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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. In Germany, average innovation performance is higher in all industries, except for low-technology manufacturing, and in the Netherlands the innovation performance distributions are more dispersed. 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 for process innovation the most negative returns are observed in the best-performing enterprises of most industries. We find that in both countries 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 suggests an interpretation of a winner-takes-all market in knowledge-intensive services.

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

"The most important discovery [from microeconometric investigations] was the evidence on the pervasiveness of heterogeneity and diversity in economic life" – James J. Heckman, Nobel Lecture, December 8, 2008"

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1 Introduction

Over the past two decades, studies on productivity using longitudinal micro-level data sets have revealed two stylized facts. *First*, there exist tremendous differences in productivity across firms, even within narrowly defined industries, which are fairly persistent through time (see Bartelsman and Doms, 2000 for a survey and Haltiwanger *et al.*, 2007 for recent evidence). *Second*, within-industry firm productivity differences are larger than between-industry differences (Foster *et al.*, 2001). This ubiquity of firm-level productivity variation and persistence has spurred research into the underlying factors (Syverson, 2011). This paper reconsiders the relationship between innovation and human capital on the one hand and productivity on the other hand.

More specifically, combining firm, industry and country-level perspectives for two countries, we first investigate firm-level heterogeneity in the productivity effects of investments in innovation and human capital in manufacturing and service industries in Germany and the Netherlands. Motivated by the increasing prominence of services in European countries and the central role played by knowledge-intensive services in knowledge-based economies, we focus on high- versus low-technology industries. 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.

From a policy perspective, our study contributes to deepening our understanding of policies that affect aggregate productivity outcomes in European knowledge-based economies. It starts from the observation that over the past decade, serious concerns have been expressed about the increasing productivity gap of European firms to US firms (OECD, 2010; Roeger *et al.*, 2010).[1] 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). As a response, policy instruments have been introduced to stimulate investment in R&D and education (Lisbon Strategy 2000-2010, EU 2020, Europe 2020 Flagship Initiative Innovation Union). Given that empirical studies have shown that high-growth firms (the so-called "superstars" or "gazelles") are crucial for net job creation (see Henrekson and Johansson, 2010 for a survey; Acs, 2011), high-growth firms have received increasing attention among policymakers in recent years (European Commission, 2010; Hölzl, 2014). 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. Given 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 industry productivity distributions.

Pursuing a highly comparable cross-country industry analysis is valuable for explaining different patterns of economic phenomena across countries. The selection of our two countries is driven by the following three reasons. *First*, there are inherent institutional differences in the two countries. In Germany, the education system is characterized by a well-established, successful dual

[1] Since the mid 1990s, the productivity gap between Europe and the US has risen dramatically: GDP per hour worked in the EU has decreased from 98.3 percent of the US level in 1995 to 82.5 percent in 2012.

education system –combining general, transferable skills and structured learning on the job– supportive for providing high-quality technical skills and for creating a high degree of specialization of skilled employees.[2] *Second*, there are marked differences in the nature of innovation activity in the two countries. In contrast to the Netherlands, the innovation and production system in Germany is largely based on incremental customization of products rather than on radical innovation, which in turn maintains an existing industrial structure rather than stimulating the emergence of new industries (Streeck, 1997). *Third*, highly comparable microdata sets are available in these countries, allowing us to conduct a reliable international comparative study.

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 reallocation 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.

A detailed look at our data uncovers 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 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*,

[2] A unique feature of the Germany education system is that the principle of the dual system of vocational training is applied to tertiary education. Vocational education is the most relevant category of training in Germany: About two thirds of the workforce have a vocational degree. Another distinguishing characteristic is that the vocational pathway is regarded as a high status route into employment (Cedefop, 2008).

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.[3] 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 provides a short review of the related literature. Section 3 elucidates our empirical strategy. Section 4 discusses the data for Germany and the Netherlands. Section 5 presents some stylized facts. Section 6 reports the results. Section 7 concludes.

2 Related literature

There is a vast empirical literature on the effect of investments in R&D and innovation on firm productivity. On average, the private returns to R&D are strongly positive and somewhat higher than for ordinary capital (see Mairesse and Sassenou, 1991 for an early comprehensive survey, and Wieser, 2005 and Hall *et al.*, 2010 for recent surveys). However, there is mixed evidence on heterogeneous returns to R&D expenditures. For example, Coad and Rao (2008) find strongly increasing productivity effects for high-growth firms in US high-technology manufacturing. Segarra and Teruel (2011) show that the returns to internal R&D are higher for low-productive firms while the returns to external R&D are only positive for high-productive firms in Catalan manufacturing and services. Mata and Wörter (2013) report only positive returns to external R&D for high-growth firms in Swiss manufacturing. Peters *et al.* (2013) reveal that the long-run net benefits of R&D are increasing with higher levels of productivity in German manufacturing firms. Pisu (2006) does not report any effect, neither for high- nor for low-productive firms in UK manufacturing and services. 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). There is very limited evidence on heterogeneous returns to product and process innovation. Coad and Rao (2008) find a positive effect of innovativeness for high-growth firms in the upper tail of the distribution but not for the average firm's sales growth. Goedhuys and Sleuwaegen (2010) estimate positive product innovation returns but negative process innovation returns for high-productive entrepreneurial firms in Africa.

Likewise, there is a vast empirical literature on the effects of human capital on firm productivity. On average, human capital returns are found to be significantly positive at the micro level. Using matched employer-employee data sets, Lebedinski and Vandenberghe (2014) for Belgium, Turcotte and Rennison (2004) for Canada, Fox and Smeets (2011) for Denmark, Abowd *et al.* (1999) for France, Galindo-Rueda and Haskel (2005) and Haskel *et al.* (2005) for the UK,

[3] The latter result no longer holds for Germany in regressions that also control for unobserved firm heterogeneity.

