Accepted: 22 September 2023

DOI: 10.1111/labr.12256

ORIGINAL ARTICLE

Complementarities among types of education in affecting firms' productivity

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Funding information
Swiss State Secretariat for Education, Research, and Innovation

Abstract

This article uses Swiss firm-level panel data to show that complementarities among workers with different types of education affect firms' productivity. We consider workers with four different types of education: 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 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. Altogether, our findings highlight the importance of vertical and horizontal education diversity within firms.

JEL CLASSIFICATION

J24, L25

1 | INTRODUCTION

A common policy issue found in many OECD countries is the strengthening of vocational education and training (VET) programs.[1] Often in these OECD countries, policymakers consider VET particularly effective in producing high labor force participation and in reducing youth unemployment (OCDE, 2010).

Yet despite a growing body of literature on VET, little evidence exists on the extent of complementarities among the workers with VET education and workers without VET education in determining firms' productivity. Existing articles either focus on high-versus low-educated workers or on aggregate diversity measures (e.g., Ciccone & Peri, 2006; Moretti, 2004; Parrotta et al., 2014). However, insights into the complementarities among differently educated workers are particularly important for the countries in which the workforce is highly heterogeneous with respect to education and where the majority of workers have a VET education. For instance, in Switzerland about two third of youngest enters VET after compulsory education, typically through a dual-track VET, which combines practical training within a firm and general education in a vocational school, while only about one fifth attend general education schools which gives direct access to university. (SERI, 2018).

Furthermore, given that the theoretical literature suggests two opposing effects of workforce educational diversity, it is critical to understand if different types of labor affect firm productivity. 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 (Backes-Gellner et al., 2017; Bolli et al., 2018; Carlile, 2002; Faems & Subramanian, 2013; Hong & Page, 2001; Weitzman, 1998). Additionally, educational diversity increases firms' absorptive capacity (Cohen & Levinthal, 1989, 1990; Quintana-Garca & Benavides-Velasco, 2008). On the other hand, other researchers assert 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 a high cognitive distance between workers, can increase levels of conflict, mistrust, and misunderstanding (e.g., Joshi & Jackson, 2003).

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

We extend the empirical literature beyond the applied education dichotomy by showing that workers with different types of education affect firms' productivity. In our analysis, we estimate partial elasticities of substitution between types using the panel data on Swiss firms that were collected by the KOF Swiss Economic Institute between 2005 and 2015. We subdivide the input factor labor into four types into four types: the *Lower* educated workers (who have no post-secondary education), *Trained* workers (who have an upper secondary VET education), *Advanced* workers (who have a tertiary professional education), and *Academic* workers (who

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

have a tertiary academic education). In addition, we include capital as the fifth type of input. Using these five types of inputs, we regress them in the form of a translog production function on a measure of the 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 and 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 is something that standard methods such as OLS and fixed-effects estimators cannot account for. We then evaluate the effects of firms having different sizes 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 pairs of workers, namely the lower and trained workers as well as the lower and academic workers. Furthermore, our results suggest a high substitutability between academic and advanced workers. By contrast, advanced and trained workers show only a small substitutability. In terms of firm characteristics, the results are surprisingly similar for both low-tech and high-tech industries. Service industries, particularly modern ones, show higher substitutability and higher complementarity depending on the combination of workers. Moreover, our estimations of elasticities show that large firms have higher levels of substitutability and complementarity.

The remainder of the article 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. 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, namely the high-educated and the low-educated workers (e.g., Acemoglu & Angrist, 2000; Ciccone & Peri, 2006; Moretti, 2004). 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 with one another.

Over the last two decades, a growing body of literature in personnel economics (Bender et al., 2018; Grund & Westergård-Nielsen, 2008; Lazear, 1998) 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 allows. This argument is particularly true for countries in which a large part of the workforce has a VET education. High heterogeneity across education in certain countries—such as those with a diffused VET system—imposes an accurate evaluation on the extent of the externalities among workers and on the effects of workforce educational diversity on firms' productivity.

The majority of the studies that examine the impact of workforce educational diversity on both productivity and innovation performance quantify spillovers in terms of diversity indexes. Using Irish firm data, McGuirk and 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, namely primary school, lower secondary school, upper secondary school, tertiary non-degree, tertiary degree, and 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, as results depend on the estimation procedure used. In a similar way but using a Danish linked employer–employee data set, Østergaard et al. (2011) measure horizontal educational diversity at the tertiary level and find that diversity improves a firm's innovative capabilities. However, this effect decreases for higher levels of horizontal diversity.

Finally, Bolli et al. (2018) 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, such diversity increases a firm's ability to explore new knowledge or develop new products; on the other hand, it can negatively affect the commercialization of R&D and innovative activities.

While the larger part of the existing literature on workforce diversity aggregate education groups in diversity indexes, only a 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 the firm level. In particular, she estimates the impact of coworkers' education on individual wages. The results show higher educational spillovers for workers with VET or academic education than for workers with low education levels. These findings suggest that within occupations, workers become more productive when working with workers who have 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.

A noteworthy contribution is that 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 the wages of tertiary-educated workers—albeit with a diminishing effect. This increase in wages can be interpreted as a measure of labor productivity. However, in their article they investigate spillover to workers with tertiary training, without distinguishing between academic or professional tertiary education.

Finally, Arvanitis et al. (2010) use Swiss data to analyze how workers from different education groups contribute to labor productivity—including workers with VET education. 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 is a factor that is highly heterogeneous with respect to education, and it is one of the main inputs in a firms' production functions. However, the literature on workforce diversity suggests two opposing effects of the interaction among workers with different educations.

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 (Backes-Gellner et al., 2017; Bolli et al., 2018; Carlile, 2002; Faems & Subramanian, 2013; Hong & Page, 2001; Weitzman, 1998). Educational diversity also increases absorptive capacity, thus making it easier for firms to identify valuable knowledge that comes from the research activities of other firms and institutions, including promising new ideas and technologies (Cohen & Levinthal, 1989, 1990; Quintana-Garca & Benavides-Velasco, 2008).

On the other hand, diversity can generate negative effects that result 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, which could be due to the high cognitive distance between workers (e.g., Joshi & Jackson, 2003). In addition to this, educational diversity might increase communication costs (Dahlin et al., 2005; Stasser & Titus, 1985; Wittenbaum & Stasser, 1996). In sum, given that firms face a trade-off between the benefits and the costs of educational diversity, the theoretical predictions on the effect of educational diversity on firm outcomes remain ambiguous.

2.3 | Hypotheses

Thus far, the literature on educational diversity shows two opposing effects on productivity. First, educational diversity can increase productivity because a variety of skills can contribute to the processes of decision making and problem-solving, and such diversity increases firms' absorptive capacity. When this occurs, we call this effect the “cross-fertilization effect.” However, when educational diversity creates interaction difficulties, which in turn increases the levels of conflict and mistrust as well as communication costs, we call these effects the “communication and coordination effects.”

While the literature shows mixed findings regarding 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 the workers have similar skills sets. 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 a stylized symmetrical form (even though the U-shape is not necessarily symmetrical). The figure shows which of the two opposing effects might predominate over the other with respect to different skills distances.

