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Author(s):
Bolli, Thomas; Pusterla, Filippo

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Thomas Bolli and Filippo Pusterla

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KOF

ETH Zurich
KOF Swiss Economic Institute
LEE G 116
Leonhardstrasse 21
8092 Zurich, Switzerland

Phone +41 44 632 42 39
Fax +41 44 632 12 18
www.kof.ethz.ch
kof@kof.ethz.ch

Complementarities among Types of Education in Affecting Firms' Productivity*

Thomas Bolli & Filippo Pusterla‡

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Abstract

This paper uses Swiss firm-level panel data to estimate how complementarities among workers with different types of education affect firms' productivity. We subdivide workers by education into four groups: no post-secondary education, upper secondary vocational education and training (VET), tertiary professional education, and tertiary academic education. To account for possible endogeneity, we exploit within-firm variation and employ a recent structural estimation technique that uses intermediate inputs as a proxy for unobserved productivity shocks. Our results suggest that workers with an upper secondary VET education are complementary to workers with a tertiary academic education, while workers with no post-secondary education are complementary to workers with a tertiary professional education. In terms of firm characteristics, the results are surprisingly similar for low- and high-tech industries. Service industries, particularly modern ones, show both higher substitutability and higher complementarity, depending on the combination of workers. Large-size firms also show higher levels of substitutability and complementarity.

JEL-Classification: J24, L25

Keywords: complementarity, education, diversity, productivity

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‡ETH Zurich, KOF Swiss Economic Institute, Leonhardstrasse 21, 8092 Zurich, Switzerland. Corresponding address: pusterla@kof.ethz.ch

1 Introduction

Strengthening vocational education and training (VET) programs[1], is a policy issue in many OECD countries, where policymakers consider VET particularly effective in producing high labor force participation and reducing youth unemployment (OCDE, 2010). Yet despite a growing body of literature on VET, little evidence exists on the extent of complementarities among workers with VET educations and other workers in determining firms' productivity. Existing papers either focus on high- and low- educated workers or on aggregate diversity measures (e.g., Moretti, 2004; Ciccone & Peri, 2006; Parrotta et al., 2014). However, insights into the complementarities among differently educated workers are particularly important for countries in which the workforce is highly heterogeneous with respect to education (e.g., Austria, Germany, and Switzerland) and where the majority of workers have a VET education. Furthermore, given that the theoretical literature suggests two opposing effects of workforce educational diversity, learning how different types of labor interact in determining productivity is critical.

On the one hand, some researchers argue that educational diversity might increase productivity because varied bodies of knowledge can be combined to improve the processes of decision-making and problem-solving (e.g., Weitzman, 1998; Carlile, 2002; Hong & Page, 2001; Faems & Subramanian, 2013; Bolli et al., 2017; Backes-Gellner et al., 2017). Additionally, educational diversity increases firms' absorptive capacity (Cohen & Levinthal, 1989, 1990; Quintana-García & Benavides-Velasco, 2008). On the other hand, other researchers argue that diversity can generate negative effects due to interaction difficulties and poor cooperation among workers (Becker, 1957; Lazear, 1998, 1999). Moreover, educational diversity, which implies high cognitive distance between workers, can increase levels of conflict, mistrust, and misunderstanding (e.g., Joshi & Jackson, 2003).

In this paper, we embed these two opposing effects of workforce educational diversity in a framework in which the degree of complementarity follows a U-shape relationship. We argue that groups of workers having similar sets of skills show low complementarity in determining firms' productivity. Complementarity rises if the distance of workers' skills sets increases. However, when skills distance becomes too large, we expect the degree of complementarity between workers to decrease again.

[1] We use the terms "VET" and "Professional Education and Training" (PET) for education programs that prepare their students for labor market entry in specific occupations. VET refers to upper secondary education, while PET to tertiary education. "Occupation" refers to the profession for which a young person receives training and is synonymous with vocation or trade.

We extend the empirical literature beyond the applied education dichotomy by evaluating how complementarities among workers with different types of education affect firms' productivity. In our analysis, to estimate partial elasticities of substitution between types, we use panel data on Swiss firms collected by the KOF Swiss Economic Institute between 2005 and 2015. We subdivide the input factor labor into four types: "Lower" educated workers have no post-secondary education, "Trained" workers have an upper secondary VET education, "Advanced" workers have a tertiary professional education, and "Academic" workers have a tertiary academic education. Using these five types of inputs—these four plus capital—we regress them in the form of a translog production function on a measure of firm's value added.

To curb unobserved heterogeneity, we rely on within-firm variation. Moreover, as unobservable productivity shocks might affect input composition, we also employ a recent structural estimation technique suggested by Levinsohn & Petrin (2003). This approach allows researchers to use intermediate inputs as a proxy for unobserved productivity shocks. By applying this approach, we can account for possible simultaneity bias, which standard methods such as OLS and fixed-effects estimators cannot. We evaluate the effects of firms having different size and operating in different industries.

Our results suggest that Trained and Academic workers are complementary in determining firms' productivity, while Lower workers are complementary to Advanced workers. We find evidence of substitutability between Lower and Trained workers, as well as between Lower and Academic workers. Furthermore, our results suggest high substitutability between Academic and Advanced workers. In contrast, Advanced and Trained workers show only small substitutability. In terms of firm characteristics, the results are surprisingly similar for low- and high-tech industries. Service industries, particularly modern ones, show both higher substitutability and higher complementarity, depending on the combination of workers. Moreover, our estimations of elasticities show that large-size firms have higher levels of substitutability and complementarity.

The remainder of the paper is organized as follows. Section 2 reviews the literature, presents the conceptual background of the study, and derives our hypotheses. Section 3 describes the data set, and Section 4 explains our estimation strategy. Section 5 presents the results of the model estimation, and Section 6 reports our robustness checks, focusing on the role of capital in firms' production functions. Section 7 concludes.

2 Literature Review and Hypotheses

2.1 Literature Review

Most of the current literature on education complementarities considers only two types of workers: high- and low- educated (e.g., Acemoglu & Angrist, 2000; Moretti, 2004; Ciccone & Peri, 2006). However, while focusing on only two groups of workers has the advantage of reducing complexity, it provides no guidance on how multiple education types interact.

Therefore, over the last two decades a growing body of literature in personal economics (Lazear, 1998; Grund & Westergård-Nielsen, 2008; Bender et al., 2016) has stressed the necessity of looking at the labor component in a more differentiated way, because the composition of the workforce is more complex than a two-skill level system would allow. This argument is particularly true for countries in which a large part of the workforce has a VET education. High heterogeneity across education—e.g., in countries having a diffused VET system—imposes accurate evaluation on the extent of externalities among workers and, more generally, on the effects of workforce educational diversity on firms' productivity.

The majority of the studies examining the impact of workforce educational diversity on productivity and innovation performance quantify spillovers in terms of diversity index. Using Irish firm data, McGuirk & Jordan (2012) estimate the impact of educational diversity on the propensity for introducing product or process innovation. They calculate a Blau diversity index at the regional level, using six educational categories (primary school, lower secondary school, upper secondary school, tertiary non-degree, and tertiary degree or higher). Their estimations suggest that educational diversity has a positive effect on product innovation but not on process innovation. Furthermore, they find evidence that tertiary-educated workers increase firms' absorptive capacity.

Parrotta et al. (2014) analyze the effect of educational diversity on firms' performance. Using a Danish matched employer-employee data set, they calculate a firm-level Herfindhal diversity index, which covers both horizontal educational diversity (i.e., field of study) and vertical educational diversity (i.e., level of education). Their findings on the impact of labor diversity on productivity are mixed, depending on the estimation procedure. Likewise using a Danish linked employer-employee data set, Østergaard et al. (2011) measure horizontal educational diversity at the tertiary level, finding that it improves a firm's innovative capabilities. This effect, however, decreases for higher levels of horizontal diversity.

Finally, Bolli et al. (2017) focus on the effect of educational diversity across the innovation value chain. Using Swiss firm-level panel data, they also develop a Herfindahl index based on four categories of educational degrees. They find that vertical education diversity improves the extensive margin of R&D and product innovation, while it has almost no significant effect on process innovation, R&D intensity, or product innovation intensity. They argue that educational diversity creates a trade-off for firms. On the one hand, diversity increases a firm's ability to explore new knowledge or develop new products; on the other hand, diversity negatively affects the commercialization of R&D and innovative activities.

While the larger part of the existing literature on workforce diversity aggregate education groups in a diversity indexes, only few studies focus on the spillovers between single groups. Among these studies, Wirz (2008) is one of the first who consider human capital spillovers of VET at firm level. She estimates the impact of co-workers' education on individual wages. The results evidence higher educational spillovers for workers with VET or academic education than for workers with low education levels. These findings suggest that, within occupation, workers become more productive when working with workers having higher education. Furthermore, the higher the education level of workers, the larger the gain in productivity. Wirz (2008) hypothesizes that this productivity gain may be due to the higher learning capacities of highly educated workers.

Noteworthy is the contribution of Backes-Gellner et al. (2017), who find evidence of positive spillovers from VET-educated workers on higher educated workers. Using a Swiss employer-employee data set, they show that an increase in the number of workers with an upper secondary VET degree increases—but with a diminishing effect—the wages of tertiary-educated workers, which can be interpreted as a measure of labor productivity.

Finally, Arvanitis et al. (2010) use Swiss data to analyze the contributions of workers from different education groups—including those with VET educations—on labor productivity. Although their study is not primarily focused on educational spillovers, the results of their quantile regressions reveal large sector-specific differences in the contribution of VET between high-productivity and low-productivity firms. The positive and significant effect detected at the industry level may be explained by differences in the distribution of high-productivity firms across industries. Their findings emphasize the importance of considering heterogeneity across firms.

2.2 Theoretical Background

Productivity refers to firms' ability to obtain outputs by optimally combining inputs. Labor, a factor that is highly heterogeneous with respect to education, is one of the main inputs in firms' production functions. However, the literature on workforce diversity suggests two opposing effects of the interaction among workers with different education.

