; renting and business activities
Other services (OS)	**50 to 52** Wholesale; retail; motor trade **60** Land transport, transport via pipelines **63** Supporting and auxiliary transport activities, activities of travel agencies **90** Sewage and refuse disposal, sanitation and similar activities

Note: Data for hotel and restaurants (55), financial intermediation (65 to 67), public administration and defence, compulsory social security (75), education (80), health and social work (85), activities of membership organization n.e.c. (91), recreational, cultural and sporting activities (92), other service activities (93), activities of households (95 to 97) and extra-territorial organizations and bodies (99) are not available.

Appendix B : Statistical annex

Table B.1: Estimation sample by country and 21-industry

	GERMANY				THE NETHERLANDS			
	# obs.	%	**# firms**	%	**# obs.**	%	**# firms**	%
Food	493	4.2	298	4.5	1,421	5.8	810	5.5
Textile	365	3.1	198	3.0	405	1.6	226	1.5
Wood	715	6.1	411	6.2	311	1.3	180	1.2
Chemicals	543	4.6	316	4.8	909	3.7	425	2.9
Plastics	528	4.5	292	4.4	590	2.4	295	2.0
Glass	357	3.1	205	3.1	466	1.9	264	1.8
Metal	1,124	9.6	596	9.0	1,926	7.8	1,134	7.6
Machinery	973	8.3	539	8.1	1,532	6.2	855	5.8
Electrical engineering	1,349	11.5	761	11.5	829	3.4	471	3.2
Vehicles	402	3.4	236	3.6	555	2.3	324	2.2
Furniture/recycling	337	2.9	196	3.0	528	2.1	332	2.2
Wholesale	468	4.0	243	3.7	4,624	18.8	2,841	19.1
Transport	801	6.8	448	6.8	2,954	12.0	1,744	11.8
Telecomm.	64	0.5	37	0.6	116	0.5	74	0.5
Computer	500	4.3	309	4.7	1,067	4.3	770	5.2
Technical services	712	6.1	388	5.8	964	3.9	611	4.1
Consultancy	394	3.4	253	3.8	1,360	5.5	933	6.3
Other business related serv.	808	6.9	503	7.6	2,699	11.0	1,697	11.4
Renting	237	2.0	112	1.7	218	0.9	143	1.0
Retail	282	2.4	137	2.1	1,056	4.3	668	4.5
RD services	247	2.1	156	2.4	56	0.2	44	0.3
Total	11,699	100.0	6,634	100.0	24,586	100.0	14,841	100.0

Table B.2: Panel structure: Number of participations

# of participation	GERMANY				THE NETHERLANDS			
	# obs.	%	**# firms**	%	**# obs.**	%	**# firms**	%
1	3,582	30.6	3,582	54.0	9,177	37.3	9,177	61.8
2	3,446	29.5	1,723	26.0	6,130	24.9	3,065	20.7
3	2,391	20.4	797	12.0	4,395	17.9	1,465	9.9
4	1,520	13.0	380	5.7	3,144	12.8	786	5.3
5	760	6.5	152	2.3	1,740	7.1	348	2.3
Total	11,699	100.0	6,634	100.0	24,586	100.0	14,841	100.0

Table B.3: Firm-level persistence in the closeness to the technological frontier, based on TFP (transition rates)