To develop our hypotheses regarding the skills distance between workers, we focus on the main types of education in the Swiss educational system, namely the types 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 and transferable skills) and their degree of practical skills (e.g., occupation-specific skills and soft skills). Figure 2 illustrates a hypothetical location of the groups along these two dimensions and summarizes our hypotheses on the complementarity or substitutability of the workers in the four educational groups. While we test the plausibility of this location below, confirming the location based on rigourously estimated skill distances remains beyond the scope of this article.

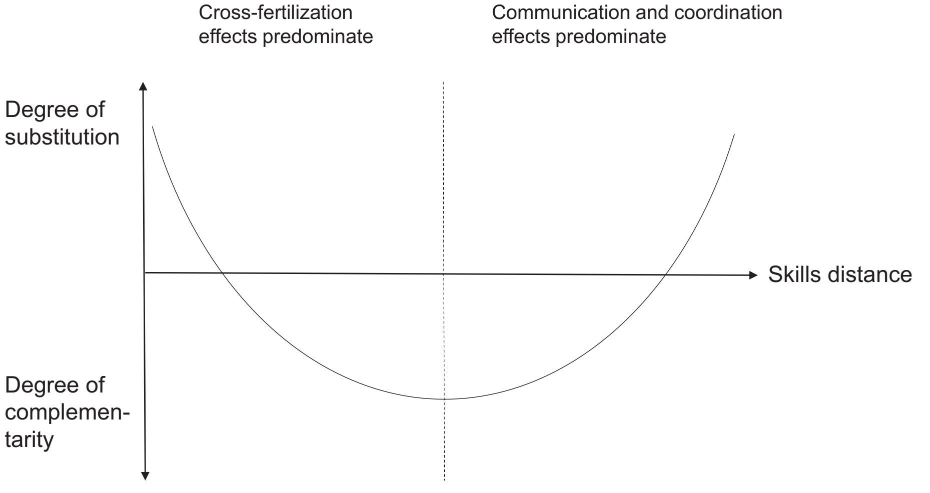

FIGURE 1 Stylized representation of skills distance and degree of complementarity.

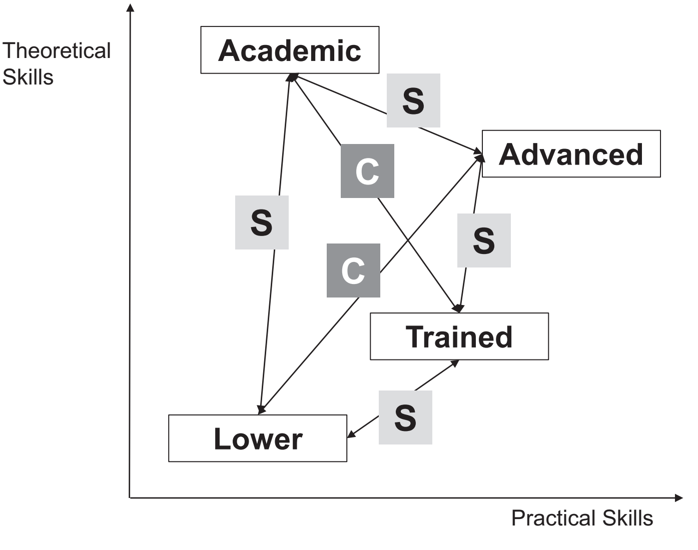

FIGURE 2 Hypotheses on complementarities (C) and substitutability (S) between workers with different types of education in determining firms' productivity.

The four groups of workers have different profiles. Lower educated workers have no post-secondary education; they have relatively low theoretical skills and poor practical skills. Trained workers have an upper secondary VET that provides them with a mix of practical skills and theoretical skills. Advanced workers have a tertiary-level professional education. In comparison to the Trained workers, Advanced workers have substantially more theoretical skills, along with some practical skills that are more developed. Lastly, Academic workers have a tertiary academic education. While they have a very high level of theoretical skills, their set of practical skills is on average lower than that of the Trained or Advanced worker groups.

From the U-shaped relationship between workers' skill distance and the degree of complementarity, we derive our hypotheses on the complementarity (C) and substitutability (S) between the four types of differently educated workers. In forming these hypotheses, we assume that the other factors, which might influence the level of practical or theoretical skills (e.g., on-the-job experience) hold constant. Furthermore, our hypotheses on the inverse relationship between skills distance and complementarity consider distance as a broad concept, and hence we refrain from distinguishing whether the skills distance derives from gaps in practical skills, in theoretical skills, or in both.

2.4 | Plausibility of the skills distance between workers

To develop our hypotheses, we classify the four group of workers along their degree of practical and theoretical skills. To make this hypothetical location of the workers along these dimensions plausible, we attempt to approximate it empirically. Specifically, we approximate the extent of practical and theoretical skills by looking at the type and requirement level of activities performed by workers of each worker group.

The KOF Innovation Survey—the dataset used for the empirical analyses in this article—does not contain information about workers' skills, but only information about their education. Therefore, only to check the plausibility of our hypotheses we use data from the Swiss Earnings Structure Survey (SESS). The SESS is a biannual, mandatory firm survey about the employees of the firms conducted by the Swiss Federal Office of Statistics since 1994. The SESS covers about 50 per cent of total employment in Switzerland in 2010. To get closer to the KOF innovation survey, we restrict the SESS sample by only including individuals aged between 18 and 65 years who work in the private sector and have full information available regarding their education.

For checking the plausibility of our hypotheses, we use detailed information about workers' characteristics. This includes the highest educational attainment. Furthermore, we capture the extent of practical and theoretical skills based on two variables. First, we use a variable that captures the main type of activity carried out by each worker. These activity types resemble the Generalized Work Activity contained in the US O*NET Program, but the data is less detailed as it only differentiates between 24 activity types compared with the 41 activity types rated for all occupations in the O*NET data (Tsacoumis & Willison, 2010). In the SESS, each worker is assigned one type of activity. Table 1 reports our rough classification of these 24 activity types into practical and theoretical activities.

Second, we use a variable that captures the requirement level of activities. This variable uses four categories to measure how demanding and difficult the work is. Specifically, requirement level 4 denotes a job that involves performing the most demanding and difficult work, level

TABLE 1 Classification of Swiss Earnings Structure Survey-activity types into practical and theoretical activities.

Practical activities	Theoretical activities
Production and processing of products	Target and strategy definition of the company
Activities in the construction sector	Accounting and personnel management
Setting up, operating, and maintaining machines	Assessment, consulting, and certification
Restoring, arts handcrafts	Research and development
Office and secretarial work	Analyzing, programming, and operating
Other commercial and administrative activities	Plan, construct, draw, and design
Logistics, support tasks	Medical, nursing, and social activities
Purchase and sale of raw materials and capital goods	Pedagogical activities
Transport of people, goods, and news	
Securing, guarding	
Personal and clothes care	
Cleaning and public hygiene	
Hospitality and housekeeping activities	
Culture, information, entertainment, sports, and leisure	
Other	

3 denotes a job that requires independent and qualified work, level 2 denotes a job requiring professional and technical skills, while level 1 denotes a job involving simple and repetitive activities.