Hellerstein *et al.* (1999), Haltiwanger *et al.* (1999, 2007) and Moretti (2004) for the US, and Van Biesebroeck (2011) for Zimbabwe all find positive effects of workers' skills on *firm/plant* productivity. 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 using a composite human capital variable accounting for both certified skills (educational attainment) and uncertified skills acquired through on-the-job training and experience.[4] To our knowledge, our study is the first to examine human capital returns at different points of the conditional productivity distribution. 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). Under the assumption of competitive labor markets, they capture heterogeneous productivity effects of workers' skills.[5]

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. Traced back to the seminal papers of Gerschenkron (1962) and Atkinson and Stiglitz (1969), the distance-to-frontier literature has its roots in studies on development and technological capabilities. In *macro/meso studies*, the unit of analysis is national economies or specific industries and one identifies the national technology frontier for a specific industry or the global frontier for a specific industry in a specific country. Existing articles include Griffith *et al.* (2003, 2004) on R&D intensity in a panel of industries across 12 OECD countries, Nicoletti and Scarpetta (2003) on product market regulation in a cross-country cross-industry panel of 18 OECD countries, Aghion *et al.* (2004) on threat of entry in UK industries, Aghion *et al.* (2005) on product market competition in UK industries, Acemoglu *et al.* (2006) on openness to trade, entry costs and schooling level in a cross-country panel of about 100 non-OECD countries, 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, Chandra *et al.* (2009) on competition in a panel of industries in Brazil, India, China and Korea, Amable *et al.* (2010) on competition in a cross-country cross-industry panel of 17 OECD countries, Bourlès *et al.* (2010) on competition in a panel of industries across 10 OECD countries and D'Costa *et al.* (2013) on how the impact of nation-wide structural policies on regional productivity growth depends on a region's distance to the frontier using a panel of regions in OECD countries.

[4] 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).

[5] Hellerstein *et al.* (1999) pioneered an approach of jointly estimating a plant-level wage equation with a production function aimed at investigating the divergence between productivity premiums associated with worker characteristics (such as education, age, gender) and the corresponding wage premiums. Many longitudinal studies on matched worker-firm data have applied this method (see van Ours and Stoeldraijer, 2011 and Vandenberghe and Waltenberge, 2013 for references).

At the *micro level*, one identifies a national or within-industry frontier that reflects the best technology in (an industry within) a country and evaluates how a firm's or establishment's distance to this frontier affects its economic performance. Applying the distance-to-frontier concept at the micro level acknowledges the large and persistent productivity dispersion across firms in many countries and advocates that heterogeneous firms should select strategies that depend on their relative performance. Three distinct methods are used in micro-level studies: (*i*) evaluating the impact of a firm's distance to the industry frontier and its interaction with relevant variables on economic performance/decisions thereby closely following the macro approach, (*ii*) assessing the influence of various strategies on a firm's economic performance at different points of the conditional performance distribution and (*iii*) estimating a technology convergence equation.[6] Existing studies using the first method include Aghion *et al.* (2004) on the influence of distance to the frontier and its interaction with foreign firm entry on incumbent performance using a panel of UK establishments, Acemoglu *et al.* (2007) on the impact of distance to the frontier on decentralization of investment decisions in panels of British establishments and French firms, Alder (2010) on the impact of distance to the frontier (in levels and interacted with competition) on product innovation using a panel of enterprise data in 40 developing and transition countries, Arnold *et al.* (2010) on the impact of distance to the frontier when evaluating the impact of product market regulation on firm-level productivity using a panel of European firms, and Ben Yahmed and Dougherty (2012) on the impact of import penetration on firms' productivity growth taking into account heterogeneity in firms' distance to the frontier using a firm panel of OECD countries. In addition to the studies mentioned above, existing studies using the second method include Coad (2008) on the impact of R&D expenditures and patents on a firm's market value at different points of the conditional Tobin's q distribution and Hölzl and Friesenbichler (2010) on the differential impact of R&D and innovation for high-growth firms in countries close to the technological frontier using firm data from the third Community Innovation Survey in 16 countries. Existing studies using the third method include Griffith *et al.* (2003) on the role of foreign presence in raising the speed of convergence to the technological frontier using a panel of British establishments, Nishismura *et al.* (2005) on the speed of convergence –taking explicitly into account possible biases caused by exits– in IT- and non-IT industries using a panel of Japanese firms, Sabirianova Peter *et al.* (2012) on whether more efficient firms have a higher probability than less efficient firms of moving up in the overall distribution of productive efficiency in any given year and on factors affecting the evolution of the efficiency gap using a panel of firms in the Czech Republic and Russia, and Bournakis *et al.* (2013) on the role of investment in R&D in achieving productivity convergence using a panel of British firms. Combining the first and second method, we evaluate how the impact of human capital and innovation vary at different points of the conditional productivity distribution while controlling for a firm's distance to the industry frontier. Linking country-specific firm-level data to examine which countries and industries are at the global frontier to single country micro data to construct distances to both the global and national frontier, Bartelsman *et al.* (2008) bridge the macro and micro approaches by assessing how the productivity growth of UK firms is influenced by both the global and national frontiers.

In a more narrow sense, our study is most closely related to Vandenbussche *et al.* (2006), Inklaar

[6] At the macro level, a country/industry's distance to the technology or productivity frontier are two closely related concepts. At the micro level, however, a firm's distance to the industry frontier might be operationalized in different ways depending on the question under investigation (see Coad, 2011 for a discussion). Following the tradition in the productivity convergence literature, we operationalize the concept of distance to the industry frontier by sorting firms according to their value of labor productivity (see infra).

et al. (2008), Madsen *et al.* (2010) and Madsen (2014). 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. Using a panel of 21 OECD countries covering the period 1870-2009, Madsen (2014) finds that –controlling for innovation variables and international knowledge spillovers– changes in educational attainment and the interaction between education and the distance to the world technology frontier have been influential for productivity growth over the past 140 years.

3 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 4.4. 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.

We estimate this production function at the country-industry level using four different estimation methods that differ in the 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 for cross-sectional data, first introduced in Koenker and Bassett's (1978) seminal contribution, can be written as:

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

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:

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

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. The estimation of a quantile model with fixed effects is not trivial because its intrinsic non-linearity implies that standard demeaning techniques are not feasible. In order to take unobserved heterogeneity into account, quantile regression models for panel data have recently been developed:

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

Following the seminal paper of Koenker (2004) on the estimation of quantile regression models for longitudinal data, most of the literature on quantile regression estimators for panel data propose inference procedures based on the assumption that the number of periods goes to infinity when the sample size goes to infinity. Under this assumption, Koenker (2004) and Lamarche (2010) suggest a penalized quantile regression estimator that simultaneously estimates quantile regression coefficients for a set of quantiles and fixed effects. Galvao (2011) extends the approach to dynamic panel data models with individual-specific intercepts. Abrevaya and Dahl (2008) suggest a correlated random-effects model based on the ideas of Mundlak (1978) and Chamberlain (1984). Canay (2011) proposes a simple two-step estimator that does not require specifying a penalty parameter and that is consistent and asymptotically normal when both the number of firms n and the number of periods T approach infinity.[7] Chernozhuk *et al.* (2013) provide identification and estimation of quantile effects in nonseparable models. Koenker (2004), Lamarche (2010) and Canay (2011) assume that the fixed effects α_i are pure location shifters, i.e. they affect all quantiles in the same way.