	GERMANY						**THE NETHERLANDS**					
	<q20	**q20 - <q40**	**q40 - <q60**	**q60 - <q80**	**q80 - <q95**	**≥q95**	**<q20**	**q20 - <q40**	**q40 - <q60**	**q60 - <q80**	**q80 - <q95**	**≥q95**
	Population[a)]											
CTF_t^{TFP}	CTF_{t+1}^{TFP}											
<q20	**81.15**	13.81	2.95	1.30	0.59	0.19	**78.11**	14.86	4.17	1.93	0.72	0.21
q20 - <q40	13.88	**66.52**	14.85	3.56	1.05	0.13	11.95	**66.06**	16.08	4.46	1.23	0.23
q40 - <q60	2.54	15.48	**64.24**	15.17	2.31	0.27	3.30	14.73	**63.04**	15.65	2.80	0.49
q60 - <q80	1.03	3.71	16.04	**66.08**	12.31	0.84	1.57	4.34	14.03	**67.12**	11.95	0.99
q80 - <q95	0.76	1.82	3.44	16.55	**71.30**	6.13	0.80	1.49	3.50	15.85	**72.34**	6.02
≥q95 (frontier)	0.60	1.42	1.95	3.60	17.47	**74.96**	0.68	0.99	1.27	3.51	17.16	**76.38**
CTF_t^{TFP}	CTF_{t+2}^{TFP}											
<q20	**70.57**	19.74	5.32	2.93	1.06	0.38	**58.54**	24.85	9.20	4.96	1.82	0.64
q20 - <q40	20.26	**51.19**	19.92	6.37	1.74	0.51	20.45	**42.19**	24.57	9.24	2.94	0.61
q40 - <q60	4.61	21.97	**48.81**	19.81	4.15	0.64	7.59	22.96	**38.72**	23.64	5.96	1.13
q60 - <q80	1.98	6.14	22.12	**51.14**	17.03	1.60	3.77	8.92	21.34	**45.45**	18.30	2.22
q80 - <q95	1.48	3.68	6.34	23.53	**56.08**	8.89	1.93	3.56	7.37	24.88	**52.62**	9.63
≥q95 (frontier)	1.15	3.45	4.44	6.58	28.45	**55.92**	1.86	2.04	3.25	7.87	28.88	**56.09**
	Estimation sample[b)]											
CTF_t^{TFP}	CTF_{t+2}^{TFP}											
<q20	**66.58**	20.99	6.68	4.01	1.47	0.27	**60.36**	24.26	9.04	3.89	1.69	0.76
q20 - <q40	22.14	**46.29**	20.50	8.68	1.76	0.63	21.50	**40.00**	25.79	9.57	2.50	0.64
q40 - <q60	4.34	23.63	**45.59**	20.56	5.49	0.38	6.68	24.59	**38.87**	24.03	4.84	0.98
q60 - <q80	2.53	5.81	24.49	**48.74**	16.67	1.77	3.70	9.12	23.84	**44.12**	16.51	2.71
q80 - <q95	2.05	5.60	7.65	21.64	**52.61**	10.45	2.15	3.83	7.75	25.68	**49.49**	11.10
≥q95 (frontier)	1.09	5.43	4.35	5.43	27.17	**56.52**	1.79	1.46	3.90	11.71	30.89	**50.24**

Notes: CTF^{TFP} is divided into six categories based on the annual 20^{th}, 40^{th}, 60^{th}, 80^{th} and 95^{th} percentiles. a) DE: 33,869 observations, NL: 238,259. observations. b) DE: 10,928 observations, NL: 24,591 observations.

Table B.4: Mean regression (OLS and FE): Firm-level returns to human capital and innovation, by country and industry

		GERMANY						THE NETHERLANDS					
		MANUFACTURING			**SERVICES**		**TOTAL**	**MANUFACTURING**			**SERVICES**		**TOTAL**
		HT	**MT**	**LT**	**KIS**	**OS**		**HT**	**MT**	**LT**	**KIS**	**OS**	
OLS	HC	-0.013	0.121*	0.554***	-0.010	0.343**	0.110***	0.001	0.379***	0.284**	0.349***	0.726***	0.569***
		(0.067)	(0.070)	(0.130)	(0.052)	(0.153)	(0.032)	(0.075)	(0.044)	(0.132)	(0.043)	(0.050)	(0.035)
	$L1.CTF$	0.894***	0.823***	0.866***	1.478***	1.399***	1.280***	0.540***	0.330***	0.239***	1.251***	1.293***	1.068***
		(0.101)	(0.057)	(0.106)	(0.092)	(0.087)	(0.038)	(0.095)	(0.036)	(0.056)	(0.066)	(0.048)	(0.027)
	PD	0.017***	0.017***	0.026***	0.039***	0.069***	0.029***	0.015**	0.004**	0.014***	0.043***	0.053***	0.036***
		(0.005)	(0.003)	(0.006)	(0.006)	(0.007)	(0.002)	(0.006)	(0.002)	(0.004)	(0.004)	(0.004)	(0.002)
	PC	-0.033	-0.013	-0.039	-0.095***	-0.101**	-0.036***	-0.058*	-0.036***	-0.031	-0.092***	-0.092***	-0.075***
		(0.026)	(0.016)	(0.025)	(0.030)	(0.041)	(0.011)	(0.031)	(0.009)	(0.020)	(0.023)	(0.023)	(0.009)
FE	HC	-0.082	-0.032	0.160	0.024	0.189	0.041	0.202	0.174***	-0.217	-0.022	0.038	0.053
		(0.121)	(0.085)	(0.136)	(0.062)	(0.199)	(0.042)	(0.181)	(0.057)	(0.153)	(0.049)	(0.068)	(0.035)
	$L1.CTF$	0.537***	0.497***	0.256***	0.884***	0.680***	0.567***	0.190**	0.214***	0.223***	0.623***	0.545***	0.443***
		(0.116)	(0.052)	(0.058)	(0.144)	(0.121)	(0.046)	(0.082)	(0.036)	(0.081)	(0.064)	(0.054)	(0.026)
	PD	0.007	0.017***	0.011***	0.029***	0.023***	0.020***	0.015**	0.008***	0.018***	0.023***	0.028***	0.022***
		(0.007)	(0.003)	(0.004)	(0.006)	(0.007)	(0.002)	(0.007)	(0.002)	(0.004)	(0.003)	(0.003)	(0.002)
	PC	-0.010	-0.036***	-0.007	-0.012	-0.043*	-0.023***	-0.032	-0.002	-0.001	-0.018	-0.049***	-0.031***
		(0.025)	(0.012)	(0.015)	(0.020)	(0.026)	(0.009)	(0.037)	(0.008)	(0.017)	(0.014)	(0.012)	(0.007)