We combine these two variables to create a proxy of practical and theoretical skills. Concretely, we approximate practical (theoretical) skills by the percentage of workers in each education group that conducts skilled practical (theoretical) activities. We define skilled as activities of requirement level 3 or 4. The results of this procedure are reported in Table 2. This table suggests that only 5 per cent of Lower educated workers conduct skilled practical activities and only 2.9 per cent of Lower educated workers conduct skilled theoretical activities. About 16 per cent of Trained workers conduct practical activities and an additional 10 per cent conduct skilled theoretical activities. About a quarter of Advanced workers conduct skilled practical activities and about half of them conduct skilled theoretical activities. This discrepancy increases even more for Academic workers, of which 64 per cent conduct skilled theoretical activities while 18 per cent conduct skilled practical activities.

Figure 3 graphically illustrates the skills distances based on the procedure, as reported in the last column of Table 2. This figure provide thus a plausible map for four education groups considered in this article according to their extent of practical and theoretical skills. The dotted lines reports the “skills frontier,” which represent the highest possible combination of practical and theoretical skills according to our theoretical scheme applied to the SESS data. This figure plausibilizes the conceptual mapping presented in Figure 2 and thus supports our hypotheses, though the indirect approach of approximating skills prevents us from measuring skills distances directly.

TABLE 2 Derivation of approximation of practical and theoretical skills.

	Percentage of workers: By education group, skills, and requirement level (per cent)				Practical/ theoretical skills (per cent)
	Level 1: simple and repetitive activities	Level 2: professional and technical skills	Level 3: independent and qualified work	Level 4: most demanding and difficult work	
Lower					
Practical	61.3	23.0	4.5	0.5	5.0
Theoretical	3.8	4.0	2.0	0.9	2.9
Trained					
Practical	11.8	46.3	15.3	1.0	16.3
Theoretical	1.4	14.2	8.5	1.5	10.0
Advanced					
Practical	1.8	10.7	19.3	5.3	24.6
Theoretical	0.5	13.5	34.4	14.5	48.9
Academic					
Practical	1.1	5.7	11.1	6.7	17.8
Theoretical	0.5	11.5	32.3	31.1	63.4

Note: Practical (theoretical) skills are approximated by the percentage of workers in each education group that conducts skilled practical (theoretical) activities of requirement level 3 or 4.

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. This article-based survey,[2] which closely resembles the EU Community Innovation Survey, contains information on 1500 to 2500 firms in each wave. The response rates are 38.7 per cent (2005), 36.1 per cent (2008), 35.9 per cent (2011), 32.7 per cent (2013), and 30.0 per cent (2015). To assess possible biases caused by companies not answering the questionnaire, the KOF Swiss Economic Institute conducts a non-response analysis for every wave (Spescha & Woerter, 2019). Specifically, the Institute conducts telephone interviews with a sample of 500 non-responding companies. The non-response analysis suggests that the data is representative.

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.

[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.

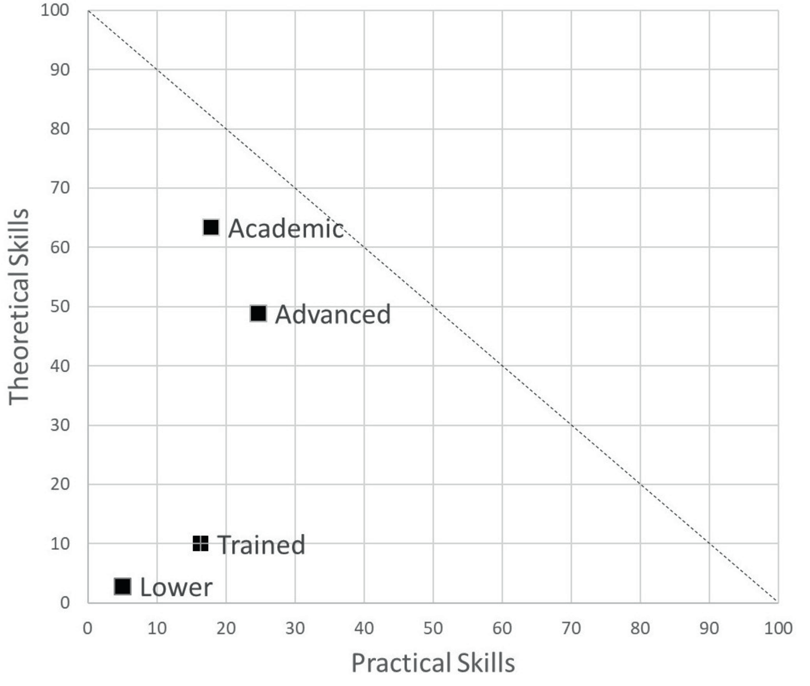

FIGURE 3 Validation of the skills distance between workers. The dotted line represent the skills frontier.

3.1 | Variable description and summary statistics

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

Table 3 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 as well as data on the values of capital stock and labor inputs. All monetary units are expressed in nominal terms.

Information about workforce composition is available for all waves. In our specification, we consider the education categories of four types of workers. The subdivision of workers into four categories is driven by the categorization used in the Swiss Innovation Survey.[3] This survey asks firms about the number of full-time equivalent workers and the share of workers in five education categories. Combining these variables yields the number of full-time equivalent workers in each category. We group the two categories of workers having no post-compulsory education and being in the process of undertaking an apprenticeship, and classify them as *Lower*. Furthermore, the survey asks about the share of workers having completed an apprenticeship, which we classify as *Trained*, and the share workers having completed an education higher than an

[3]A very small share of Swiss students quit the education system with "only" a high school degree. Therefore the survey does not explicitly include high school as a category in the questionnaire.

TABLE 3 Variables description and summary statistics.

Variable	Description	*N*	Mean	St. dev.	Min	Max	Per cent of 0's in the variable
Dependent variable							
Value added[a]	Total value added (in million)	7701	52.6	373.5	0.04	17589.3	0
Independent variables							
Capital[a]	Total capital stock of the firm (in million)	7701	764.2	25948.6	0.0002	1,122,100	0
Lower[a]	Total number of untrained employees and dual vocational education and training (VET) students in a firm	7701	57.0	285.3	0	12536.7	0.07
Trained[a]	Total number of employees in a firm with an upper secondary VET education	7701	109.4	721.7	0	27130.5	0.02
Advanced[a]	Total number of employees in a firm with a professional tertiary education (incl. university of applied sciences)	7701	35.9	219.6	0	11738.7	0.09
Academic[a]	Total number of employees in a firm with a conventional university (academic) tertiary education	7701	19.0	115.8	0	4770.0	0.38
Instrumental variable							
Intermediary goods[a]	Purchasing costs for intermediary inputs in a firm (in million)	7701	62.7	548	0.01	32,830	0
Control variable							
Industry dummies	Industries are grouped in 33 industries according to the NACE Rev 1.1 classification						
Year dummies	Dummy for every survey wave						

[a]This variable enters in log. Value added, capital stock, and intermediary inputs are expressed in real terms.