Given that the Canay (2011) estimator eliminates the fixed effects beforehand, making its implementation computationally simple regardless of the number of fixed effects included in the analysis, we apply this estimator to obtain the quantile returns to human capital and innovation taking into account unobserved firm heterogeneity ($FEQR$). More specifically, the Canay (2011) estimator consists of the following two steps. The *first* step involves a within estimation of the linear regression $y_{it} = x_{it}^{'}\beta_{\mu} + \alpha_i + u_{it}$ with $E(u_{it}|x_i, \alpha_i) = 0$. From the estimation of β_{μ}, one computes the firm-specific effects $\widehat{\alpha}_i \equiv \frac{1}{T}\sum_{t=1}^{T}(y_{it} - x_{it}^{'}\widehat{\beta}_{\mu})$. The *second* step involves running a standard quantile regression of $\widetilde{y}_{it} \equiv y_{it} - \widehat{\alpha}_i$ on all explanatory variables x_{it} in order to obtain quantile regression estimates for β_{θ}. Inference is based on bootstrapped standard errors from individual resampling. As mentioned above, the Canay (2011) estimator treats α_i as a simple location shift and, therefore, does not depend on the quantiles. This implies that the firm fixed effects affect the productivity of all firms within the same industry in the same way regardless of where the firms are located in the productivity distribution. Other recent studies implementing the Canay (2011) estimator include e.g. Foster-McGregor *et al.* (2013), Ohinata and van Ours (2013), Binder *et al.* (2014) and Cingano *et al.* (2014).

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

[7] Using Monte Carlo simulations, Canay (2011) shows that (*i*) already with $T = 10$, the bias is fairly low irrespective of the value of n and (*ii*) the Canay (2011) estimator performs as well as the Koenker (2004) estimator.

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).[8]

4 Data description

Combining firm, industry and country-level perspectives for two countries, our analysis primarily serves the purpose of uncovering heterogeneous returns to human capital and innovation at varying points of the conditional productivity distribution using firm-level data in Germany and the Netherlands. As mentioned above, the selection of the two countries is motivated by (*i*) differences in the education system in the two countries, (*ii*) differences in the nature of innovation activity in the two countries and (*iii*) the ability to build two highly comparable microdata sets that span the period 1998-2008. The latter ensures that our results reflect underlying economic differences which enables us to perform a reliable international comparative study.

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.

4.1 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

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

employees, the share of high-skilled employees, intermediate input costs (including energy costs and intermediate services) and the stock of tangible assets (physical capital).

4.2 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).[9] 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.

4.3 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 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).[10] 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).[11] Table A.6 in Appendix A provides details on the industry breakdown of manufacturing and services depending on their technological intensity.

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

[10] 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.

[11] The OECD classification of manufacturing industries according to their technology intensity is based both on direct R&D intensity (R&D expenditures divided by production and R&D expenditures divided by value added)and R&D embodied in intermediate and investment goods (see Hatzichronoglou, 1997). For service in-

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 4.4), 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>

4.4 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.[12] 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 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

dustries, the classification is based on skill intensity and indirect R&D measures such as technology embodied in investment or investment in ICT goods.

[12] 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.

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.[13] 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 6.3. 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-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 calculate TFP as $TFP_{it} = \ln(RLP)_{it} - \widehat{\gamma}_K \ln\left(\frac{K}{L}\right)_{it} - \widehat{\gamma}_M \ln\left(\frac{M}{L}\right)_{it} - \widehat{\gamma}_L \ln L_{it} - \sum_t \widehat{\gamma}_D D_t$.[14] 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.[15] 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.

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

[13] 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.

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

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

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.[16] 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>

5 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

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

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.

5.1 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.[17] 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 rose 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.[18] 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 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

[17] 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.

[18] 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 $k^e = k - 3$.

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>

5.2 Innovation performance distribution

While human capital intensity is consistently higher in *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>

5.3 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.[19] 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*.

[19] 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>

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.

6 Results

As a benchmark, we first present average returns to human capital and innovation in Section 6.1. Our main results are reported in Section 6.2, 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 6.3 presents the results of various robustness checks. We conclude with a discussion of the main results in Section 6.4.

6.1 Average returns to human capital and innovation

As a benchmark, we estimate average returns to human capital and innovation using Eq. (1). Tables 6 and 7 present OLS and FE results respectively. From Table 6, 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%). One potential explanation for these differential average human capital returns could be that because of the well-developed dual education system in Germany, human capital differences between low- and high-skilled employees are narrower than in the Netherlands. Table 6 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 7 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 6 and 7 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 6, it follows that average returns to process innovation are significantly negative in both countries and larger in absolute terms in services.[20] 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-technology manufacturing in *DE*.

6.2 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 6.2.1). In Section 6.2.2, we additionally account for firm-fixed effects in the quantile regressions.

6.2.1 Not accounting for firm-fixed effects

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

Table 8 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.[21] 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 dashed 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 8 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

[20] 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.

[21] 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 8 shows results for some selected quantiles.

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.

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 8 and Graph 4 about here>

The middle part of Table 8 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 rate 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 8 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 6.1. 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 9. 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 8) 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.[22]

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 left.

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 9 about here>

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

6.2.2 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. 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.[23] The only discrepancy between the main estimation sample and the restricted one is that 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.

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

Table 10 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. In general, taking into account unobserved firm heterogeneity does not exert a profound impact on the shape of human capital, process innovation and product innovation returns. In the following three paragraphs, we limit the discussion to those cases where the $FEQR$ estimates deviate significantly from the standard QR estimates.

The upper part of Table 10 and Graph 7 focus on the heterogeneous productivity effects of human capital. Contrary to the standard QR estimates, we find that accounting for firm fixed effects leads to (i) strongly increasing rates of returns to human capital as we move up through the productivity distribution in Knowledge-intensive services in *DE*, implying that the best-performing enterprises in that industry seem to enjoy the highest rates of return to human capital and (ii) positive but diminishing rates of returns to human capital in High-technology manufacturing in *NL*.