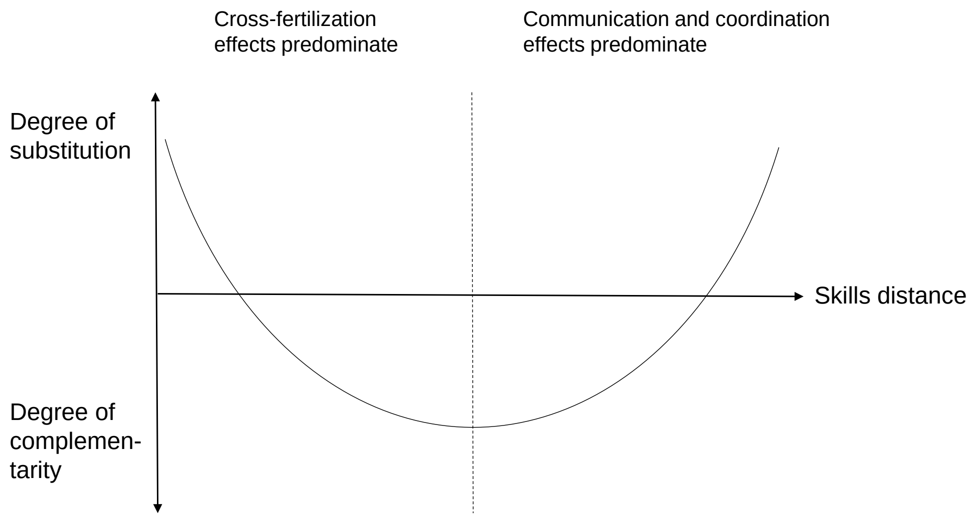
On the one hand, spillovers across workers depend on the variety of knowledge that the workers provide (Jovanovic & Rob, 1989). Thus educational diversity might increase productivity performance because the combination of various bodies of knowledge can improve the processes of decision-making and problem-solving (e.g., Weitzman, 1998; Carlile, 2002; Hong & Page, 2001; Faems & Subramanian, 2013; Bolli et al., 2017; Backes-Gellner et al., 2017). Educational diversity also increases absorptive capacity, making it easier for firms to identify valuable knowledge coming from the research activities of other firms and institutions, including promising new ideas and technologies (Cohen & Levinthal, 1989, 1990; Quintana-García & Benavides-Velasco, 2008).

On the other hand, diversity can generate negative effects resulting from interaction difficulties and poor cooperation between workers (Becker, 1957; Lazear, 1998, 1999). Furthermore, social identity theory suggests that educational diversity can also increase levels of conflict, mistrust, and misunderstanding, due to high cognitive distance between workers (e.g., Joshi & Jackson, 2003). Moreover, educational diversity might increase communication costs (Wittenbaum & Stasser, 1996; Stasser & Titus, 1985; Dahlin et al., 2005). In sum, given that firms face a trade-off between the benefits and the costs of educational diversity, theoretical predictions on the effect of educational diversity effect on firm outcomes remain ambiguous.

2.3 Hypotheses

Thus far, the literature on educational diversity shows two opposing effects on productivity. When educational diversity increases productivity—because a variety of skills can contribute to the processes of decision-making and problem-solving, and because such diversity increases firms' absorptive capacity—we call this effect the "cross-fertilization effect". But when educational diversity creates interaction difficulties, increases the levels of conflict and mistrust, and generally increases communication costs, we call these effects the "communication and coordination effects".

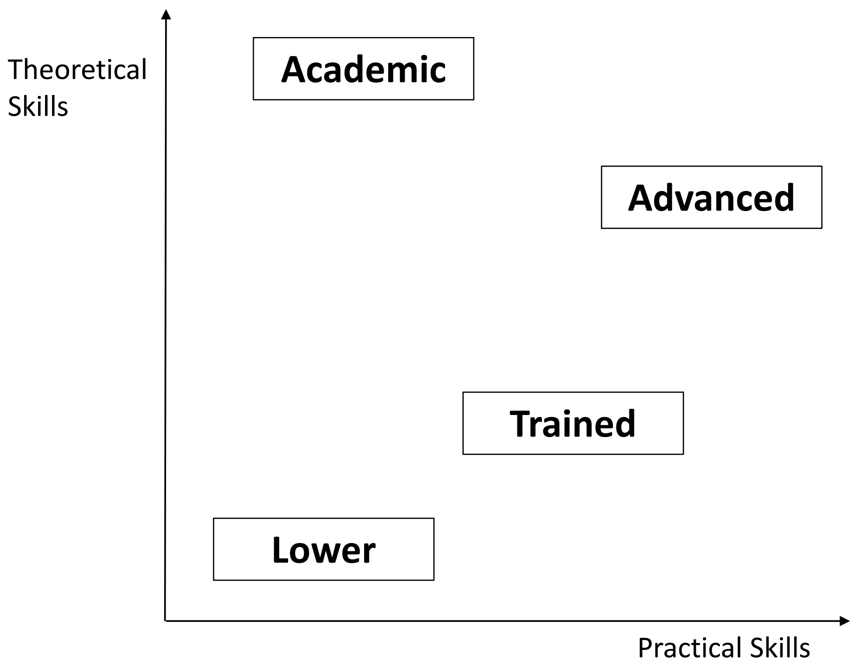
Figure 1: Stylized representation of skills distance and degree of complementarity



While the literature shows mixed findings on which effect predominates, we argue that the net effect depends on the skills distance between workers. Our hypothesis is that the two opposing effects create a U-shaped relationship between workers' skills distance and the degree of complementarity. We hypothesize that substitutability is high when workers' skills sets are similar. As workers' skills distance increases, substitutability decreases—and thus complementarity increases. In such a case, the cross-fertilization gains predominate over the communication and coordination costs. However, when the skills distance becomes too large, we observe a decrease in the degree of complementarity between workers—and thus an increase in substitutability. From a certain level of skills distance, the communication and coordination costs offset the cross-fertilization benefits by increasing skills distance. Figure 1 illustrates this U-shaped pattern in stylized symmetrical form (even though the U-shape isn't necessarily symmetrical). The figure shows which of the two opposing effects might predominate with respect to different skills distances.

To develop our hypotheses about the skills distance between workers, we focus on the main types of education (in the Swiss educational system) that appear in the Swiss labor market. Specifically, we classify workers along two broad generic dimensions: their degree of theoretical skills (e.g., cognitive skills, transferable skills) and their degree of practical skills (e.g., occupation-specific skills, soft skills). Figure 2 illustrates the hypothetical location of the groups along these two dimensions.

Figure 2: Illustration of the skills distance

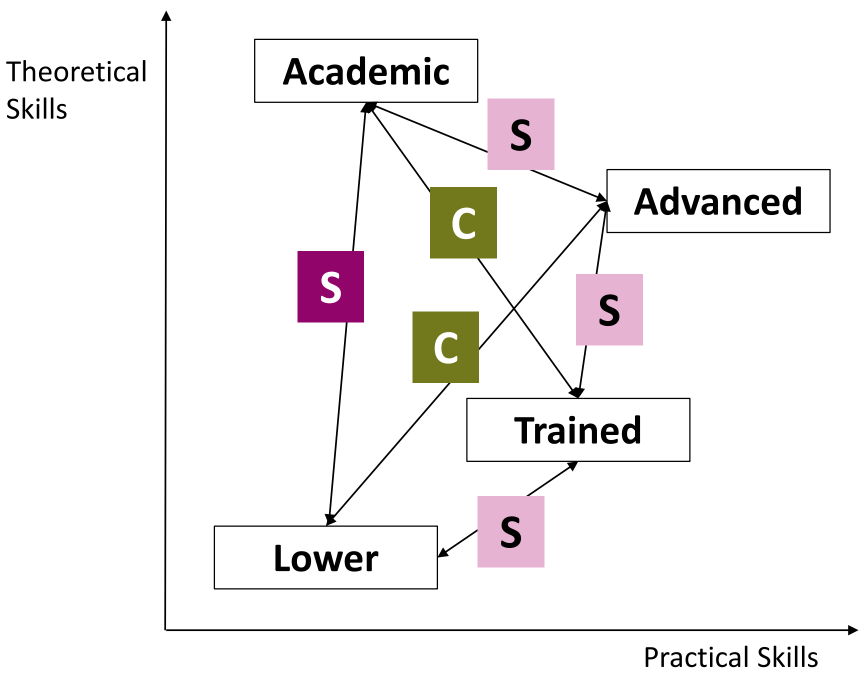


The first group of workers, Lower educated workers, have no post-secondary education. They have relatively low theoretical skills and poor practical skills. The second group of workers, Trained workers, have an upper secondary vocational education and training (VET) that provides them with a mix of practical skills and theoretical skills. The third group, Advanced workers, have a tertiary-level professional education. In comparison to the Trained workers, Advanced workers have substantially more theoretical skills, along with some more developed practical skills. The fourth group, Academic workers, have a tertiary academic education. While they have very a high level of theoretical skills, their set of practical skills is relatively limited.

From the U-shaped relationship between workers' skill distance and the degree of complementarity, we formulate our hypotheses on the complementarities between the four types of differently educated workers.

Figure 3 summarizes our hypotheses on the complementarity or substitutability of workers in the four educational groups. In making these hypotheses, we assume that other factors that might influence the level of practical or theoretical skills (e.g., on-the-job experience) hold constant.

Figure 3: Hypotheses on complementarities (C) and substitutability (S) between workers with different types of education in determining firms' productivity



We start by examining the relationship between Lower and Trained workers. According to our framework, the skills distance between these two groups is relatively small. We therefore hypothesize that firms can relatively easily substitute Lower workers and Trained workers.

H1a: Lower and Trained workers are substitutes in affecting firms' productivity.

In the relationship between Lower and Advanced workers, the skills distance is clearly larger than the one between Lower and Trained workers. This greater distance is likely sufficiently large that firms can profit from the different knowledge that Lower and Advanced workers bring to the firm. Therefore, we hypothesize that these two groups are complementary in affecting firms' productivity.

H1b: Lower and Advanced workers are complementary in affecting firms' productivity.

Our distance framework also suggests that the skills distance between Lower and Academic workers is the greatest. We therefore expect that the negative effects dominate the net effect of workforce diversity. In other words, we assume that the coordination and communication costs between these two groups might offset the gains from different knowledge and increased absorptive capacity. We thus expect substitutability between these two groups of workers.

H1c: Lower and Academic workers are substitutes in affecting firms' productivity.