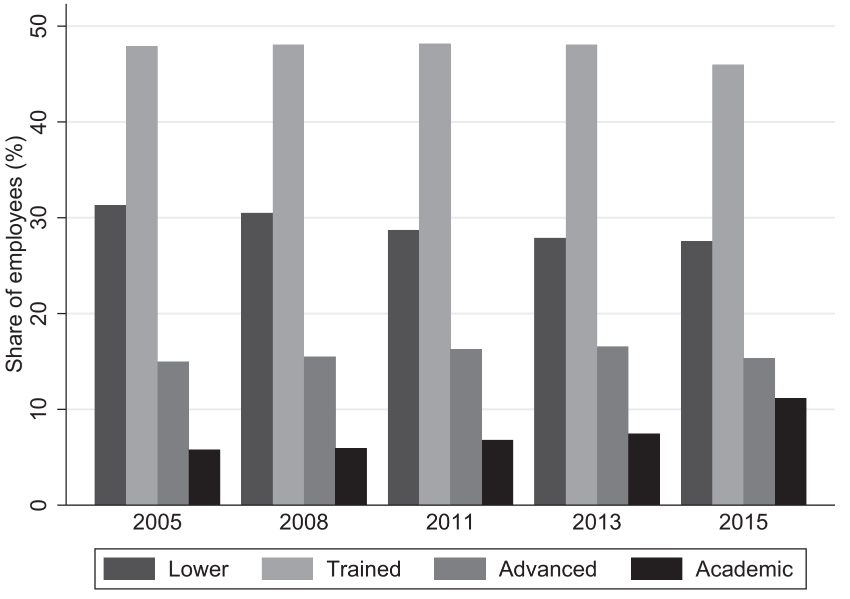

FIGURE 4 Workforce composition over time. The share of the four education groups sum up to 100 per cent in every year.

apprenticeship, which we classify as *Advanced*. Finally, the survey asks about the share of workers having an academic education, which we classify as *Academic*.

Similar to Spescha & Woerter (2021), we derive the capital stock using the perpetual inventory approach. The initial capital stock is calculated by dividing the first positive value of fixed investment by an interest rate of 5 per cent. For subsequent periods, the annual gross investment is added to the capital stock, while the capital stock is always depreciated by 5 per cent.

The sample used for the empirical estimates consists of an unbalanced panel of 7701 firms and about two observations per firm.[4] This sample includes all firms with information on firms' value added and capital stock, as well as complete information on workers' education.

Table 3 also reports the summary statistics of firms' purchasing costs of intermediary goods, as displayed in the last row. 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 from 2005 to 2015.

Figure 4 shows the evolution of workers' education types as a percentage of total employment. From this histogram, we can see 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 per cent over the entire period. On the other hand, the percentage of Lower workers has decreased

[4]The unbalanced structure of the panel might raise concerns about potential attrition bias. To address this concern, we perform the BGLW test (see Becketti et al., 1988; Fitzgerald et al., 1998) for attrition bias. Specifically, we find no correlation between the dependent variable and dummy variables indicating firms' entry and/or exit from the panel.

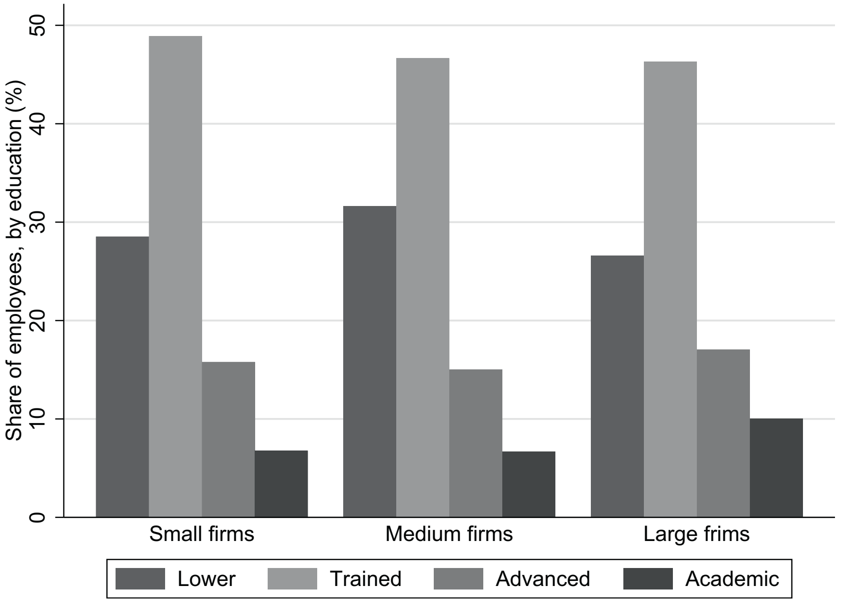

FIGURE 5 Workforce composition by firm size. Small-size firms have <50 employees; medium-size firms between 50 and 249; large-size firms have >250 employees. For every firm size, the share of the four education groups totals to 100 per cent.

over time. Nevertheless, this group was still the second largest in 2015, accounting for about 27 per cent of the workforce. Advanced workers show a relatively constant trend at around 15 per cent of the workforce. Although Academic workers are the smallest group, they show the largest relative increase over time with about 10 per cent of the workforce in 2015. However, the definition of the educational group in the 2015 wave differs from that in previous surveys. In the 2015 questionnaire, the definition of *academic workers* was extended to include graduates of a UAS, whereas in the previous questionnaires, graduates of a UAS were included in the group of Advanced workers. Therefore, the sharp increase in the percentage of Academic workers and the decrease in the percentage of Advanced workers in 2015 is at least partly due to this change in definition. Nevertheless, this change in definition does not have a significant impact on the results of our estimates.[5]

The composition of the workforce differs considerably between subgroups of firms. The figure illustrated in Figure 5 displays the decomposition of the educational groups by firm size. It is worth highlighting the differences in the share of Lower workers who are more prevalent in medium-sized firms. Trained workers constitute the biggest education group in the workforce in all sub-samples, with shares ranging from 45 per cent to 50 per cent. Workers with advanced skills are distributed almost equally across all firms, irrespective of firm size, while Academic workers are proportionally over-represented in large firms.

The workforce composition varies the most by industry, as depicted in Figure 6. Notably, the comparison of the first two panels reveals large differences between low-tech and high-tech manufacturing. Low-tech manufacturing exhibits a disproportionate representation of Lower workers, whereas high-tech manufacturing has significantly higher numbers of Academic and