<Insert Table 10 and Graph 7 about here>

From the middle part of Table 10 and Graph 8, it follows that controlling for unobserved firm heterogeneity influences the shape of returns to product innovation in Low-technology manufacturing in *DE* and in High-technology manufacturing in *NL*. More specifically, we observe (i)

[23] Detailed OLS, FE and standard QR estimation results are provided in our Online Statistical Appendix.

hump-shaped returns to product innovation rather than an increasing effect of product innovation along quantiles in Low-technology manufacturing in *DE* and (*ii*) gradually increasing returns to product innovation in High-technology manufacturing in *NL*. Hence, the positive complementarity effect between product innovation and proximity to the frontier vanishes in Low-technology manufacturing in *DE* but shows now up in High-technology manufacturing in *NL*. Note that although we corroborate a U-shaped influence along the quantiles of the productivity distribution in all German industries, except for Low-technology manufacturing, this U-shape has become wider and the returns to product innovation have become very stable for a broader range of quantiles.

<Insert Graph 8 about here>

The lower part of Table 10 and Graph 9 show that taking into account unobserved firm heterogeneity mainly affects the shape of returns to process innovation in *DE*. Contrary to the standard QR estimates, the negative decreasing rates of returns to process innovation in Low-technology manufacturing and both service industries no longer hold. Instead, we find (*i*) negative decreasing rates of returns in Medium-technology manufacturing suggesting a negative complementarity effect between process innovation and proximity to the frontier whilst (*ii*) an increasing shape is detected in Other services. For the latter, the estimated returns are significantly negative up to the 60^{th} percentile.

<Insert Graph 9 about here>

C. Impact on industry productivity distribution

The relatively minor differences between the $FEQR$ and the standard QR estimates appear to result in relatively large differences in the impact of our main variables on the distributional characteristics of productivity in both countries (see Table 11). In *DE*, we no longer find that human capital increases the productivity dispersion and kurtosis in 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 unobserved firm heterogeneity. As a result, any significant influence on the characteristics of industry productivity distributions disappears, except for Other services. Both product and process innovation affect the dispersion and the kurtosis in Other services negatively. In *NL*, we no longer observe 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, any significant impact of process innovation on the distributional characteristics of productivity vanishes when controlling for unobserved firm heterogeneity.

<Insert Table 11 about here>

6.3 Robustness checks

To check the robustness of our results using the main estimation sample, we performed a large number of sensitivity checks.[24] The first set of robustness checks relates to our explanatory

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

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 no longer find decreasing returns to human capital in Knowledge-intensive services. 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.

6.4 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.[25] Becoming a "superstar" seems to be extremely difficult if one is already quite successful. 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.

[25] This finding is less consistent across different estimates in *DE*, though (see $FEQR$ 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.

7 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 no longer holds for Germany once unobserved firm heterogeneity is taken into account. Suggestive evidence for the Netherlands suggests an interpretation of a winner-takes-all market in knowledge-intensive services. 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.

Our analysis can be pursued in several directions, either to explain some of our findings or to examine some new developments. *First*, numerous studies have followed the Crépon *et al.* (1998) approach to investigate the interrelations between R&D, innovation, and productivity at the firm level. One natural extension of our productivity framework is to endogenize the innovation or knowledge production function following Crépon *et al.* (1998) and use an instrumental variables estimator for quantile regression in panel data with fixed effects which is consistent for small time periods (Powell, 2014). This would allow us to investigate (*i*) whether heterogeneous returns to R&D expenditures feed through in heterogeneous returns to innovation and (*ii*) the role of firm-level innovation persistence in explaining firm-level persistence in productivity. *Second*, given that our study provides evidence of large heterogeneity in the returns of human capital across countries and across industries, another potential research avenue is to exploit our rich matched employer-employee data and build on the Hellerstein *et al.* (1999) methodology to examine the divergence between productivity premiums associated with worker characteristics (such as education, age and gender) and the corresponding wage premiums. Such issues are naturally investigated within a quantile regression framework. A *final* promising direction of research is to apply the moment-based approach developed by Lochner and Shin (2014) to our production function framework to disentangle sorting effects from effects due to labor market frictions in the context of total factor productivity dispersion.

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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 $\left(PD = \ln\left(\frac{SSPD \times SALES}{L}\right)\right)$ 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

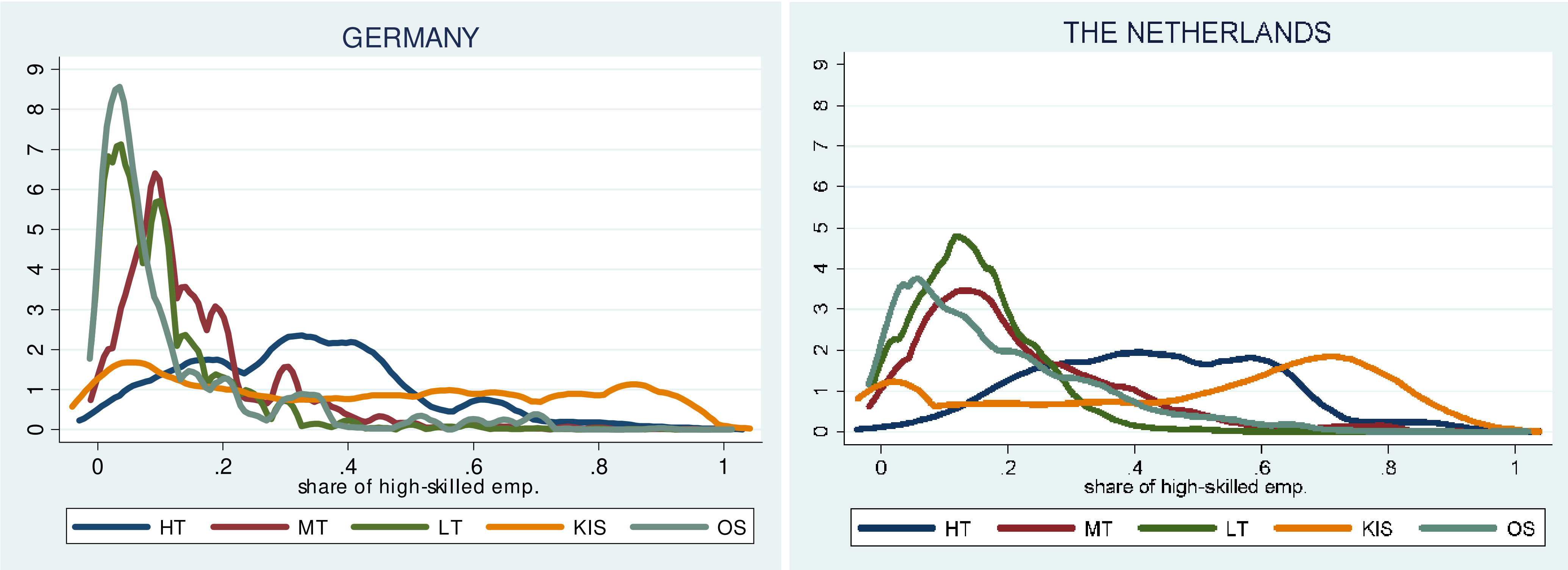
Note: Human capital is measured as the share of high-skilled employees, defined as employees having a college or university degree.