Trained and Advanced workers, despite their different levels of vocational education, have very strong practical skills. They differ principally in term of theoretical skills that are larger in the case of Advanced. Altogether, given the relatively small skills distance, our hypothesis is that firms can substitute these two groups of workers.

H1d: Trained and Advanced workers are substitutes in affecting firms' productivity.

The skills distance between Trained and Academic workers is clearly larger than that between Trained and Advanced workers. However, we expect that, for Trained workers, the skills distance to Academic workers is not as great as the distance between Lower and Academic workers (a distance so great that the communication and coordination effects predominate). Trained and Academic workers are therefore sufficiently distant from one another to gain from diversity but not too distant to suffer from the communication and coordination effects. We therefore expect that Trained and Academic workers will profit from working together and hypothesize a complementary relationship.

H1e: Trained and Academic workers are complementary in affecting firms' productivity.

Finally, Advanced and Academic workers share a relatively similar set of skills. Both have tertiary educations, albeit of different kinds, with Advanced workers clearly having more practical skills and Academic workers more theoretical skills. Nevertheless, we expect the skills distance between them to not be very great. We therefore hypothesize that Advanced and Academic workers are substitutes.

H1f: Advanced and Academic workers are substitutes in affecting firms' productivity.

As for the industry of activity, the theoretical literature suggests a more positive effect of workforce diversity in firms operating in more creative industries (e.g., Lazear, 1998; Hong & Page, 2001; Alesina & La Ferrara, 2002; Garnero et al., 2014). We therefore expect to find larger complementarities in firms operating in a high-tech manufacturing industry or a modern services industry, rather than in low-tech manufacturing or traditional service industries.

H2: Complementarities among workers are greater in creative industries than in more traditional ones.

For firm size, the literature suggests that educational diversity might affect productivity in a more pronounced way in small firms, where coworkers interact more frequently (e.g., Stahl et al., 2010). In contrast, in large-size firms we expect diversity to trigger productivity in a less pronounced way, because workers are more likely to be subdivided into teams or departments and to interact more with workers having similar educations and sets of skills. We thus hypothesize complementarity to be greater, or substitution to be smaller, in small-size firms than in medium or large ones.

H3: Complementarities among workers are greater in small-size firms than in medium and large ones.

3 Data and description of variables

The panel data we employ stems from the innovation surveys conducted by the KOF Swiss Economics Institute in 2005, 2008, 2011, 2013, and 2015. For our robustness checks, we also consider the waves from 1996, 1999, and 2002. This paper-based survey[2], which closely resembles the EU Community Innovation Survey, contains information on 1,500-2,500 firms in each wave. The response rates are 32.5% (1996), 33.8% (1999), 39.6% (2002), 38.7% (2005), 36.1% (2008), 35.9% (2011), 32.7% (2013), and 30.0% (2015). The surveys are based on stratified random samples drawn from the Swiss business census for firms with more than five employees. Stratification is on 33 industries and within each industry on three firm-size classes.

3.1 Variable description and summary statistics

The survey comprises basic firm characteristics such as workforce composition, gross revenues, investment activities, and purchasing costs. Unfortunately, the survey does not contain direct information on each firm's capital. Therefore, drawing on the information on the level of investments, we use the perpetual inventory approach to approximate capital stock.

Table 1 presents descriptive information about our dependent, independent, and instrumental variables. To estimate each firm's production function, we need data about the firm's value-added and on the values of capital stock and labor inputs.

[2] Questionnaires of the survey are available at `https://www.kof.ethz.ch/en/surveys/structural-surveys/kof-innovation-survey.html` in French, German, and Italian.

Table 1: Variables description and summary statistics

Variable	Description	Obs	Mean	St. Dev.	Min	Max
Dependent Variable						
Value added*	Total value added	7701	5.26e+07	3.74e+08	42298.6	1.76e+10
Independent Variables						
Capital*	Total capital stock of the firm	7701	7.64e+08	2.59e+10	200.0	1.12e+12
Lower*	Total number of untrained employees and dual VET students in a firm	7701	57.0	285.3	0.0	12536.7
Trained*	Total number of employees in a firm with an upper secondary VET education	7701	109.4	721.7	0.0	27130.5
Advanced*	Total number of employees in a firm with a professional tertiary education (incl. university of applied sciences)	7701	35.9	219.6	0.0	11738.7
Academic*	Total number of employees in a firm with a conventional university (academic) tertiary education	7701	19.0	115.8	0.0	4770.0
Instrumental Variable						
Intermediary goods*	Purchasing costs for intermediary inputs in a firm	7701	6.27e+07	5.48e+08	10320.5	3.28e+10

Notes: * This variable enters in log.

Information about workforce composition is available for all firms in our data set for all waves from 1996 to 2015. In our specification, we consider the four types of worker educations categories previously discussed: Lower workers with no post-secondary education (including dual VET students), Trained workers with an upper secondary vocational education, Advanced workers with a professional tertiary education (including university of applied sciences), and Academics workers with a tertiary academic education.

We derive capital stock using the perpetual inventory approach. As survey waves before 2005 did not contain information on investments, information on capital stock is only available from 2005. Therefore, including capital in our econometric model reduces the panel data to 2005-2015. For this restricted period, we end up with 7,701 observations having information for all variables considered in our econometric model. Section 6 presents robustness estimations that use the entire time series (with 13,366 observations) but omit capital as an input factor.

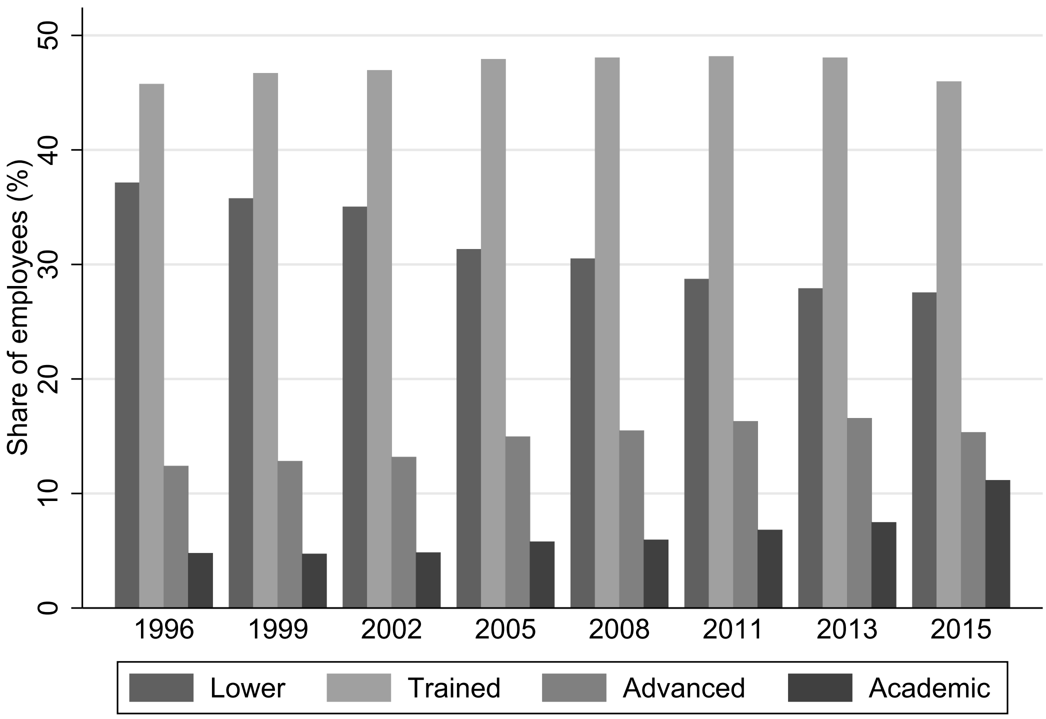
Table 1 reports, in the last row, the summary statistics of firms' purchasing costs of intermediary goods. This variable—albeit not directly part of the firm's production function—is crucial for the identification strategy we present in Section 4.1.

3.2 Descriptive information on workforce composition

This section presents the evolution of the workforce composition. We show the evolution of the entire time series, 1996-2015, even though we use the period 1996 to 2002 only in our robustness analyses.

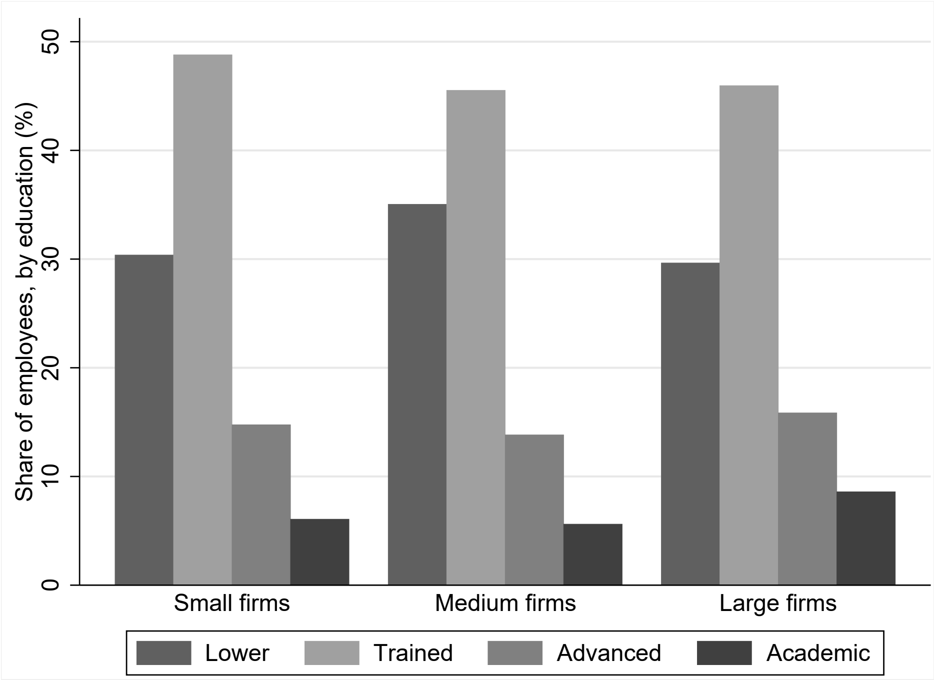
Figure 4 presents the evolution of workers' education types as a percentage of total employment. From this histogram, we can observe in aggregate that the percentage of Trained workers is the largest in the workforce, and that this percentage has remained almost constant at a value of 45% over the last two decades. In contrast, the percentage of Lower workers has clearly declined over time. Nevertheless, in 2015 this group was still the second largest, with a percentage of roughly 27% of the workforce. Advanced workers show a slightly positive trend, with about 15% of the workforce. Although Academics are the smallest group, they show the largest relative increase over time, with about 10% of the workforce in 2015. However, the definition of educational groups in wave 2015 differed from that in the earlier surveys. In the 2015 questionnaire, the definition of *academic workers* was extended to include graduates of a university of applied sciences (UAS), whereas the earlier questionnaires put graduates of a UAS in the group of Advanced workers. Therefore, the sharp increase of the percentage of Academic workers and

Figure 4: Workforce composition over time



Notes: The share of the four education groups sum up to 100% in every year.