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

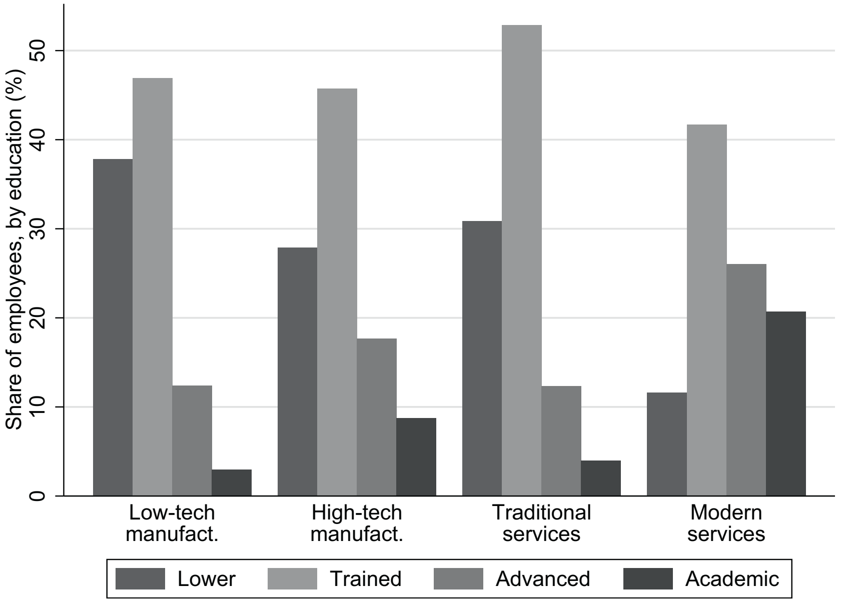

FIGURE 6 Workforce composition by industry. Industries are grouped as in Arvanitis et al. (2017) according to NOGA 08 classification: Low-tech manufacturing comprehends following industries: Food/beverages/tobacco (10/11/12), textiles/clothing (13/14/15), wood (16), paper (17), printing (18), rubber/plastics (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), and 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 and 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 and leasing (68/77/81), personal services (96). Modern services comprehend following industries: Telecommunications (53/61), publishing/media (58/59/60), information technology and services (62/63), banks and insurance (64/65/66), technical commercial services (71/72), and 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 per cent.

Advanced workers. Similarly, the split between traditional and modern services shows large differences. Firms engaged in modern services exhibit a higher proportion of Academic and Advanced workers, while Trained and Lower workers largely dominate traditional services.

Overall, the growing importance of Academic workers and the decline in the share of less-educated ones is partly explained by the growing share of firms in the high-tech sector occurred during the last decades.

4 | EMPIRICAL STRATEGY

4.1 | Translog production function

To assess complementarities among different labor inputs, we use a 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 the firm's 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. The 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 3, all four groups have a minimum value of 0, meaning that no group appears in all the firms with at least one unit. Because all variables enter into the estimations in logs, we add a value of 1 to all variables before taking logarithms. In so doing, we prevent that variables would take undefined values and so avoid to generate missing values in the data.

OLS estimations of translog production function might suffer from possible bias due to time-invariant unobserved heterogeneity or from simultaneity (i.e., short-run endogeneity of firms' education-mix composition). While fixed effect (FE) estimations can solve time-invariant unobserved heterogeneity, simultaneity remains unsolved using standard estimation procedures. Because the size of firms' productivity shocks has a tendency to change over time, FE estimations are not able to solve the simultaneity between input usage and unobserved productivity shock. Thus, both OLS and FE estimators are likely to 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 and Pakes (1996), who consider the investment level in a two-stage procedure, Levinsohn and Petrin (2003) suggest using intermediate inputs (e.g., materials) as a proxy for the unobservable productivity shocks.

We follow the Levinsohn and Petrin (2003) approach—which we term as the LP approach hereafter—and we redefine the production function as follows:

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

where v_{it} is the log of value added of firm i at time t, K_{it} is the log of capital stock, $L_{p,it}$ denotes the log of the number of workers with education p, and γ_i and μ_t introduce the firm and time FEs, respectively. The error term has two components: ω_{it} is the productivity component which is potentially endogenous, and η_{it} is the part of the 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, that is, $\omega_{it}{=}h(K_{it},M_{it})$.

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 and 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 $\widehat{\beta}_k$ is defined as the solution of:

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

We construct standard errors for $\widehat{\beta}_l$ and $\widehat{\beta}_k$ by using a bootstrapping approach with 100 repetitions. In the bootstrap procedure, we account for the panel structure of the data and apply block bootstrap clustered at the firm level.

We conduct all estimations of the translog production function using STATA (Version 15). We calculate the LP procedure from the *prodest* command developed by Rovigatti and Mollisi (2018), and we apply a third-order polynomial for the estimation of the first stage.[6] We demean all dependent variables at either the sample mean or the sub-sample mean. According to Cohen et al. (2013), demeaning predictors have interpretational advantages and can eliminate non-essential multicollinearity. Furthermore, for the robustness test, we combine the LP approach with FE to better account for time-invariant unobserved heterogeneity.

An important note here is that capital enters in Equation (1) only with a linear term. In other words, capital 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 thus interact capital with all labor inputs.

4.2 | Allen elasticities of substitution

Once we have coefficients for the linear, quadratic, and interaction terms, we estimate the elasticities of substitution. Starting with the definition of Allen (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:

[6]The robustness checks that apply fourth-, fifth-, and sixth-order polynomials provide qualitatively similar results.

$$\mathrm{AES}_{pq,i} = \frac{\sum_p f_{p,i} L_{p,i}}{L_{p,i} L_{q,i}} \frac{F_{pq,i}}{F_i} \tag{5}$$

where $f_{p,i}$ is the partial derivatives of the production function f for firm i, F_i is the determinant of the bordered Hessian matrix, and $F_{pq,i}$ is the cofactor of $f_{pq,i}$. Inputs p and q are considered substitutes if $\mathrm{AES}_{pq,i} > 0$, while they are complements if $\mathrm{AES}_{pq,i} < 0$.

AES is symmetric, and it 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 the 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.

It should be noted that the estimated AESs capture the average substitutability of two worker groups. Hence, this average substitutability of two worker groups might mask substantial heterogeneity of the substitutability across particular tasks in a firm and also tasks across firms. To address this issue to some extent, we complement the estimates of AESs for the average firm using the estimates of AESs for the average firm in four industry types and three firm-size categories.

5 | RESULTS

This section presents the results of our estimation procedure, which aims to identify the complementarities between different labor inputs. Table 4 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) using the LP approach[7] and then calculating AESs according to Equation (5).

The upper part of first column in Table 4 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 use the LP approach in a similar way to estimate a Cobb–Douglas production function with only capital and labor (e.g., Konings & Vanormelingen, 2015; Marino et al., 2016; Parrotta et al., 2014). The linear coefficients for labor, which we subdivide into four educational groups (Lower, Trained, Advanced, and Academic workers), are all positive. While the 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 marginal return, 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 the monotonicity and the quasi-concavity conditions are satisfied for each observation, and it was found that more than half of the observations

[7]Our baseline estimations apply the LP procedure without firm FE, while Table A1 reports the estimations of the LP procedure with firm FE. Except for modern services, results in this table are very similar to the LP estimation reported in Table 4. The inclusion of firm FE implies that only within-firm variation in inputs is used to identify the parameters of the production function, which tends to magnify the importance of any measurement error in the data, since capital is rather sticky at the firm level and it creates a problem for the identification of the capital coefficient, which may be underestimated.

TABLE 4 Complementarities among workers with different types of education in affecting firms' productivity.