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 Euro (in constant prices of 2005).

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



Graph 2: Innovation performance distribution, by country and industry

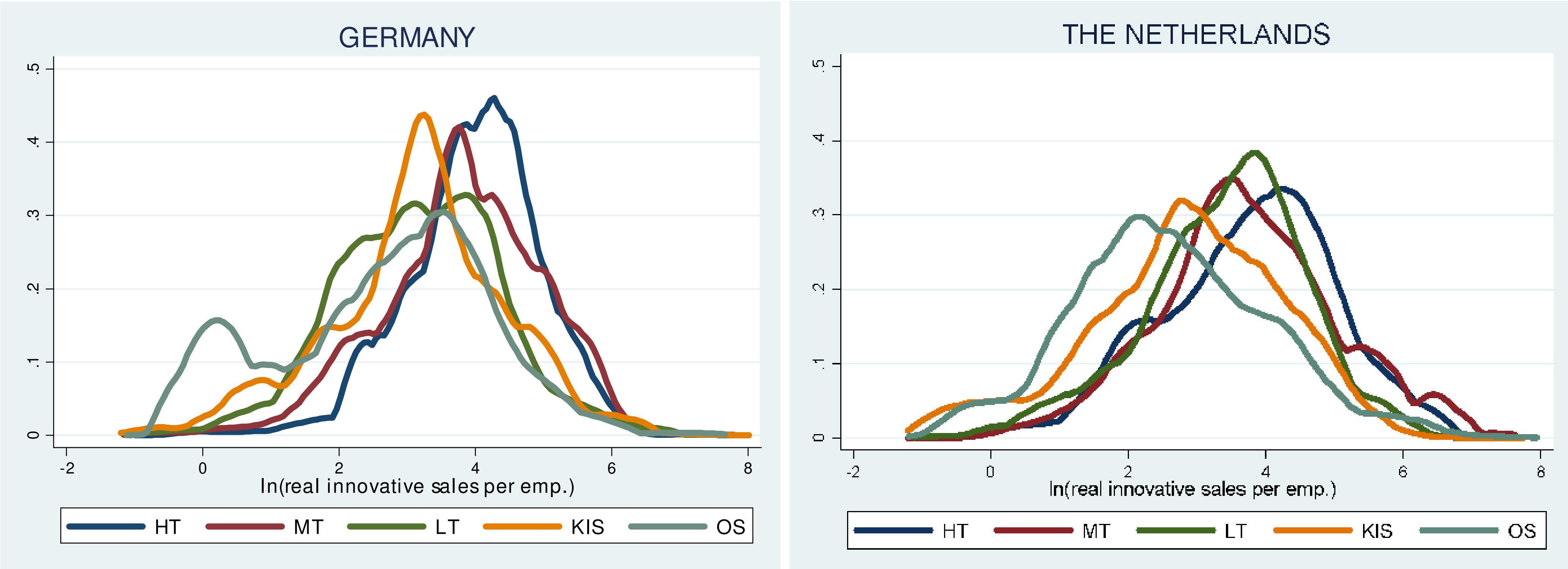


Table 5: Labor productivity distribution 2000-2008, by country and industry

		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 Euro (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.

Graph 3: Productivity distribution, by country and industry

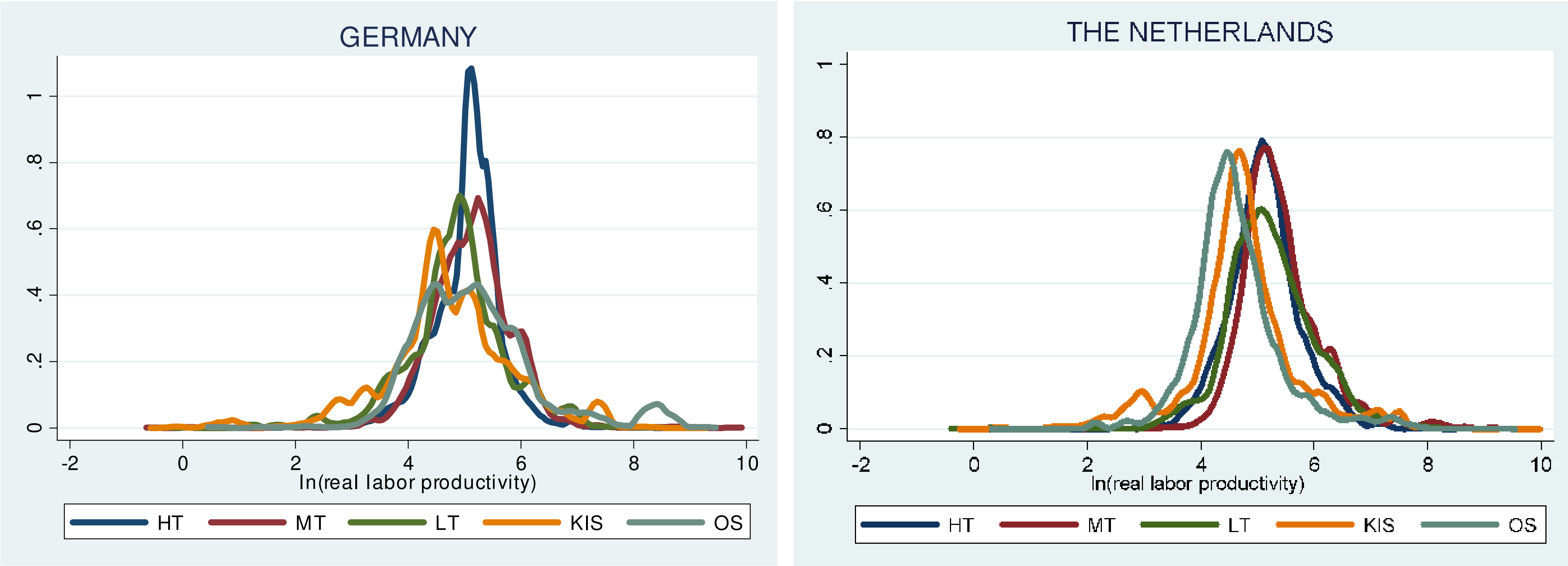


Table 6: Mean regression (OLS): Firm-level returns to human capital and innovation, by country and industry