Figure 5: Workforce composition by firm size



Notes: **Small**-size firms have <50 employees; **Medium**-size firms between 50 and 249; **Large**-size firms have >250 employees. For every firm size the share of the four education groups sum up to 100%.

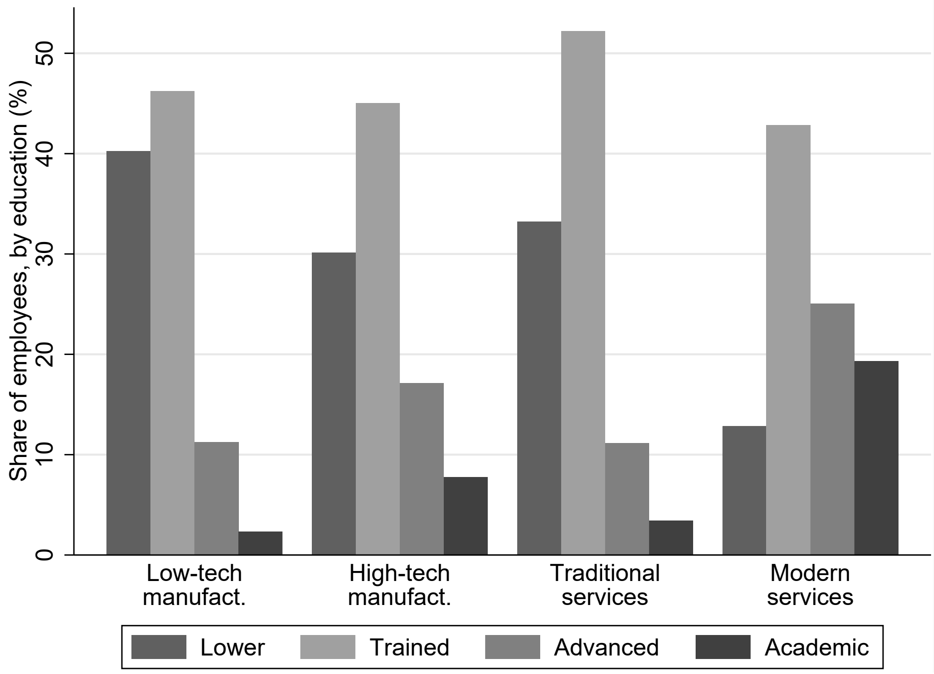
the decrease of the percentage of Advanced workers in 2015 is (at least partially) attributable to this change of definition. Nevertheless, this change of definition has no substantial effects on the results of our estimations[3].

The workforce composition differs substantially across sub-groups of firms. Figure 5 shows the subdivision of the education groups by firm size. Noteworthy are the differences in the share of Lower workers, who tend to predominate in medium-size firms. Trained workers in all sub-samples constitute the largest education group in the workforce, between 45% and 50%. Advanced workers are almost equally distributed in all firms, regardless of their size. Finally, Academic workers are proportionally overrepresented in large-size firms.

However, as Figure 6 shows, the largest differences in the workforce composition are by industry. A comparison of the first two sub-plots for example reveals large differences between low-tech and high-tech manufacturing. Low-tech manufacturing employs disproportionately more Lower workers; high-tech manufacturing, considerably more Academic and Advanced workers. The split between traditional and modern service industries also shows large differences. Academic and Advanced workers disproportionately appear in firms operating in modern services, while Trained and Lower workers largely dominate traditional services.

[3]Robustness analyses excluding the 2015 wave show qualitatively consistent results.

Figure 6: Workforce composition by industry



Notes: industries are grouped as in Arvanitis et al. (2017) according to NOGA 08 classification: **Low-tech manufacturing** comprehends following industries: Food/Beverages/Tobacco (10/11/12), Textiles/Clothing (13/14/15), Wood (16), Paper (17), Printing (18), Rubber/Plastics (22), Non-metallic Minerals (23), Basic Metals (24), Fabricated Metals (25), Repair/Installation (33), Other Manufacturing (31/321/322/323/324/329), Energy (35), Water/Environment (36/37/38/39), Construction (41/42/43); **High-tech manufacturing** comprehends following industries: Chemicals (19/20), Pharmaceuticals (21), Electronic and Optical Products (261/262/263/264/2651/266/267/268), Watches/Clocks (2652), Electrical Equipment (27), Machinery & Equipment (28), Vehicles (29/30), Medical Instruments (325). **Traditional services** comprehend following industries: Wholesale Trade (45/46), Retail Trade (47/95), Accommodation/Restaurants (55/56), Transportation (49/50/51/52/79), Real Estate, Rental & Leasing (68/77/81), Personal Services (96). **Modern services** comprehend following industries: Telecommunications (53/61), Publishing/Media (58/59/60), Information Technology & Services (62/63), Banks & Insurance (64/65/66), Technical Commercial Services (71/72), Other Commercial Services (69/70/73/74/78/80/82). For every group of industries the four share of workers' type of education sum up to 100%.

4 Empirical strategy

4.1 Translog production function

To assess complementarities among different labor inputs, we use quantitative regression analysis. We follow the interaction approach (Ennen & Richter, 2010) and estimate translog production functions that allow us to identify complementarities among inputs (e.g., Berndt & Christensen, 1973). Specifically, we identify the determinants of productivity by including a measure of firms' capital stock and the number of workers with different types of education. Each educational group of workers enters the estimation three times: in a linear form, in a quadratic form, and in an interaction form with the other labor inputs. Quadratic terms allow us to capture economies of scale, while the interaction terms allow us to capture the relationship among workers with different types of education.

As previously reported in Table 1, all four groups have a minimum value of 0, meaning that no group of workers is employed in all firms with at least one unit. Because all variables enter in the estimations in logs, we add one to all variables before taking logarithms. By doing so, we avoid to generate variables with negative values.

OLS estimations of translog production function might suffer from possible bias due to time-invariant unobserved heterogeneity or from simultaneity (short-run endogeneity of firms' education-mix composition). While fixed effect (FE) estimations can solve time-invariant unobserved heterogeneity, simultaneity remains unsolved by standard estimation procedures. Because the size of firms' productivity shocks changes over time, FE estimations are not able to solve the simultaneity between input usage and unobserved productivity shock. Thus, both OLS and FE estimators would provide inconsistent estimates of the translog production function parameters.

To overcome this endogeneity issue, we use the control function approach, which represents a valid alternative for productivity estimations. Building on the influential work of Olley & Pakes (1996), who consider investment level in a two-stage procedure, Levinsohn & Petrin (2003) suggest using intermediate inputs (e.g., materials) as a proxy for the unobservable productivity shocks.

We follow the Levinsohn & Petrin (2003) approach—hereafter, LP—and redefine the production function as:

$$v_{it} = \alpha + \beta_k \; K_{it} + \sum_{p=1}^{4} \; \beta_{l,p} \; L_{p,it} + \frac{1}{2} \; \sum_{p=1}^{4} \; \sum_{q=1}^{4} \; \beta_{l,pq} \; L_{p,it} \; L_{q,it} + \beta_m M_{it} + \gamma_i + \mu_t + \omega_{it} + \eta_{it} \tag{1}$$

where v_{it} is the log of value added of firm i at time t. K_{it} is the log of capital stock, while $L_{p,it}$ denotes the log of the number of workers with education p. M_{it} represents the log of intermediate inputs. γ_i and μ_t introduce firm and time fixed effects, respectively. The error term has two components: ω_{it} is the productivity component which is potentially endogenous, η_{it} is the part of error term that is uncorrelated to the inputs.

The demand for intermediate inputs M_{it}=$m(\omega_{it}, K_{it})$ depends on firms' capital K_{it} and the unexpected productivity shock ω_{it}. Under the assumption that the demand function is monotonically increasing in ω_{it}, we can invert it and express the unobservable productivity shock as a function of the two observed inputs, i.e. ω_{it}=$h(K_{it}, M_{it})$

We can now rearrange the production function in the following way:

$$v_{it} = \sum_{p=1}^{4} \beta_{l,p} \; L_{p,it} + \frac{1}{2} \sum_{p=1}^{4} \sum_{q=1}^{4} \beta_{l,pq} \; L_{p,it} \; L_{q,it} + \phi_{it}(K_{it}, M_{it}) + \gamma_i + \mu_t + \eta_{it} \tag{2}$$

where

$$\phi_{it}(K_{it}, M_{it}) = \alpha + \beta_k K_{it} + h(K_{it}, M_{it})$$

As Levinsohn & Petrin (2003) suggest, using a third-order polynomial approximation of K_{it} and M_{it} in place of $h(K_{it}, M_{it})$ allows us to estimate in the first stage the following equation:

$$v_{it} = \delta_0 + \sum_{p=1}^{4} \beta_{l,p} \; L_{p,it} + \frac{1}{2} \sum_{p=1}^{4} \sum_{q=1}^{4} \beta_{l,pq} \; L_{p,it} \; L_{q,it} + \sum_{j=0}^{3} \sum_{k=0}^{3-j} \delta_{jk} K_{it}^{j} M_{it}^{k} + \gamma_i + \mu_t + \eta_{it} \tag{3}$$

This first stage gives us estimates of $\widehat{\beta_{l,p}}$ and $\widehat{\phi_{it}}$. By using the predicted value for $\widehat{\phi_{it}}$, we are now able to compute for any candidate value β_k^* a prediction of $h(K_{it}, M_{it})$ for all periods t: $\widehat{h_{it}} = \widehat{\phi_{it}} - \beta_k^* K_{it}$ and use it to predict a consistent approximation of $E[h_t|h_{t-1}]$:

$$\widehat{h_{it}} = E[h_t|h_{t-1}] = \gamma_0 + \gamma_1 h_{t-1} + \gamma_2 h_{t-1}^2 + \gamma_3 h_{t-1}^3 + \psi it$$

Finally, the estimate of $\hat{\beta}_k$ is defined as the solution of:

$$\min_{\beta_k^*} \sum_t (v_{it} - \sum_{p=1}^{4} \widehat{\beta_{l,p}} \; L_{p,it} + \frac{1}{2} \sum_{p=1}^{4} \sum_{q=1}^{4} \widehat{\beta_{l,pq}} \; L_{p,it} \; L_{q,it} - \beta_k^* K_{it} - E[\widehat{h_t|h_{t-1}}])^2 \tag{4}$$

We construct standard errors for $\hat{\beta}_l$ and $\hat{\beta}_k$ by using a bootstrapping approach with 100 repetitions.