Notes: Sample: firms with 2 or more observations. $SIZE$, CAP, MAT, GP, $EAST$ (for DE), time dummies and industry dummies (total sample) have been included in both OLS and FE regressions but are not reported here. Number of observations: See Table 1.

Table B.5: Quantile regression (QR): Firm-level returns to human capital and innovation, by country and industry

		GERMANY						THE NETHERLANDS					
		HT	**MT**	**LT**	**KIS**	**OS**	**TOTAL**	**HT**	**MT**	**LT**	**KIS**	**OS**	**TOTAL**
HC	q10	-0.157	-0.140**	0.100	0.282***	0.109	-0.025	0.045	0.175***	0.096	0.651***	0.715***	0.326***
		(0.102)	(0.067)	(0.077)	(0.078)	(0.132)	(0.041)	(0.075)	(0.027)	(0.068)	(0.057)	(0.067)	(0.033)
	q25	0.029	-0.011	0.300***	0.149***	0.148	0.083***	0.066	0.247***	0.115**	0.594***	0.692***	0.433***
		(0.077)	(0.049)	(0.089)	(0.047)	(0.096)	(0.029)	(0.052)	(0.025)	(0.053)	(0.046)	(0.051)	(0.031)
	q50	0.080	0.119***	0.547***	0.041	0.329**	0.153***	-0.001	0.321***	0.259***	0.320***	0.694***	0.481***
		(0.051)	(0.040)	(0.127)	(0.052)	(0.133)	(0.019)	(0.056)	(0.030)	(0.065)	(0.042)	(0.037)	(0.0283)
	q75	0.120	0.140**	0.906***	-0.136**	0.484***	0.170***	-0.106	0.352***	0.311***	0.040	0.704***	0.507***
		(0.088)	(0.070)	(0.263)	(0.067)	(0.151)	(0.036)	(0.111)	(0.043)	(0.110)	(0.039)	(0.056)	(0.029)
	q90	0.093	0.334***	0.533*	-0.383***	0.560*	0.139***	-0.114	0.545***	0.360*	-0.077	0.692***	0.640***
		(0.141)	(0.128)	(0.280)	(0.101)	(0.306)	(0.040)	(0.125)	(0.071)	(0.188)	(0.064)	(0.078)	(0.045)
L1.CTF	q10	0.708***	0.626***	0.497***	1.227***	0.792***	0.839***	0.316**	0.112***	0.080***	0.790***	1.0961***	0.704***
		(0.140)	(0.049)	(0.049)	(0.136)	(0.099)	(0.040)	(0.115)	(0.023)	(0.028)	(0.062)	(0.052)	(0.024)
	q25	0.638***	0.493***	0.396***	1.245***	0.901***	0.870***	0.333***	0.159***	0.078***	0.984***	1.143***	0.840***
		(0.080)	(0.040)	(0.025)	(0.090)	(0.084)	(0.034)	(0.079)	(0.020)	(0.017)	(0.078)	(0.038)	(0.023)
	q50	0.640***	0.549***	0.435***	1.252***	1.195***	1.016***	0.472***	0.190***	0.092***	1.266***	1.249***	0.983***
		(0.081)	(0.039)	(0.057)	(0.106)	(0.064)	(0.036)	(0.093)	(0.023)	(0.022)	(0.058)	(0.032)	(0.025)
	q75	0.774***	0.624***	0.691***	1.520***	1.621***	1.278***	0.567***	0.236***	0.142***	1.455***	1.412***	1.168***
		(0.079)	(0.051)	(0.105)	(0.108)	(0.102)	(0.040)	(0.129)	(0.024)	(0.036)	(0.064)	(0.046)	(0.023)
	q90	1.346***	0.792***	1.300***	1.756***	1.628***	1.461***	0.748***	0.303***	0.233***	1.500***	1.516***	1.324***
		(0.206)	(0.048)	(0.100)	(0.145)	(0.143)	(0.040)	(0.112)	(0.043)	(0.073)	(0.106)	(0.057)	(0.037)