	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 7: 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 8: Standard quantile regression (QR): Firm-level returns to human capital and innovation, by country and industry

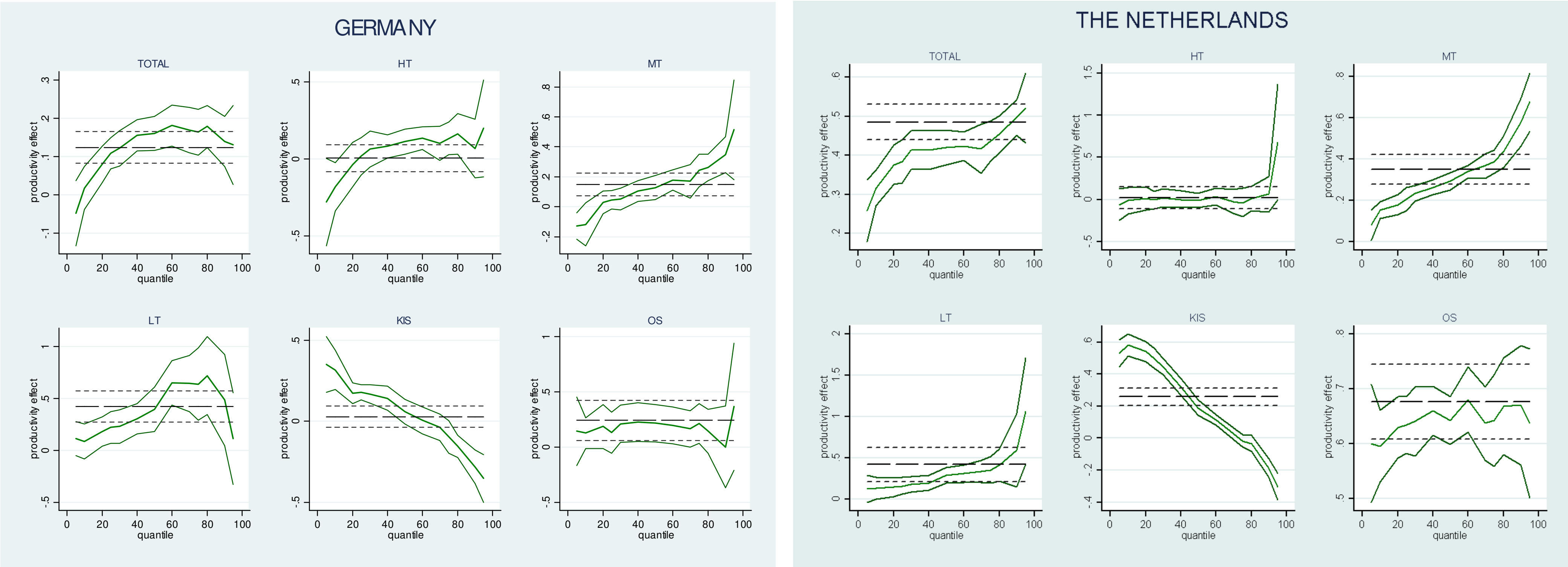
		GERMANY						**THE NETHERLANDS**					
		HT	**MT**	**LT**	**KIS**	**OS**	**TOTAL**	**HT**	**MT**	**LT**	**KIS**	**OS**	**TOTAL**
HC	q10	-0.181**	-0.117	0.087	0.318***	0.126*	0.018	-0.014	0.152***	0.131*	0.582***	0.596***	0.316***
		(0.080)	(0.073)	(0.086)	(0.062)	(0.072)	(0.029)	(0.081)	(0.021)	(0.069)	(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 8 - Continued**:** Standard 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)

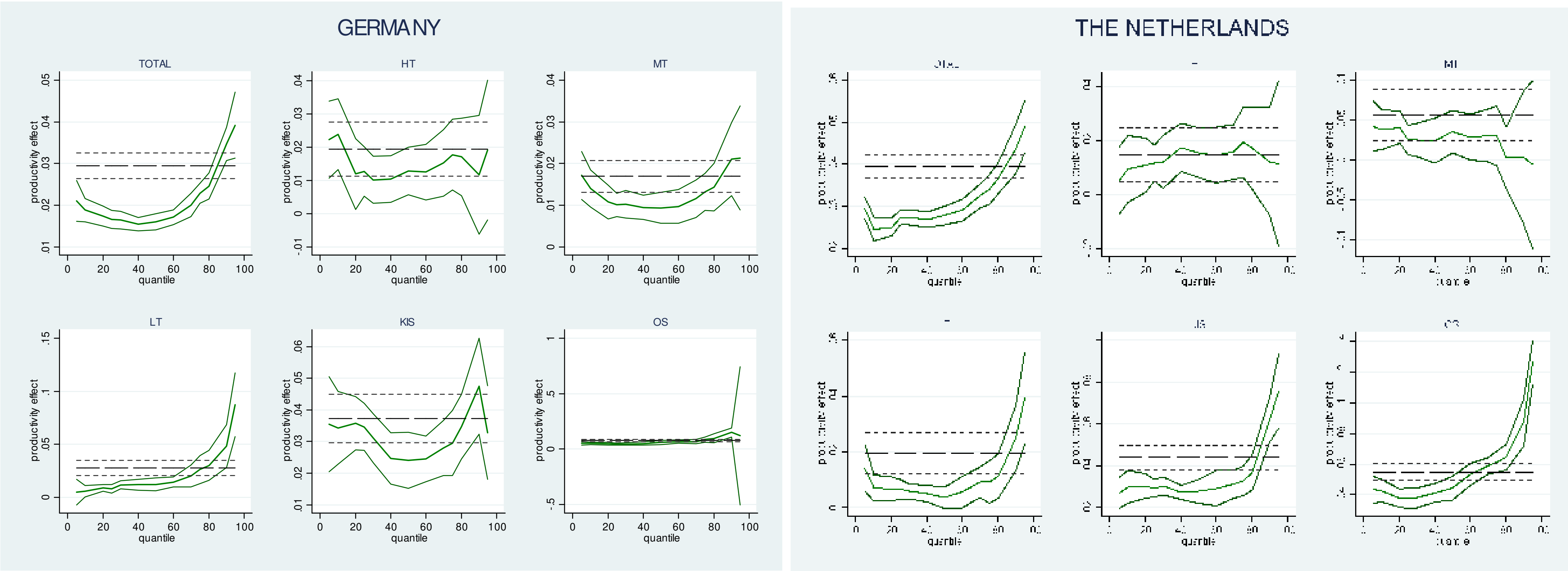
Notes: The dependent variable is ln(real labor productivity). Significance level of ***1%, **5%, *10%. Bootstrapped standard errors (20 replications).
Quantile regressions additionally include *GP*, *EAST* (for *DE*) and time dummies. Number of observations: See Table 6.
Results are based on pooled simultaneous-quantile 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.