We conduct all estimations of the translog production function with STATA (Version 15). We calculate LP procedure from the *prodest* command developed by Mollisi & Rovigatti (2017). We demean all dependent variables at (sub-)sample mean. According to Cohen et al. (2013), demeaning predictors have interpretational advantages and eliminate non-essential multicollinearity. Furthermore, as a robustness test, we combine the LP approach with FE to better account for time-invariant unobserved heterogeneity.

Importantly, capital enters in equation 1 only with a linear term. It is not interacted with the labor inputs. In our baseline model, we therefore assume perfect substitutability across labor types and capital. In Section 6 we relax this assumption and interact capital with all labor inputs.

4.2 Allen Elasticities of Substitution

Once we have coefficients for the linear, quadratic, and interaction terms, we can estimate elasticities of substitution. Starting with the definition of Allen et al. (1938), we follow Henningsen (2018) and calculate for every firm the Allen elasticity of substitution (AES) between pth and qth labor inputs quantity (L_p,L_q) in the following way:

$$AES_{p,q} = \frac{\sum_p f_p L_p}{L_p L_q} \frac{F_{pq}}{F} \tag{5}$$

where f_p is the partial derivatives of the production function f, F is the determinant of the bordered Hessian matrix, and F_{pq} is the cofactor of f_{pq}. Inputs p and q are considered substitutes if $AES_{p,q} > 0$, while they are complements if $AES_{p,q} < 0$.

AES, which is symmetric, is a measure of the substitutability between inputs. Specifically, AES measures the changes in the marginal rate of technical substitution between input p and input q. As marginal rates of technical substitution are meaningless if the monotonicity condition is not satisfied, the interpretation of AES is meaningful only for observations that satisfy monotonicity. Furthermore, to give AES an economic interpretation, we consider only firms for which the quasi-concavity condition is satisfied. Together with the assumption of monotonicity, quasi-concavity implies that isoquants are convex and thus well-behaved.

5 Results

This section presents the results of our estimation procedure, which aims at identifying complementarities between different labor inputs. Table 2 reports the main results for both the entire sample and the sub-samples of firms according to their characteristics. Our approach consists of first estimating equation 1 by using the LP approach[4] and then calculating AESs according to equation 5.

[4]Our baseline estimations apply the LP procedure without firm FE, while Table A1 in the Appendix reports the estimations of the LP procedure with firm FE. Results in this table, except for modern services, are very similar to the LP estimation reported in Table 2.

Table 2: Complementarities among workers with different types of education in affecting firms' productivity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All firms	Manufacturing		Services		Small-size	Medium-size	Large-size
		Low-tech	High-tech	Traditional	Modern			
Translog estimation								
Capital	0.112***	0.124***	0.0733	0.125***	0.0909***	0.0477	0.107***	0.0719***
	(0.00329)	(0.0445)	(0.0464)	(0.0319)	(0.0313)	(0.0290)	(0.0321)	(0.0279)
Lower	0.179***	0.279***	0.153***	0.159***	0.0367	0.198***	0.183***	0.135***
	(0.00837)	(0.0130)	(0.0105)	(0.0169)	(0.0242)	(0.0103)	(0.0128)	(0.0179)
Trained	0.386***	0.395***	0.319***	0.424***	0.373***	0.460***	0.342***	0.331***
	(0.0113)	(0.0161)	(0.0273)	(0.0186)	(0.0283)	(0.0177)	(0.0215)	(0.0298)
Advanced	0.158***	0.137***	0.130***	0.150***	0.266***	0.189***	0.159***	0.144***
	(0.00812)	(0.0118)	(0.0156)	(0.0162)	(0.0184)	(0.0129)	(0.0105)	(0.0205)
Academic	0.140***	0.0736***	0.118***	0.148***	0.240***	0.171***	0.103***	0.125***
	(0.00862)	(0.0148)	(0.0102)	(0.0220)	(0.0157)	(0.0241)	(0.00982)	(0.0193)
Lower^2	0.125***	0.158***	0.101***	0.140***	0.111***	0.215***	0.131***	0.0661***
	(0.00706)	(0.0175)	(0.0126)	(0.0163)	(0.0343)	(0.0201)	(0.0162)	(0.0168)
Trained^2	0.123***	0.117***	0.106***	0.125***	0.124***	0.154***	0.0816***	0.0813***
	(0.0131)	(0.0152)	(0.0181)	(0.0187)	(0.0298)	(0.0208)	(0.0249)	(0.0232)
Advanced^2	0.0863***	0.105***	0.0520*	0.0409	0.135***	0.158***	0.116***	0.0303
	(0.0150)	(0.0170)	(0.0297)	(0.0372)	(0.0204)	(0.0249)	(0.0147)	(0.0325)
Academic^2	0.0752***	0.0579***	0.0459***	-0.0126	0.127***	0.101***	0.0894***	0.0623***
	(0.0111)	(0.0190)	(0.0145)	(0.0315)	(0.0173)	(0.0341)	(0.0199)	(0.0151)
Lower*Trained	-0.0726***	-0.126***	-0.0528***	-0.0855***	-0.0360	-0.107***	-0.0881***	-0.00789
	(0.00824)	(0.0152)	(0.0108)	(0.0112)	(0.0270)	(0.0166)	(0.0128)	(0.0150)
Lower*Advanced	-0.0302***	-0.0456***	-0.0442***	-0.0277	-0.0151	-0.0730***	-0.0123	-0.0281*
	(0.00977)	(0.0118)	(0.0134)	(0.0181)	(0.0161)	(0.0121)	(0.00992)	(0.0160)
Lower*Academic	-0.0216**	-0.0113	-0.0324***	-0.0316	-0.0161	-0.0686***	-0.0160*	-0.00909
	(0.00857)	(0.0116)	(0.00918)	(0.0232)	(0.0183)	(0.0232)	(0.00938)	(0.0114)
Trained*Advanced	-0.0459***	-0.0293***	-0.0444**	-0.0380*	-0.0708***	-0.0809***	-0.0354**	-0.00338
	(0.00892)	(0.00928)	(0.0209)	(0.0196)	(0.0231)	(0.0204)	(0.0154)	(0.0155)
Trained*Academic	-0.0418***	-0.00892	-0.0400***	-0.0451**	-0.0576***	-0.102***	-0.0462***	-0.0434***
	(0.00592)	(0.0130)	(0.0122)	(0.0217)	(0.0184)	(0.0166)	(0.0133)	(0.0165)
Advanced*Academic	-0.0203*	-0.0340**	0.0199	0.0360	-0.0625***	-0.0458**	-0.0197*	0.00270
	(0.0107)	(0.0164)	(0.0188)	(0.0258)	(0.0119)	(0.0230)	(0.0116)	(0.0171)
N	7701	2725	1767	1959	1075	3405	3038	1258
N satisfying monotonicity and quasi-concavity	3243	1155	896	938	348	1082	1102	701
Allen Elasticities of Substitutions (AES)								
$\text{AES}_{Lower,Trained}$	2.716	1.781	2.596	3.059	5.562	3.799	3.953	5.237
$\text{AES}_{Lower,Advanced}$	-2.770	-1.636	-2.444	-3.607	-5.719	-3.039	-2.961	-4.736
$\text{AES}_{Lower,Academic}$	3.020	1.707	2.428	5.535	5.924	3.275	2.413	4.161
$\text{AES}_{Trained,Advanced}$	1.547	1.777	1.290	1.618	1.773	1.394	1.696	1.346
$\text{AES}_{Trained,Academic}$	-1.662	-1.744	-1.256	-2.301	-1.630	-1.612	-1.415	-1.094
$\text{AES}_{Advanced,Academic}$	5.480	5.223	6.112	9.928	2.558	5.249	3.212	3.822
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Industry fixed effects	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Translog production functions estimated with Levinsohn-Petrin method. Dependent variable is total value added. All variables in logs and demeaned to the (sub-)sample mean. Standard errors clustered at firm level in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Allen partial Elasticities of Substitution (AES) are calculated for every firm satisfying monotonicity and quasi-concavity conditions using the coefficients of the translog estimation and own input quantities. Industries grouped according NOGA 08 classification as in Figure 6. Small-size firms have <50 employees, medium-size firms between 50 and 249, and large-size firms >250 employees.

The upper part of first column in Table 2 reports the results of the translog estimation on the full sample. The coefficient for *Capital* (0.112) is in line with that of other studies that similarly use the LP approach to estimate a Cobb-Douglas production function with only capital and labor (e.g., Parrotta et al., 2014; Konings & Vanormelingen, 2015; Marino et al., 2016). The linear coefficients for labor, which we subdivide into four educational groups (*Lower*, *Trained*, *Advanced*, and *Academic* workers), are all positive. While quadratic terms of the labor inputs are also positive, all interaction terms show negative coefficients. All coefficients are highly statistically significant. The positive quadratic coefficients suggest a possible increasing return to scale, implying that the production function is not well-behaved. To check whether the size of the negative interaction terms compensates for the positive values of the quadratic terms, we examine whether monotonicity and quasi-concavity conditions are satisfied for each observation. More than half of the observations satisfy these two conditions. We report the number of firms satisfying these conditions in the line below the total number of observations.