	(1) All firms	(2) Manufacturing Low-tech	(3) Manufacturing High-tech	(4) Services Traditional	(5) Services Modern	(6) Small-sized	(7) Medium-sized	(8) Large-sized
Translog estimation								
Capital	0.123***	0.125**	0.0963**	0.101***	0.0785	0.0466	0.0976***	0.0865***
	(0.0226)	(0.0495)	(0.0451)	(0.0180)	(0.0478)	(0.0355)	(0.0212)	(0.0240)
Lower	0.179***	0.279***	0.153***	0.159***	0.0367	0.198***	0.183***	0.135***
	(0.00775)	(0.0118)	(0.0116)	(0.0184)	(0.0258)	(0.0135)	(0.0135)	(0.0222)
Trained	0.386***	0.395***	0.319***	0.424***	0.373***	0.460***	0.342***	0.331***
	(0.0110)	(0.0176)	(0.0281)	(0.0238)	(0.0220)	(0.0176)	(0.0210)	(0.0263)
Advanced	0.158***	0.137***	0.130***	0.150***	0.266***	0.189***	0.159***	0.144***
	(0.00741)	(0.0127)	(0.0181)	(0.0211)	(0.0244)	(0.0135)	(0.0120)	(0.0257)
Academic	0.140***	0.0736***	0.118***	0.148***	0.240***	0.171***	0.103***	0.125***
	(0.00871)	(0.0150)	(0.0138)	(0.0250)	(0.0161)	(0.0195)	(0.0110)	(0.0182)
Lower^2	0.125***	0.158***	0.101***	0.140***	0.111***	0.215***	0.131***	0.0661***
	(0.00857)	(0.0184)	(0.0165)	(0.0161)	(0.0273)	(0.0167)	(0.0184)	(0.0157)
Trained^2	0.123***	0.117***	0.106***	0.125***	0.124***	0.154***	0.0816***	0.0813***
	(0.0116)	(0.0198)	(0.0234)	(0.0197)	(0.0393)	(0.0241)	(0.0216)	(0.0224)
Advanced^2	0.0863***	0.105***	0.0520**	0.0409	0.135***	0.158***	0.116***	0.0303
	(0.0170)	(0.0180)	(0.0254)	(0.0287)	(0.0200)	(0.0251)	(0.0131)	(0.0419)
Academic^2	0.0752***	0.0579**	0.0459***	−0.0126	0.127***	0.101***	0.0894***	0.0623***
	(0.00909)	(0.0258)	(0.0172)	(0.0407)	(0.0186)	(0.0330)	(0.0181)	(0.0171)
Lower* trained	−0.0726***	−0.126***	−0.0528***	−0.0855***	−0.0360	−0.107***	−0.0881***	−0.00789
	(0.00745)	(0.0116)	(0.0126)	(0.0128)	(0.0242)	(0.0171)	(0.0158)	(0.0175)

TABLE 4 (Continued)

	(1) All firms	(2) Manufacturing Low-tech	(3) Manufacturing High-tech	(4) Services Traditional	(5) Services Modern	(6) Small-sized	(7) Medium-sized	(8) Large-sized
Lower* advanced	−0.0302***	−0.0456***	−0.0442***	−0.0277**	−0.0151	−0.0730***	−0.0123	−0.0281*
	(0.00841)	(0.0112)	(0.0126)	(0.0141)	(0.0189)	(0.0135)	(0.0105)	(0.0159)
Lower* academic	−0.0216***	−0.0113	−0.0324***	−0.0316	−0.0161	−0.0686***	−0.0160*	−0.00909
	(0.00669)	(0.0120)	(0.00944)	(0.0207)	(0.0144)	(0.0158)	(0.00938)	(0.0119)
Trained* advanced	−0.0459***	−0.0293**	−0.0444**	−0.0380*	−0.0708***	−0.0809***	−0.0354**	−0.00338
	(0.0113)	(0.0137)	(0.0209)	(0.0198)	(0.0235)	(0.0212)	(0.0148)	(0.0146)
Trained* academic	−0.0418***	−0.00892	−0.0400**	−0.0451**	−0.0576***	−0.102***	−0.0462***	−0.0434***
	(0.00884)	(0.0148)	(0.0169)	(0.0229)	(0.0147)	(0.0202)	(0.0124)	(0.0150)
Advanced* academic	−0.0203*	−0.0340**	0.0199	0.0360	−0.0625***	−0.0458***	−0.0197**	0.00270
	(0.0119)	(0.0166)	(0.0128)	(0.0270)	(0.0146)	(0.0171)	(0.00868)	(0.0222)
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 (AESs)								
$AES_{Lower,Trained}$	2.750	2.024	2.730	2.967	6.160	3.876	3.890	5.506
	(0.0136)	(0.000460)	(0.0264)	(0.0376)	(0.163)	(0.0288)	(0.0257)	(0.0703)
$AES_{Lower,Advanced}$	−2.728	−2.061	−2.542	−3.401	−6.360	−3.053	−2.971	−4.953
	(0.0136)	(0.000493)	(0.0283)	(0.0532)	(0.163)	(0.01960)	(0.0190)	(0.0681)
$AES_{Lower,Academic}$	2.976	2.406	2.587	5.417	6.251	3.505	2.511	4.349
	(0.0182)	(0.00208)	(0.0297)	(0.128)	(0.175)	(0.0428)	(0.0195)	(0.0631)
$AES_{Trained,Advanced}$	1.544	1.640	1.324	1.578	1.746	1.427	1.675	1.266
	(0.00589)	(0.00102	(0.0135)	(0.0160)	(0.0185)	(0.00782)	(0.0121)	(0.0105)

(Continues)

TABLE 4 (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All firms	Manufacturing		Services		Small-sized	Medium-sized	Large-sized
		Low-tech	High-tech	Traditional	Modern			
$AES_{Trained,Academic}$	−1.633	−1.921	−1.306	−2.284	−1.621	−1.648	−1.443	−1.076
	(0.00766)	(0.000676)	(0.0134)	(0.0353)	(0.0182)	(0.0175)	(0.0110)	(0.0109)
$AES_{Advanced,Academic}$	5.481	4.609	6.282	10.03	2.572	5.399	3.400	3.977
	(0.0417)	(0.00219)	(0.114)	(0.143)	(0.0260)	(0.0687)	(0.0359)	(0.0669)
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Industry fixed effects	✓	✓	✓	✓	✓	✓	✓	✓

Note: 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 of coefficients are firm-level block-bootstrapped with 100 repetitions. Allen partial Elasticities of Substitution (AESs) are based on firms satisfying monotonicity and quasi-concavity conditions using the coefficients of the translog estimation and own input quantities. AESs are the average of the median AESs across firm-level block-bootstrapps with 200 repetitions. Standard errors of AESs are based on these block-bootstraps. Industries grouped according NOGA 08 classification as in Figure 6. Small-sized firms have <50 employees, medium-sized firms between 50 and 249, and large-sized firms >250 employees.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

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 firms that satisfy monotonicity and quasi-concavity conditions. The bottom part of Table 4 shows the median values of AES for all pairs of labor inputs. The negative values for $AES_{Lower,Advanced}$ and $AES_{Trained,Academic}$ show that these two pairs of inputs are complementary in firms' production processes. For example, the way to interpret the negative value of −2.7 for $AES_{Lower,Advanced}$ is as follows: If the price ratio between Lower and Advanced workers increases by 1 per cent, a typical firm that keeps output quantity constant and adjusts all inputs quantities will increase the quantity ratio between Lower and Advanced workers by ∼2.7 per cent. 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 −1.749.