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



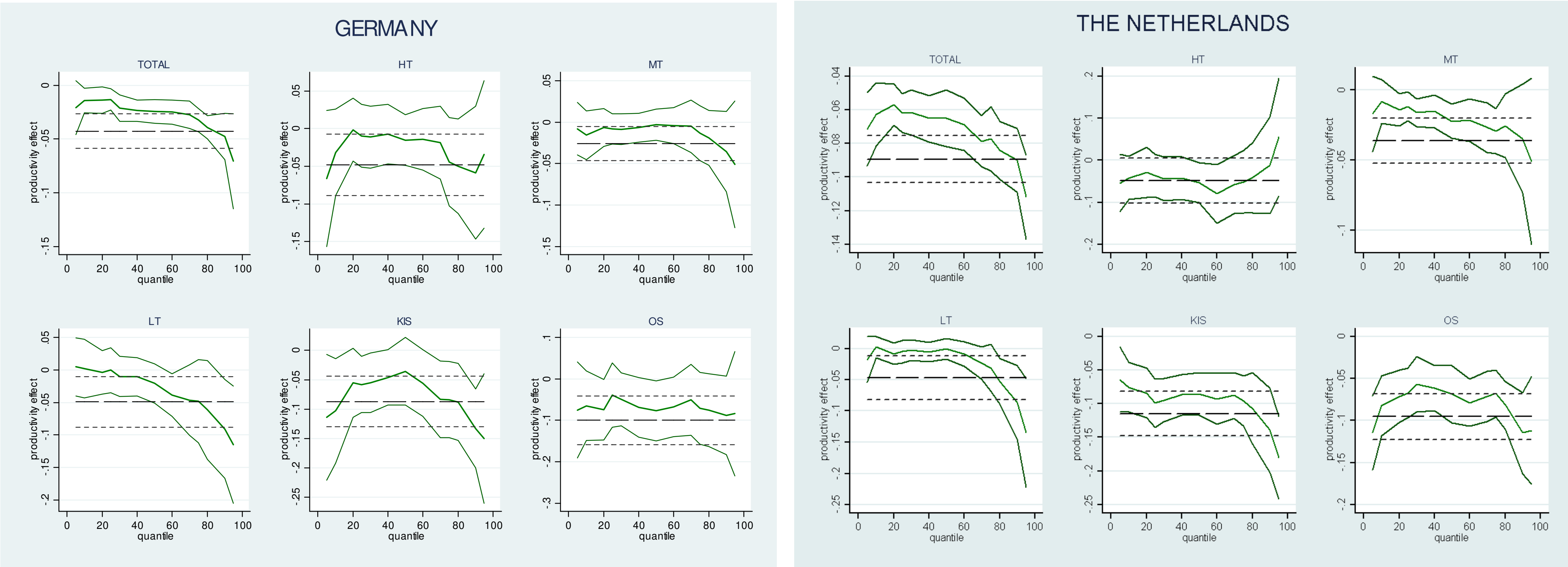
Note: Solid lines present coefficient estimates and 95% confidence intervals of quantile regressions. For comparison, dashed lines mark coefficient estimates and 95% confidence intervals of the OLS regression.

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.

Table 9: 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)

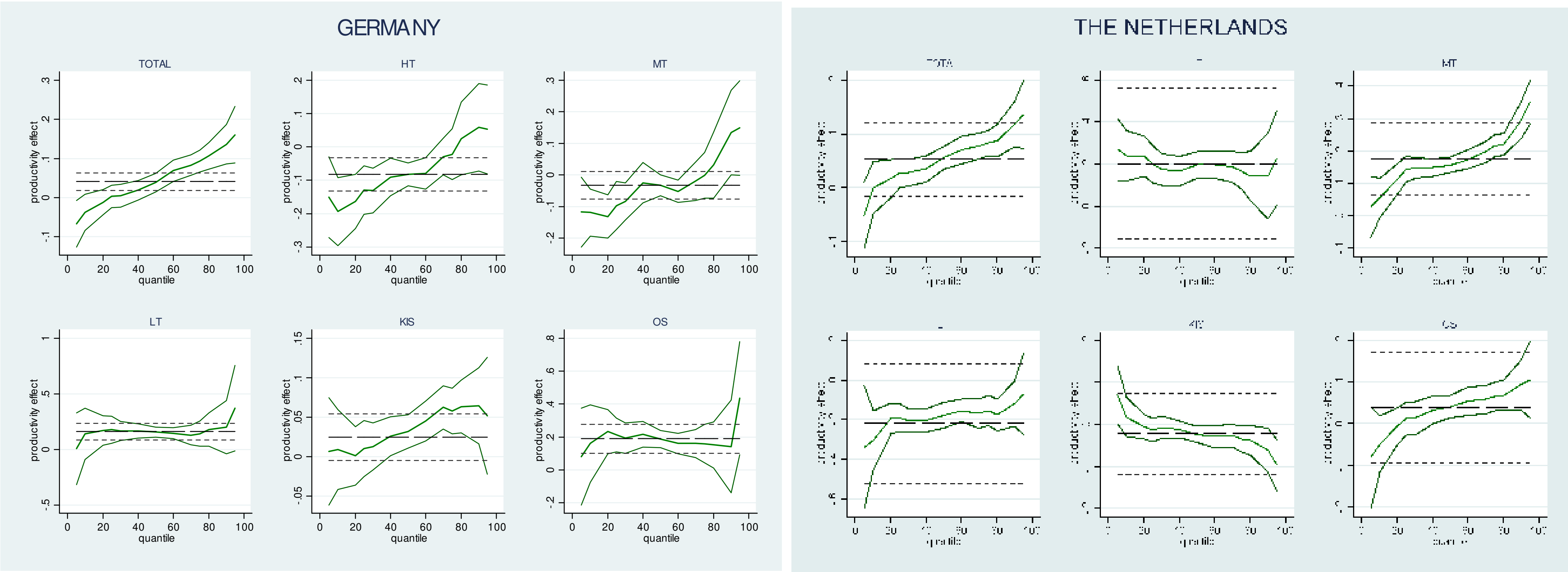
Notes: Significance level of ***1%, **5%, *10%. Tests are based on standard QR results in Table 8.