According to equation 5, we can use the coefficients of the translog production function and the input quantities to calculate AESs for each single firm. As previously explained, we calculate AESs only for firm satisfying monotonicity and quasi-concavity conditions. The bottom part of Table 2 shows the median values of AES for all pairs of labor inputs. The negative values for $\text{AES}_{Lower,Advanced}$ and $\text{AES}_{Lower,Advanced}$ show that these two pairs of inputs are complementary in firms' production processes. The interpretation of negative values, for example, for -2.77 for $\text{AES}_{Lower,Advanced}$, is as follows: If the price ratio between Lower and Advanced workers increases by 1%, a typical firm that keeps output quantity constant and adjusts all inputs quantities will increase the quantity ratio between Lower and Advanced workers by approximately 2.77%. The size of the coefficients suggests that complementarities are greater between Lower and Advanced workers than between Trained and Academic workers, which has an AES of -1.66.

In contrast, a positive AES means that, if the price ratio between labor inputs L_p and L_q increases, firms that keep output quantity constant and adjust all inputs quantity will substitute L_q for L_p, and therefore decrease the quantity ratio between L_p and L_q. Our calculations of AESs reveal that firms at the median of the distribution show substitutability between Lower and Trained workers, between Lower and Academic workers, between Trained and Advanced workers, and between Advanced and Academic workers. The substitution effect is greatest between Advanced and Academic workers (5.48) and smallest between Trained and Advanced workers (1.54). These results confirm hypotheses H1a-H1f, which predict that Lower and Advanced as well as Trained and Academic workers are complementary in affecting firms' productivity, while all other pairwise combinations of these four education groups are substitutes.

In section 3 we showed that workforce composition differs by firm size and industry. We now look at how elasticities of substitution differ across firm characteristics. Columns (2)-(5) of Table 2 present the estimations of the translog production function and the corresponding AESs by industry type and columns (6)-(8) show the results by firm size.

We focus first on the estimations by industry. The coefficients of the translog production function show that the contribution of *Capital* is different across industries. Specifically, capital is particularly important in low-tech manufacturing, but less so in traditional services. For the four labor components, we also observe large differences across the four sub-samples. The linear and quadratic coefficients for Lower workers are particularly high in low-tech industries. The coefficients for Trained workers suggest a relatively similar contribution across industries. Finally, the linear and quadratic coefficients for Advanced and Academic workers suggest that these workers largely contributes to firms' productivity in modern services compared to other industries.

The majority of the coefficients of the interaction terms are negative. The drawback of subdividing the sample in sub-sectors is that sample size shrinks and estimates become less precise—even though the vast majority of coefficients are still highly statistically significant. While we can still compute AESs for these sub-samples, we are aware that less precise translog coefficients might lead to less precise values of AESs. The elasticities reported in columns (2)-(5) show patterns similar to those in column (1). Lower and Advanced workers are complementary, as are Trained and Academic workers. All other pairwise combinations of the labor inputs suggest substitutability. Even though the direction of the elasticities is similar across sub-samples, the size of complementarity and substitutability differs. The complementarity between Lower and Advanced workers is greater in high-tech manufacturing and in modern services than in low-tech manufacturing and in traditional services. The opposite patterns occur for the complementarities between Trained and Academic workers. Furthermore, the substitution between Trained and Advanced workers is overall low in all four sectors, suggesting a generally small substitutability between these two types of labor.

In sum, we cannot completely confirm hypothesis H2, stating that workforce diversity has a more positive effect in creative industries—as, for example, in high-tech manufacturing and modern services. Instead, we observe that the pattern in the modern services is different from that in the other three sub-samples. One possible explanation is the workforce composition in these industries, with a particularly high proportion of Academic workers and below-average proportion of Lower workers in modern services.

We focus now on estimation by firm size. The estimations across firm size in Table 2, columns (6)-(8), show patterns similar to those in the full sample—reported in column (1). Complementarities occur both between Lower and Advanced workers and between Trained and Academic workers. All other pairwise combinations of these four education groups reveal substitutability. The elasticities for small- and medium-size firms are relatively similar. Large-size firms show greater substitutability both between Lower and Trained workers and between Lower and Academic workers. However, for large-size firms, the translog estimation is less precise. These imprecise coefficients may explain the differences in elasticities between large-size firms and the full sample. In brief, the estimations cannot confirm the hypothesis H3 of greater complementarities or smaller substitution in small-size firms.

6 Robustness checks

Thus far, we specified the translog production function so that capital enters only in a linear way. In this section, we test two alternative specifications, each of which differently considers the input factor capital.

6.1 Interacting capital

In equation 1, our baseline estimation, the input factor capital entered in firm value added only linearly. However, capital can be particularly important in the production process when it is combined with a particular type of labor (e.g., with workers having a certain type of education).

Following the influential work of Griliches (1969), a large number of studies[5] show that capital is particularly complementary to highly educated workers while less complementary to lower-educated workers. In this robustness test, we include in our model specification interaction terms between capital and the four labor inputs, as well as the quadratic term for capital. By doing so, we estimate a full translog production function.

Table 3 shows both the baseline estimations and the full translog versions, which include the interaction terms between *Capital* and the four labor inputs. We present the results of all

[5] See, e.g.,Yasar & Paul (2008) and Correa et al. (2017) as examples of implementation in translog framework.

estimation procedures previously explained: OLS in columns (1) and (2), FE in columns (3) and (4), LP in column (5) and (6), and FE LP in columns (7) and (8).

We focus first on the OLS estimations. By introducing $Capital^2$, the quadratic term for capital, we observe a shift of the linear term of $Capital$ from positive to negative. This shift, together with the positive coefficient of the quadratic term, suggests increasing return to scale of the input factor capital. By comparing columns (1) and (2), we also observe that the inclusion of capital does not affect the estimation of the labor coefficients. The coefficients of the interaction terms between $Lower * Capital$ and $Academic * Capital$ are relatively small, while the coefficients of $Trained * Capital$ and $Advanced * Capital$ are relatively large and statistically significant. As in the baseline estimation, we use the coefficients of the translog production function to calculate AESs. The values reported in the bottom part of Table 3 suggest that estimating the full translog production function has a relatively small impact on AESs. The sign of the elasticities is the same. Indeed, only for AESs related to Lower workers we do obtain slight higher values.

The FE estimations in columns (3) and (4) also show that adding the term $Capital^2$ shifts the sign of the linear coefficient for $Capital$ from positive to negative. The coefficients of the labor inputs do not change when we estimate the full translog, while the coefficients of the interaction terms between capital and labor show no unusual patterns. However, the reduced number of observations that satisfy both monotonicity and quasi-concavity conditions may partly explain the changes in the size of AESs reported in the bottom part of the table. Nevertheless, there are no changes of sign in AESs. This finding means that two labor inputs—which in the baseline estimation resulted in complements (substitutes)—remain complements (substitutes) when capital is interacted.

Columns (5) and (6) report the estimation according to the LP procedure, which is our preferred procedure. In this case, adding $Capital^2$ does not shift the sign of the linear coefficient for $Capital$ from positive to negative. Instead, the negative coefficient for $Capital^2$ suggests some diminishing return-to-scale capital. As including capital does not affect the coefficients of the labor inputs, the calculated AESs in the bottom part of column (6) are almost identical to those in column (5).

Finally, columns (7) and (8) report the estimations using the FE LP method, the most demanding procedure in terms of calculation. As before, interacting the factor capital with all labor inputs has only a marginal effect on AESs.

Table 3: Complementarities among workers with different types of education in affecting firms' productivity – full translog estimations