By contrast, a positive AES means that if the price ratio between labor inputs L_p and L_q increases, firms that keep the output quantity constant and adjust all inputs quantity will substitute L_q for L_p, and therefore they will likely 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 of four pair combinations, namely between the Lower and the Trained workers, the Lower and the Academic workers, the Trained and the Advanced workers, and the Advanced and the Academic workers. The substitution effect is greatest between the Advanced and the Academic workers (5.125) and smallest between the Trained and the Advanced workers (1.62). These results confirm our prediction 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.

With regard to the AESs of Academic workers, it is worth mentioning that this group of workers is the smallest among the ones considered in this article and, as a consequence, a relatively large share of companies have no Academic workers (see Table 3). For instance, the relatively high value of $AES_{Lower,Academic}$ and $AES_{Advanced,Academic}$ could be driven by relatively few observations and should therefore be considered with caution.[8]

In Section 3, we showed that workforce composition differs by firm size and industry. We now examine how the elasticities of substitution differ across firm characteristics. Columns (2)–(5) of Table 4 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. In this regard, the literature suggests a more positive effect of workforce diversity in firms that operate in more creative industries (e.g., Alesina & La Ferrara, 2002; Garnero et al., 2014; Hong & Page, 2001; Lazear, 1998). We therefore expect to find larger complementarities in the firms that operate in a high-tech manufacturing industry or a modern services industry than in low-tech manufacturing or traditional service industries. The coefficients of the translog production function show that the contribution of *Capital* is different across industries. Capital is particularly important in low-tech manufacturing, but it is 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

[8]Robustness test in which we estimate AESs for companies having relatively high percentage of Academic workers reveal that $AES_{Lower,Academic}$ are much closer to zero than for firms with small percentage of Academic workers. However, the AES remains positive for both subsamples.

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 contribute to firms' productivity in more modern services compared with other industries.

The majority of the coefficients of the interaction terms are negative. The drawback of subdividing the sample into sub-sectors is that sample size shrinks and consequently the estimates become less precise—even though the vast majority of coefficients are still highly statistically significant. The elasticities reported in columns (2)–(5) show patterns similar to those in column (1). Lower and Advanced workers are complementary to each other, 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.[9] 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, which suggests a generally small substitutability between these two types of labor.

In summary, the results suggest that workforce diversity has a more positive effect in modern services than in the other three sub-samples. The workforce composition in modern services may explain this, as it has a high proportion of Academic workers and a below-average proportion of Lower workers.

We now focus on the estimation by firm size. In this regard, the literature suggests that educational diversity may have a more pronounced effect on productivity in small firms, where workers interact more frequently with one another (Stahl et al., 2010). In contrast, in large firms we expect diversity to trigger productivity in a less pronounced way because workers are more likely to be divided into teams or departments, and they may interact more with workers who have similar education and skills sets. Thus, we expect complementarities to be greater (or the substitutions to be smaller) in small firms than in medium or large firms.

The estimations across firm size in Table 4, as seen in columns (6)–(8), show patterns that are similar to those in the full sample—as 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-sized firms are relatively similar. Large firms show greater substitutability both between Lower and Trained workers and between Lower and Academic workers. However, the translog estimation is less precise for large firms. These imprecise coefficients may explain the differences in elasticities between large firms and the full sample. In short, the estimations do not confirm greater complementarities or less substitution in small firms. One possible explanation is the composition of the workforce in small and medium-sized firms. Because small firms have below-average share of Academic workers, the degree of substitution or complementarity between Lower, Trained and Advanced workers are smaller because there is less diversity within the firm and thus less cross-fertilization, communication, and coordination effects.

[9]Welch's tests of pairwise equality confirm that AESs for low-tech manufacturing are statistically different from the ones of high-tech manufacturing. Similarly, AESs of traditional services are statistically different from the ones of modern services.

6 | ROBUSTNESS CHECKS

6.1 | Allowing quadruple interactions

The translog production function used thus far represents a second-order approximation to an arbitrary production function. This model does not include triple interactions explicitly. However, the methodology of calculating AESs based on a translog production function has the benefit of being able to capture the interactions with other inputs by considering the changes in output due to interactions with other groups. In order to test whether the second-order approximation of the translog specification captures higher order interactions sufficiently, we conduct an additional robustness check.

Specifically, we additionally include triple and quadruple interactions across labor inputs in the production function. In this way, we account for the effect of combining three or all four educational groups of workers. Table 5 reports the production function estimations including triple and quadruple interactions for both the entire sample and the sub-samples of firms according to different characteristics.

The upper part of column (1) reports the results of the production function estimation on the full sample. The coefficients for *Capital* (0.0978) is slightly lower than the one in the baseline estimation (0.112) as reported in Table 4. The coefficients for the linear, quadratic, and interaction terms between the labor components are in line with the baseline translog estimation. The triple interaction coefficients are all positive, while the coefficient for the combination for the four labor inputs is negative. All coefficients are highly statistically significant. The interpretation of these triple and quadruple interactions is not straightforward, and we therefore focus on the AESs reported in the bottom part of the table. An important point to note is that the number of firms satisfying the monotonicity and quasi-concavity conditions is slightly higher than in the baseline results (i.e., 3621 compared with 3243 firms), which suggests that by including the triple and quadruple interactions we are able to identify the production function more accurately.

The median values of AES reported in the bottom part of Table 4 confirm the degrees of complementarity or substitutions identified in the baseline. Specifically, the negative values for $AES_{\text{Lower,Advanced}}$ and $AES_{\text{Trained,Academic}}$ confirm that these two pairs of inputs are complementary in firms′ production processes. By contrast, the positive AESs confirm that firms at the median of the distribution show substitutability in four pairs, namely between Lower and Trained workers, the Lower and Academic workers, the Trained and Advanced workers, and the Advanced and Academic workers. The magnitude of the elasticities is slightly larger than in the baseline estimates reported in column (1) of Table 4, but qualitatively it confirms the degree of substitutability or complementarity between the labor inputs.

We now look at how elasticities of substitution differ across firm characteristics. Columns (2)–(5) of Table 5 present the estimations of the production function with triple and quadruple labor interaction and the corresponding AESs by industry type. Columns (6)–(8) similarly show the results by firm size. By comparing these results with the ones of Table 4, we observe that the coefficients of the linear, quadratic, and simple interaction terms between labor components do not change markedly. None of the coefficients changes its sign, and the statistical precision remains relatively high. By contrast, for the coefficients of the triple interactions we observe large differences across the four sub-samples. Finally, the coefficients of the quadruple interaction are negative in all sub-samples and are statistically significant.

TABLE 5 Complementarities among workers with different types of education in affecting firms' productivity–quadruple interactions.