Table 10: 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)

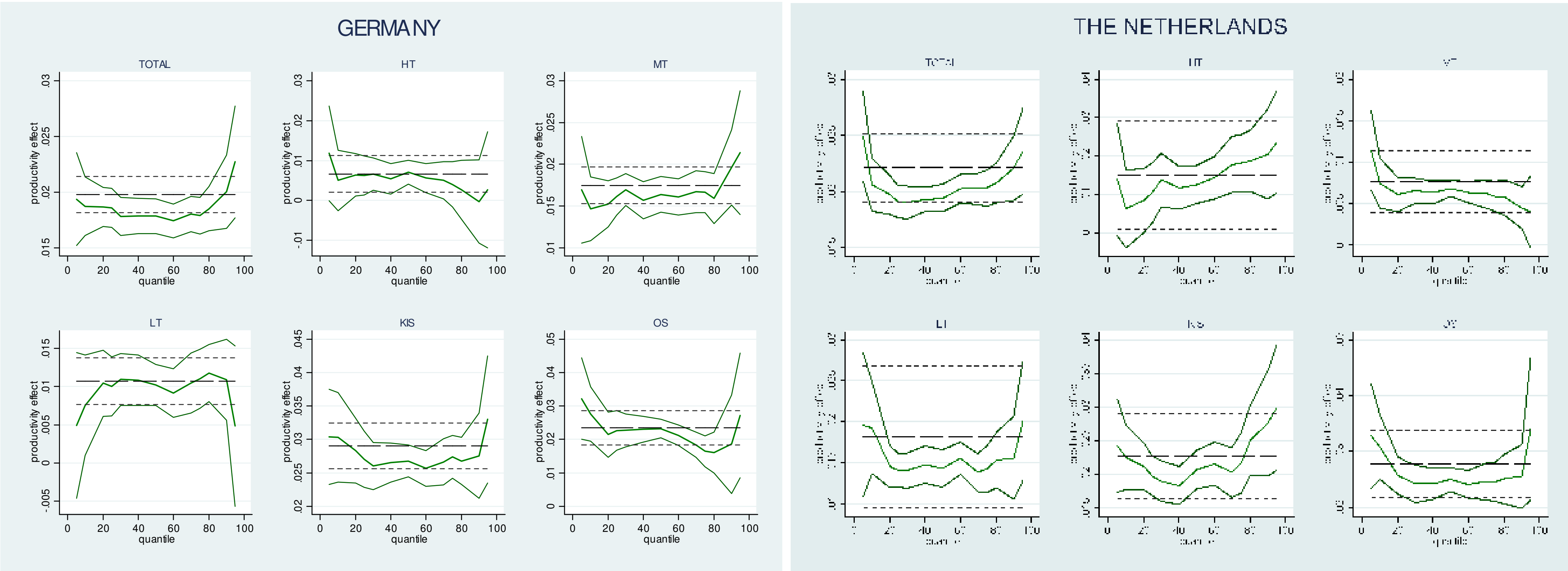
Notes: Sample: firms with 2 or more observations (DE: 8,117; NL: 15,427 observations). The dependent variable is ln(real labor productivity). Included but not reported are *SIZE*, *CAP*, *MAT*, *GP*, *EAST* (for DE), time dummies and industry dummies (only for the total sample).

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



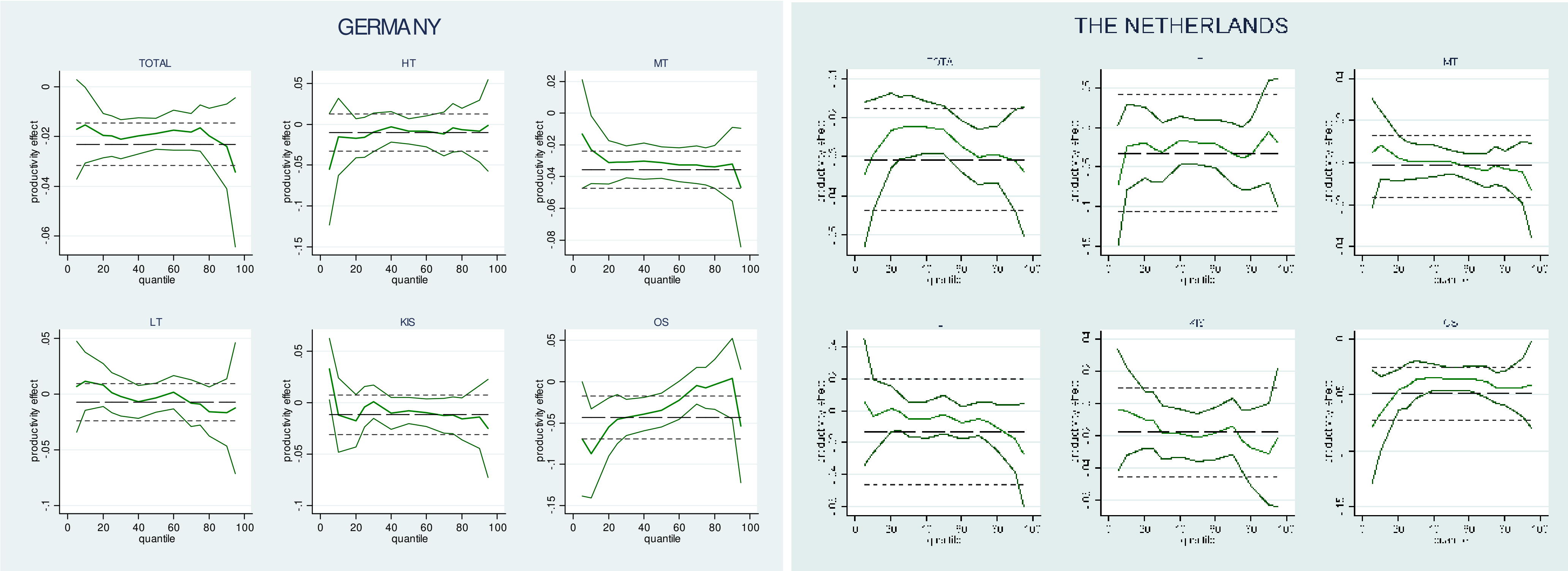
Note: Solid lines present coefficient estimates and 95% confidence intervals of quantile regressions. For comparison, dashed lines mark coefficient estimates and 95% confidence intervals of the FE regression.

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.

Table 11: 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 *FEQR* results in Table 10.

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 - WO and HBO Bachelor, WO Master	 53 60	 $5A$ $5A$	 HS HS	 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

	GERMANY				THE NETHERLANDS			
# of participation	**# 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