	(1) OLS	(2) OLS	(3) FE	(4) FE	(5) LP	(6) LP	(7) LP FE	(8) LP FE
Translog estimation								
Capital	0.103***	-0.149*	0.101**	-0.317*	0.112***	1.005	0.110***	-0.307
	(0.00771)	(0.0865)	(0.0464)	(0.178)	(0.000000298)	(0.877)	(0.00000188)	(.)
Lower	0.201***	0.201***	0.192***	0.186***	0.179***	0.180***	0.184***	0.182***
	(0.00842)	(0.00810)	(0.0227)	(0.0219)	(0.00305)	(0.00151)	(0.0168)	(0.0119)
Trained	0.471***	0.469***	0.322***	0.325***	0.386***	0.384***	0.311***	0.317***
	(0.00993)	(0.00993)	(0.0309)	(0.0300)	(0.00217)	(0.000941)	(0.00691)	(0.00451)
Advanced	0.214***	0.214***	0.127***	0.125***	0.158***	0.158***	0.122***	0.123***
	(0.00953)	(0.00961)	(0.0158)	(0.0164)	(0.00163)	(0.00313)	(0.00693)	(0.00178)
Academic	0.168***	0.170***	0.0851***	0.0791***	0.140***	0.140***	0.0786***	0.0745***
	(0.0100)	(0.0100)	(0.0143)	(0.0140)	(0.00122)	(0.00134)	(0.00524)	(0.00583)
Lower^2	0.155***	0.151***	0.100***	0.0949***	0.125***	0.127***	0.0869***	0.0836***
	(0.00990)	(0.0106)	(0.0170)	(0.0174)	(0.00628)	(0.00767)	(0.0240)	(0.0211)
Trained^2	0.141***	0.151***	0.0878***	0.101***	0.123***	0.118***	0.0853***	0.0961***
	(0.0110)	(0.0127)	(0.0181)	(0.0206)	(0.00726)	(0.0106)	(0.00267)	(0.000425)
Advanced^2	0.109***	0.118***	0.0206	0.0201	0.0863***	0.0905***	0.0193***	0.0221***
	(0.0169)	(0.0173)	(0.0197)	(0.0202)	(0.00589)	(0.00282)	(0.000865)	(0.00232)
Academic^2	0.0946***	0.0918***	0.0389***	0.0315*	0.0752***	0.0714***	0.0403***	0.0328***
	(0.0113)	(0.0115)	(0.0149)	(0.0167)	(0.00836)	(0.0101)	(0.00391)	(0.00493)
Lower*Trained	-0.0886***	-0.0862***	-0.0657***	-0.0649***	-0.0726***	-0.0731***	-0.0630***	-0.0639***
	(0.00791)	(0.00829)	(0.0132)	(0.0141)	(0.00317)	(0.00211)	(0.0109)	(0.0115)
Lower*Advanced	-0.0435***	-0.0384***	-0.00943	-0.00939	-0.0302***	-0.0267***	-0.00434	-0.00311
	(0.00850)	(0.00893)	(0.00978)	(0.0101)	(0.00133)	(0.00469)	(0.00607)	(0.00551)
Lower*Academic	-0.0247***	-0.0273***	-0.0111	-0.0174*	-0.0216***	-0.0226***	-0.0107***	-0.0166***
	(0.00730)	(0.00749)	(0.00757)	(0.00911)	(0.00600)	(0.00604)	(0.00355)	(0.00315)
Trained*Advanced	-0.0561***	-0.0404***	-0.0231*	-0.0146	-0.0459***	-0.0438***	-0.0282*	-0.0202**
	(0.0103)	(0.0107)	(0.0121)	(0.0138)	(0.00215)	(0.000782)	(0.0153)	(0.00903)
Trained*Academic	-0.0461***	-0.0458***	-0.0318***	-0.0405***	-0.0418***	-0.0470***	-0.0341***	-0.0435***
	(0.00905)	(0.00975)	(0.0102)	(0.0135)	(0.00145)	(0.000965)	(0.00384)	(0.00508)
Advanced*Academic	-0.0306***	-0.0265**	-0.00201	-0.00353	-0.0203***	-0.0194**	-0.00159	-0.00222
	(0.0116)	(0.0117)	(0.0106)	(0.0112)	(0.00561)	(0.00764)	(0.00524)	(0.00899)
Capital^2		0.0158***		0.0336**		-0.0796		-0.311***
		(0.00564)		(0.0168)		(0.0543)		(0.00153)
Lower*Capital		0.00209		0.00813		-0.00274		0.00677***
		(0.00576)		(0.0125)		(0.00434)		(0.00258)
Trained*Capital		-0.0166*		-0.0135		0.00733**		-0.00924**
		(0.00858)		(0.0169)		(0.00286)		(0.00389)
Advanced*Capital		-0.0235***		-0.00613		-0.00821		-0.00958
		(0.00764)		(0.0116)		(0.00909)		(0.0123)
Academic*Capital		0.00283		0.0231		0.00720***		0.0220***
		(0.00678)		(0.0155)		(0.00210)		(0.00452)
N	7701	7701	7701	7701	7701	7701	7701	7701
N satisfying monotonicity and quasi-concavity	2738	2234	3969	1067	3243	3226	4034	4026
Allen Elasticities of Substitutions (AES)								
$AES_{Lower,Trained}$	3.885	6.781	4.548	12.37	2.716	2.752	2.848	3.360
$AES_{Lower,Advanced}$	-4.575	-7.422	-5.542	-13.16	-2.770	-2.756	-2.849	-3.391
$AES_{Lower,Academic}$	4.490	8.728	7.490	11.72	3.020	2.996	2.994	3.396
$AES_{Trained,Advanced}$	2.628	2.054	2.555	0.676	1.547	1.577	1.636	1.600
$AES_{Trained,Academic}$	-2.674	-2.241	-3.449	-0.541	-1.662	-1.698	-1.600	-1.544
$AES_{Advanced,Academic}$	2.330	2.336	2.853	0.826	5.480	5.302	5.019	4.652
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Industry fixed effects	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Translog production functions estimated with different methods. Dependent variable is total value added. All variables in logs and demeaned to the (sub-)sample mean. Standard errors clustered at firm level. t statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Allen partial Elasticities of Substitution (AES) are calculated for every firm satisfying monotonicity and quasi-concavity conditions using the coefficients of the translog estimation and own input quantities.

In sum, interacting capital with the labor inputs does not substantially change the estimations of the translog production function. The corresponding AESs—except for the FE procedure—remain very similar to those presented in the previous section.

6.2 Excluding capital

As a second robustness check, we test the stability of the results by exploiting the entire time series from 1996 to 2015. Such estimates include about twice the number of observations of the baseline estimation for 2005-2015. Unfortunately, the waves covering the period 1996-2002 do not contain information on capital. Therefore, because the LP procedure requires capital as a time invariant variable, we cannot use this approach to estimate the translog production function over the entire time series. Instead, we conduct the estimations over the entire time series with standard OLS and FE procedures.

Table 4 presents the results of this second robustness check. For benchmarking reasons, column (1) reports the estimations with the LP method, our preferred estimator. As in Table A1, column (5) presents the estimations using the LP method and firm FE. Columns (2) and (6) report, for the same period, the OLS and the FE estimations, respectively. Even though the OLS and FE approaches do not account for simultaneity, the estimations reported here are relatively similar to the LP and FE LP estimations in columns (1) and (5). The results of these different procedures are relatively close, suggesting that simultaneity does not play a marked role in the estimation of firms' production functions. We therefore consider both OLS and FE as relatively accurate proxy for LP and FE LP, respectively.

Columns (3) and (7) exclude *Capital* from the baseline specification. As in the baseline, for these estimations we exploit the 7,701 observations covering the period 2005-2015. The exclusion of the input factor capital induces slightly higher coefficients for all labor inputs than those in the baseline specification. Hence, these results suggest that none of the four education groups carries the entire effect of capital. These specifications, which exclusively consider labor inputs as predictors of productivity, show almost the same patterns in term of sign and statistical significance of the coefficients in columns (2) and (6). In term of elasticities, the exclusion of *Capital* has no effect on the sign of AESs and only a small effect on their size. Noteworthy are the increase in complementarity between Trained and Academic workers and the increase in substitutability between Advanced and Academic workers. All other changes remain small.

Table 4: Complementarities among workers with different types of education in affecting firms' productivity – extended time series

	LP	OLS			FE LP	FE		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	2005-2015	2005-2015	2005-2015	1996-2015	2005-2015	2005-2015	2005-2015	1996-2015
Translog estimation								
Capital	0.112***	0.103***			0.114***	0.101**		
	(0.00329)	(0.00771)			(0.00000875)	(0.0464)		
Lower	0.179***	0.201***	0.234***	0.276***	0.184***	0.192***	0.196***	0.254***
	(0.00837)	(0.00842)	(0.00833)	(0.00635)	(0.0123)	(0.0227)	(0.0226)	(0.0125)
Trained	0.386***	0.471***	0.527***	0.523***	0.311***	0.322***	0.327***	0.386***
	(0.0113)	(0.00993)	(0.00943)	(0.00718)	(0.00485)	(0.0309)	(0.0305)	(0.0153)
Advanced	0.158***	0.214***	0.241***	0.234***	0.122***	0.127***	0.130***	0.155***
	(0.00812)	(0.00953)	(0.00979)	(0.00743)	(0.00419)	(0.0158)	(0.0158)	(0.00970)
Academic	0.140***	0.168***	0.187***	0.179***	0.0768***	0.0851***	0.0867***	0.0909***
	(0.00862)	(0.0100)	(0.0105)	(0.00874)	(0.00698)	(0.0143)	(0.0145)	(0.0112)
Lower^2	0.125***	0.155***	0.167***	0.175***	0.0872***	0.100***	0.103***	0.124***
	(0.00706)	(0.00990)	(0.0104)	(0.00812)	(0.0222)	(0.0170)	(0.0169)	(0.0103)
Trained^2	0.123***	0.141***	0.156***	0.160***	0.0853***	0.0878***	0.0899***	0.125***
	(0.0131)	(0.0110)	(0.0117)	(0.00984)	(0.00230)	(0.0181)	(0.0179)	(0.0124)
Advanced^2	0.0863***	0.109***	0.117***	0.101***	0.0200***	0.0206	0.0207	0.0651***
	(0.0150)	(0.0169)	(0.0177)	(0.0137)	(0.000821)	(0.0197)	(0.0198)	(0.0130)
Academic^2	0.0752***	0.0946***	0.0978***	0.0998***	0.0407***	0.0389***	0.0392***	0.0575***
	(0.0111)	(0.0113)	(0.0117)	(0.00945)	(0.00286)	(0.0149)	(0.0151)	(0.0108)
Lower*Trained	-0.0726***	-0.0886***	-0.0949***	-0.108***	-0.0621***	-0.0657***	-0.0668***	-0.0777***
	(0.00824)	(0.00791)	(0.00823)	(0.00668)	(0.00936)	(0.0132)	(0.0133)	(0.00870)
Lower*Advanced	-0.0302***	-0.0435***	-0.0420***	-0.0476***	-0.00599	-0.00943	-0.00997	-0.0239***
	(0.00977)	(0.00850)	(0.00884)	(0.00674)	(0.00548)	(0.00978)	(0.00985)	(0.00676)
Lower*Academic	-0.0216**	-0.0247***	-0.0290***	-0.0287***	-0.0107***	-0.0111	-0.0113	-0.0153***
	(0.00857)	(0.00730)	(0.00752)	(0.00598)	(0.00190)	(0.00757)	(0.00765)	(0.00555)
Trained*Advanced	-0.0459***	-0.0561***	-0.0685***	-0.0637***	-0.0283*	-0.0231*	-0.0235*	-0.0410***
	(0.00892)	(0.0103)	(0.0108)	(0.00863)	(0.0152)	(0.0121)	(0.0122)	(0.00828)
Trained*Academic	-0.0418***	-0.0461***	-0.0450***	-0.0484***	-0.0341***	-0.0318***	-0.0328***	-0.0399***
	(0.00592)	(0.00905)	(0.00945)	(0.00746)	(0.00475)	(0.0102)	(0.0103)	(0.00675)
Advanced*Academic	-0.0203*	-0.0306***	-0.0310**	-0.0192**	-0.00102	-0.00201	-0.00213	0.00115
	(0.0107)	(0.0116)	(0.0122)	(0.00948)	(0.00374)	(0.0106)	(0.0106)	(0.00762)
N	7701	7701	7701	13364	7701	7701	7701	13364
N satisfying monotonicity and quasi-concavity	3243	2738	3317	5895	3931	3969	4233	5942
Allen Elasticities of Substitutions (AES)								
$\text{AES}_{Lower,Trained}$	2.716	3.885	2.864	2.591	2.827	4.548	2.684	2.203
$\text{AES}_{Lower,Advanced}$	-2.770	-4.575	-2.976	-2.620	-2.820	-5.542	-2.801	-2.174
$\text{AES}_{Lower,Academic}$	3.020	4.490	3.252	2.969	2.890	7.490	3.167	2.288
$\text{AES}_{Trained,Advanced}$	1.547	2.628	1.607	1.643	1.624	2.555	1.747	1.542
$\text{AES}_{Trained,Academic}$	-1.662	-2.674	-1.732	-1.747	-1.560	-3.449	-1.747	-1.603
$\text{AES}_{Advanced,Academic}$	5.480	2.330	5.177	5.576	5.013	2.853	5.477	5.561
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Industry fixed effects	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Translog production functions estimated with different methods. Dependent variable is total value added. All variables in logs and demeaned to the (sub-)sample mean. Standard errors clustered at firm level. t statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Allen partial Elasticities of Substitution (AES) are calculated for every firm satisfying monotonicity and quasi-concavity conditions using the coefficients of the translog estimation and own input quantities.