PD	q10	0.015**	0.013***	0.005	0.039***	0.050***	0.019***	0.010	0.006***	0.007**	0.029***	0.029***	0.023***
		(0.007)	(0.003)	(0.003)	(0.007)	(0.009)	(0.002)	(0.007)	(0.002)	(0.003)	(0.005)	(0.005)	(0.002)
	q25	0.009**	0.010***	0.009**	0.032***	0.046***	0.016***	0.014***	0.003***	0.006***	0.026***	0.037***	0.023***
		(0.005)	(0.002)	(0.004)	(0.005)	(0.006)	(0.002)	(0.005)	(0.001)	(0.002)	(0.004)	(0.003)	(0.002)
	q50	0.012**	0.010***	0.012**	0.023***	0.055***	0.016***	0.013**	0.003**	0.006***	0.024***	0.044***	0.024***
		(0.005)	(0.002)	(0.004)	(0.005)	(0.009)	(0.002)	(0.006)	(0.001)	(0.002)	(0.004)	(0.004)	(0.002)
	q75	0.014**	0.015***	0.023***	0.031***	0.068***	0.023***	0.018**	0.000	0.007*	0.035***	0.059***	0.029***
		(0.006)	(0.003)	(0.006)	(0.004)	(0.014)	(0.003)	(0.009)	(0.002)	(0.004)	(0.006)	(0.006)	(0.002)
	q90	0.007	0.021***	0.044***	0.053***	0.106***	0.034***	0.020*	-0.006	0.022***	0.065***	0.085***	0.038***
		(0.012)	(0.005)	(0.015)	(0.008)	(0.024)	(0.004)	(0.012)	(0.004)	(0.009)	(0.010)	(0.010)	(0.003)
PC	q10	-0.031	-0.001	0.027	-0.128**	-0.041	-0.006	-0.060	-0.013*	0.006	-0.084***	-0.031	-0.053***
		(0.028)	(0.015)	(0.022)	(0.052)	(0.058)	(0.010)	(0.041)	(0.007)	(0.012)	(0.027)	(0.021)	(0.011)
	q25	-0.005	-0.008	0.005	-0.072**	-0.079**	-0.011*	-0.040	-0.019**	0.001	-0.075***	-0.042***	-0.048***
		(0.021)	(0.009)	(0.017)	(0.031)	(0.039)	(0.006)	(0.033)	(0.008)	(0.012)	(0.023)	(0.015)	(0.008)
	q50	0.005	-0.003	-0.019	-0.039	-0.086**	-0.015*	-0.047	-0.028***	-0.003	-0.035	-0.056***	-0.045***
		(0.022)	(0.009)	(0.015)	(0.033)	(0.034)	(0.009)	(0.029)	(0.007)	(0.012)	(0.023)	(0.017)	(0.008)
	q75	-0.040	-0.011	-0.044**	-0.089**	-0.057	-0.029***	-0.033	-0.031***	-0.026	-0.091***	-0.053**	-0.059***
		(0.028)	(0.012)	(0.022)	(0.036)	(0.047)	(0.011)	(0.051)	(0.009)	(0.022)	(0.025)	(0.023)	(0.010)
	q90	-0.077	-0.006	-0.070	-0.156***	-0.102***	-0.041***	-0.028	-0.026	-0.069*	-0.108***	-0.140***	-0.087***
		(0.064)	(0.025)	(0.047)	(0.060)	(0.038)	(0.012)	(0.055)	(0.019)	(0.042)	(0.038)	(0.025)	(0.015)

Notes: Sample: firms with 2 or more observations (*DE*: 8,117; *NL*: 15,427 observations). Significance level of ***1%, **5%, *10%. Bootstrapped standard errors (20 replications). Quantile regressions additionally include *GP*, *EAST* (for *DE*), time dummies and industry dummies (for total sample). Number of observations: See Table 1. Results are based on simultaneous regressions for $\theta \in \{0.05, 0.10, 0.20, 0.25, 0.30, 0.40, 0.50, 0.60, 0.70, 0.75, 0.80, 0.90, 0.95\}$. Results for other quantiles are available upon request.

Table B.6: Quantile regression (QR): Impact of human capital and innovation on industry productivity distribution, by country

		GERMANY						THE NETHERLANDS					
		HT	**MT**	**LT**	**KIS**	**OS**	**TOTAL**	**HT**	**MT**	**LT**	**KIS**	**OS**	**TOTAL**
HC	Dispersion	0.615	1.174	0.502***	-21.399	0.531**	0.345**	4.320	0.175***	0.459**	-0.873***	0.009	0.079**
		(0.738)	(0.878)	(0.127)	(155.546)	(0.249)	(0.171)	(11.68)	(0.065)	(0.192)	(0.114)	(0.046)	(0.036)
	Skewness	-0.122	-0.715	0.184	0.244	-0.079	-0.613	0.225	-0.410	-0.470	0.011	0.622	-0.289
		(1.418)	(0.767)	(0.282)	(0.231)	(0.476)	(0.645)	(0.530)	(0.478)	(0.736)	(0.121)	(5.531)	(0.552)
	Kurtosis	-0.710	1.280	1.045**	0.352	1.993**	1.297	0.405	6.885***	2.330**	-1.037***	115.4	13.02**
		(2.512)	(1.092)	(0.514)	(0.502)	(1.002)	(0.923)	(0.817)	(2.682)	(1.253)	(0.180)	(609.3)	(5.820)
L1.CTF	Dispersion	0.096	0.117***	0.271***	0.100***	0.285***	0.190***	0.260**	0.196***	0.292**	0.193***	0.108***	0.163***
		(0.060)	(0.032)	(0.068)	(0.035)	(0.038)	(0.015)	(0.115)	(0.058)	(0.124)	(0.034)	(0.018)	(0.013)
	Skewness	0.969	0.146	0.733**	0.946**	0.183	0.284**	-0.185	0.197	0.552	-0.195	0.212	0.132
		(1.050)	(0.549)	(0.309)	(0.476)	(0.189)	(0.136)	(0.553)	(0.425)	(0.529)	(0.187)	(0.180)	(0.094)
	Kurtosis	15.110*	10.876***	6.096***	10.812***	3.364***	5.645***	4.549**	5.365***	4.873**	4.854***	9.721***	6.180***
		(8.604)	(3.274)	(1.872)	(3.894)	(0.528)	(0.471)	(2.210)	(1.645)	(2.459)	(0.824)	(1.639)	(0.477)
PD	Dispersion	0.187	0.194*	0.443***	-0.007	0.192**	0.178***	0.133	-0.831	0.061	0.139	0.226***	0.108***
		(0.277)	(0.101)	(0.169)	(0.078)	(0.077)	(0.058)	(0.256)	(1.041)	(0.294)	(0.096)	(0.042)	(0.036)
	Skewness	-0.434	1.056*	0.640	-37.244	0.150	1.058**	1.451	1.119	2.126	1.608	0.364	0.927*
		(1.817)	(0.562)	(0.430)	(408.621)	(0.606)	(0.438)	(3.083)	(0.935)	(9.632)	(1.239)	(0.228)	(0.559)
	Kurtosis	4.995	7.091*	3.419*	-200.523	7.114**	7.587***	6.898	-0.012	35.00	11.00	5.285***	10.87***
		(7.763)	(4.170)	(1.822)	(2155.764)	(3.424)	(2.663)	(13.76)	(1.612)	(171.8)	(7.846)	(1.055)	(3.688)
PC	Dispersion	0.789	0.126	1.264	0.110	-0.159	0.460**	-0.091	0.229	1.112	0.097	0.116	0.096
		(0.763)	(0.710)	(1.038)	(0.218)	(0.367)	(0.226)	(0.693)	(0.205)	(1.048)	(0.177)	(0.236)	(0.080)
	Skewness	1.545	5.759	0.025	4.692	1.609	0.572	3.286	-0.578	0.677	5.896	-1.471	1.690
		(0.989)	(34.113)	(0.535)	(8.926)	(3.613)	(0.825)	(22.47)	(1.248)	(0.822)	(11.06)	(4.392)	(1.651)
	Kurtosis	3.069	2.866	0.858	16.038	-6.598	2.546**	3.864	3.389	2.324	-13.19	11.96	13.56
		(2.549)	(22.889)	(1.179)	(31.654)	(14.869)	(1.220)	(10.28)	(3.209)	(1.716)	(96.64)	(21.43)	(11.46)

Notes: Sample: firms with 2 or more observations (*DE*: 8,117; *NL*: 15,427 observations). Significance level of ***1%, **5%, *10%. Tests are based on estimation results in Table B.5.