That the patterns of our baseline specification do not significantly change when we exclude capital allow us to test our estimations for the entire time series. We are thus able to consider 13,366 observations over the period 1996-2015. The results of these estimations appear in columns (4) and (8). For OLS—column (4)—we observe slightly higher values of the translog coefficients than those we estimated for the shorter period. The standard errors for the entire time series are generally lower. In other words, being able to exploit the entire data set increases the precision of our estimations, without changing the meaning of the elasticities.

The FE procedure—column (8)—also produces more precise estimations. All coefficients are highly statistically significant, except for $Lower * Advanced$, $Lower * Academic$, and $Advanced * Academic$. Likewise, we observe slightly higher coefficients than when only considering 2005-2015.

In sum, the estimations on the entire sample produce elasticities very similar to those previously presented in columns (3) and (7). The stability of AESs to the extension of the sample also tentatively suggests that elasticities are stable over time.

7 Conclusion

This paper analyzes how complementarities among workers with different types of education affect firms' productivity. This analysis is particularly important given that the existing literature suggests two opposing effects of educational diversity. On the one hand, spillovers across workers depend on the variety of knowledge that workers provide. Therefore, educational diversity might increase firms' productivity because varied bodies of knowledge in combination can improve the processes of decision-making and problem-solving. On the other hand, diversity can generate negative effects due to interaction difficulties and poor cooperation among workers.

Most empirical studies in this field examine education complementarities by simply differentiating between high- and low-educated workers. Nevertheless, the composition of the workforce is more complex than a two-skill level system would assume, particularly for countries in which the workforce is highly heterogeneous in education and a high proportion of workers have a VET education.

This paper fill the gap it the literature by evaluating how complementarities among workers with different types of education—particularly VET education—affect firm productivity. Using Swiss firm-level panel data covering the period 2005-2015, we estimate translog production functions that consider the impact of workers with four types of education on firms' productivity. Given the coefficients of the translog estimations, we calculate Allen elasticities of substitutions between the four groups of workers.

The results suggest that complementarities among workers are high when differences in types of education are large without being too high. Indeed, we find complementarities between workers with no post-secondary education ("Lower") and workers with a tertiary professional education ("Advanced") as well as between workers with an upper secondary vocational education and training ("Trained") and workers with a tertiary academic education ("Academic"). In contrast, all other pairwise combinations of these four education groups show substitutability. Specifically, our results suggests that firms can relatively easily substitutes Lower workers for Trained workers, Lower workers for Academic workers, and Advanced workers for Academic workers, and vice versa. However, Trained and Advanced workers are found to be less substitutable than these other three pairs. Our robustness estimations show that these findings are qualitatively robust across different considerations of the input factor capital into firms' production function.

This paper has several limitations that pave the way for future research. First, as our estimations are based on survey data they therefore might suffer from measurement errors. Second, the survey structure does give us worker-level information, such as labor market experience or possible skills mismatch. Being able to control for these characteristics would allow to refine the degree of complementarity or substitution. Third, the elasticities represent average treatment effects given the actual composition of the workforce. Implications might differ across single occupations or specific education groups.

Finally, a valuable extension of this paper would enlarge the focus to the concept of the innovation value chain. Our study analyzes only total value added as the firms' output variable. However, future research could focus on other objectives of the innovation value chain. More specifically, besides looking at firm's productivity, one can consider as alternative output of the production function a measure for R&D intensity—which captures firms' knowledge creation process—or sales share generated by innovative products—which measure the ability of transforming knowledge into innovations.

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A Appendix

Table A1: Complementarities among workers with different types of education in determining firms' productivity – FE LP estimations

Dependent variable: logarithm of total value added

	(1) All firms	(2) Manufacturing low-tech	(3) Manufacturing high-tech	(4) Services traditional	(5) Services modern	(6) Small-size	(7) Medium-size	(8) Large-size
Translog estimation								
Capital	0.114***	0.0844***	0.380***	0.0859***	0.000739***	0.0156	0.0553***	0.349***
	(0.00000875)	(0.00001)	(0.0000150)	(3.73e-09)	(0.00001)	(.)	(0.00001)	(0.000005)
Lower	0.184***	0.294***	0.111***	0.167***	0.0791***	0.231***	0.247***	0.142
	(0.0123)	(0.0174)	(0.0230)	(0.0146)	(0.0148)	(0.00577)	(0.0130)	(0.107)
Trained	0.311***	0.399***	0.208***	0.283***	0.381***	0.440***	0.361***	0.217*
	(0.00485)	(0.0147)	(0.0100)	(0.0361)	(0.0204)	(0.0161)	(0.000546)	(0.114)
Advanced	0.122***	0.0961***	0.115***	0.142***	0.209***	0.171***	0.117***	0.0682
	(0.00419)	(0.0143)	(0.0407)	(0.00465)	(0.00173)	(0.00546)	(0.000395)	(0.0560)
Academic	0.0768***	0.0686***	0.0763***	-0.0104	0.166***	0.0381*	0.0539***	0.0816***
	(0.00698)	(0.00762)	(0.0177)	(0.0354)	(0.0237)	(0.0220)	(0.00644)	(0.00455)
Lower^2	0.0872***	0.168***	0.0593***	0.0432*	0.0335***	0.232***	0.138***	0.0193
	(0.0222)	(0.0102)	(0.0174)	(0.0245)	(0.00385)	(0.0247)	(0.0202)	(0.0187)
Trained^2	0.0853***	0.148***	0.0981***	0.0286	0.129***	0.139***	0.141***	0.0406
	(0.00230)	(0.00202)	(0.00656)	(0.0231)	(0.0209)	(0.00422)	(0.00461)	(0.0732)
Advanced^2	0.0200***	0.0778***	0.0565***	-0.0185	0.0353***	0.156***	0.0874***	-0.0252
	(0.000821)	(0.00512)	(0.00886)	(0.0186)	(0.00385)	(0.0197)	(0.00302)	(0.0490)
Academic^2	0.0407***	0.00889	0.0294***	0.000757	0.160***	0.197***	0.0414***	0.0169*
	(0.00286)	(0.0157)	(0.00327)	(0.0253)	(0.0177)	(0.0265)	(0.00184)	(0.00989)
Lower*Trained	-0.0621***	-0.120***	-0.0445***	-0.0356***	-0.0456***	-0.0810***	-0.0824***	-0.0146
	(0.00936)	(0.0118)	(0.00504)	(0.0130)	(0.00522)	(0.0151)	(0.0167)	(0.0296)
Lower*Advanced	-0.00599	-0.0268***	-0.0160	0.00667	0.0375***	-0.0627*	-0.00460	-0.0140
	(0.00548)	(0.00690)	(0.0114)	(0.0115)	(0.0126)	(0.0332)	(0.00586)	(0.0244)
Lower*Academic	-0.0107***	-0.00608	-0.0207	-0.00103	-0.0205***	-0.0373**	-0.00585	-0.0106
	(0.00190)	(0.00948)	(0.0224)	(0.0261)	(0.000525)	(0.0149)	(0.0119)	(0.0284)
Trained*Advanced	-0.0283*	-0.00648	-0.0458**	-0.0240***	-0.0464***	-0.0903***	0.00586	0.0192
	(0.0152)	(0.0134)	(0.0204)	(0.00556)	(0.00626)	(0.00484)	(0.0126)	(0.0355)
Trained*Academic	-0.0341***	-0.0173	-0.0184***	-0.0381**	-0.0370***	-0.0738**	-0.0237*	-0.0156
	(0.00475)	(0.0237)	(0.00288)	(0.0184)	(0.0109)	(0.0294)	(0.0139)	(0.0229)
Advanced*Academic	-0.00102	-0.0112***	0.0109	0.0547***	-0.0445***	-0.0225***	0.0119***	0.0100
	(0.00374)	(0.00398)	(0.0201)	(0.0113)	(0.00259)	(0.00510)	(0.00231)	(0.0130)
N	7701	2725	1767	1959	1075	3405	3038	1258
N satisfying monotonicity and quasi-concavity	3931	1522	890	613	526	626	1126	1031
Allen Elasticities of Substitutions (AES)								
$AES_{Lower,Trained}$	2.827	1.609	2.931	4.535	9.270	3.513	2.489	2.596
$AES_{Lower,Advanced}$	-2.820	-1.535	-2.897	-1.952	-8.721	-2.569	-1.988	-2.953
$AES_{Lower,Academic}$	2.890	2.254	2.856	4.217	6.473	2.033	1.756	3.040
$AES_{Trained,Advanced}$	1.624	1.412	1.319	0.587	1.427	1.690	1.319	1.581
$AES_{Trained,Academic}$	-1.560	-1.977	-1.351	-0.908	-0.975	-1.270	-1.251	-1.533
$AES_{Advanced,Academic}$	5.013	10.33	3.978	7.527	2.155	3.890	4.601	5.365
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Firm fixed effects	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Translog production functions estimated with FE LP method. All variables in logs and demeaned to the (sub-)sample mean. * p<0.10, ** p<0.05, *** p<0.01. Standard errors clustered at firm level in parentheses. Allen partial Elasticities of Substitution (AES) are calculated for every firm satisfying monotonicity and quasi-concavity conditions using the coefficients of the translog estimation and the own input quantities. Industries are grouped according NOGA08 classification as in Figure 6. Small-size firms have <50 employees, medium-size firms between 50 and 249, and large-size firms >250 employees.