	(1)	(2) Manufacturing	(3)	(4) Services	(5)	(6)	(7)	(8)
	All firms	Low-tech	High-tech	Traditional	Modern	Small-sized	Medium-sized	Large-sized
Production function estimation								
Capital	0.0978***	0.110***	0.0987**	0.0830***	0.0904***	0.0217***	0.103***	0.0700***
	(0.000802)	(0.00228)	(0.0455)	(0.00163)	(0.00848)	(0.00429)	(0.00183)	(0.00366)
Lower	0.152***	0.261***	0.141***	0.129***	0.0138*	0.188***	0.180***	0.148***
	(0.00579)	(0.0000696)	(0.00419)	(0.0121)	(0.00814)	(0.0112)	(0.00161)	(0.0113)
Trained	0.370***	0.370***	0.304***	0.416***	0.379***	0.467***	0.360***	0.356***
	(0.000536)	(0.00267)	(0.0146)	(0.000202)	(0.00192)	(0.00728)	(0.00193)	(0.0295)
Advanced	0.157***	0.137***	0.120***	0.153***	0.256***	0.190***	0.177***	0.167***
	(0.000660)	(0.0126)	(0.00329)	(0.0175)	(0.00114)	(0.00852)	(0.00539)	(0.00525)
Academic	0.126***	0.0691***	0.116***	0.137***	0.232***	0.172***	0.105***	0.108***
	(0.00474)	(0.00599)	(0.0233)	(0.0198)	(0.00143)	(0.00310)	(0.00345)	(0.0183)
$Lower^2$	0.120***	0.157***	0.0950***	0.127***	0.108***	0.213***	0.116***	0.0557***
	(0.00292)	(0.0105)	(0.0260)	(0.00645)	(0.00267)	(0.00601)	(0.00312)	(0.0124)
$Trained^2$	0.109***	0.115***	0.104***	0.106***	0.126***	0.138***	0.0473***	0.0732***
	(0.00236)	(0.0183)	(0.00260)	(0.0125)	(0.00853)	(0.00910)	(0.00240)	(0.00577)
$Advanced^2$	0.0879***	0.101***	0.0461*	0.0365***	0.119***	0.151***	0.105***	0.0430***
	(0.00629)	(0.0166)	(0.0253)	(0.0121)	(0.00154)	(0.0193)	(0.00486)	(0.00574)
$Academic^2$	0.0658***	0.0638***	0.0519***	−0.0205*	0.122***	0.103***	0.0790***	0.0534***
	(0.00725)	(0.00426)	(0.0134)	(0.0106)	(0.00585)	(0.0174)	(0.00169)	(0.0117)
Lower* trained	−0.0762***	−0.130***	−0.0513***	−0.0852***	−0.0318***	−0.117***	−0.116***	−0.0311***
	(0.00119)	(0.00157)	(0.0198)	(0.00563)	(0.00624)	(0.00176)	(0.00546)	(0.0101)
Lower* advanced	−0.0337***	−0.0423***	−0.0393***	−0.0256***	−0.0222**	−0.0689***	−0.0253***	−0.0303**
	(0.00302)	(0.00937)	(0.00149)	(0.00290)	(0.00998)	(0.00142)	(0.00309)	(0.0122)

TABLE 5 (Continued)

	(1)	(2) Manufacturing	(3)	(4) Services	(5)	(6)	(7)	(8)
	All firms	Low-tech	High-tech	Traditional	Modern	Small-sized	Medium-sized	Large-sized
Lower* academic	−0.0352***	−0.0240***	−0.0299***	−0.0700***	−0.0229***	−0.0741***	−0.0236***	−0.0126
	(0.00336)	(0.00149)	(0.00905)	(0.00594)	(0.00479)	(0.00113)	(0.00207)	(0.0139)
Trained* advanced	−0.0529***	−0.0350***	−0.0459**	−0.0439***	−0.0721***	−0.0763***	−0.0758***	−0.00800
	(0.00155)	(0.00133)	(0.0196)	(0.00643)	(0.00621)	(0.00794)	(0.00737)	(0.0160)
Trained* academic	−0.0473***	−0.0403***	−0.0430***	−0.0574***	−0.0640***	−0.101***	−0.0529***	−0.0629***
	(0.000349)	(0.00994)	(0.000489)	(0.0112)	(0.00609)	(0.0197)	(0.000745)	(0.000223)
Advanced* academic	−0.0199***	−0.0187***	0.0219***	0.0318***	−0.0633***	−0.0347***	−0.0129***	0.00358
	(0.00572)	(0.000106)	(0.000289)	(0.0121)	(0.000419)	(0.00940)	(0.000964)	(0.0129)
Lower* trained * advanced	0.00768***	0.00958***	0.0106***	0.00824*	0.00500**	0.0692***	0.0521***	−0.00154***
	(0.00221)	(0.00114)	(0.000176)	(0.00483)	(0.00210)	(0.0144)	(0.0177)	(0.0000886)
Lower* trained * academic	0.0140***	0.0294***	0.00413**	0.0271***	−0.00951***	0.0156***	0.0220***	0.0275***
	(0.00214)	(0.0000779)	(0.00203)	(0.00355)	(0.00169)	(0.00356)	(0.000554)	(0.00296)
Lower* advanced* academic	0.00639***	−0.00759***	−0.00137	0.0104***	0.0164***	0.0354***	0.0159***	−0.000815
	(0.0000564)	(0.00129)	(0.00414)	(0.000510)	(0.00590)	(0.00488)	(0.00311)	(0.00120)
Trained* advanced* academic	0.00325***	0.000615	0.00269***	−0.00301	0.00570	0.0136	0.0201***	0.00633**
	(0.00100)	(0.000612)	(0.000432)	(0.00215)	(0.00525)	(0.0122)	(0.00211)	(0.00258)
Lower* trained* advanced* academic	−0.00304***	−0.00321***	−0.00327***	−0.00355**	−0.00167***	−0.00619**	−0.0200*	−0.00504***
	(0.000754)	(0.000557)	(0.000257)	(0.00147)	(0.000445)	(0.00272)	(0.0113)	(0.0000458)
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Industry fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
N	7701	2725	1767	1959	1075	3405	3038	1258
N satisfying monotonicity and quasi-concavity	3621	975	754	848	352	287	362	768

(Continues)

TABLE 5 (Continued)

	(1)	(2) Manufacturing	(3)	(4) Services	(5)	(6)	(7)	(8)
	All firms	Low-tech	High-tech	Traditional	Modern	Small-sized	Medium-sized	Large-sized
Allen elasticities of substitutions (AESs)								
$AES_{Lower,Trained}$	6.686	3.916	6.730	5.599	18.94	6.498	21.87	25.06
	(0.0425)	(0.0527)	(0.101)	(0.0944)	(0.553)	(0.226)	(1.344)	(0.779)
$AES_{Lower,Advanced}$	−6.113	−3.399	−6.933	−4.755	−12.93	−3.666	−16.69	−32.13
	(0.0522)	(0.0389)	(0.106)	(0.0894)	(0.547)	(0.0669)	(1.133)	(1.121)
$AES_{Lower,Academic}$	4.930	2.295	5.370	3.465	12.30	2.243	17.53	41.00
	(0.0392)	(0.0260)	(0.0815)	(0.0647)	(0.511)	(0.0272)	(1.299)	(1.513)
$AES_{Trained,Advanced}$	3.964	4.132	4.005	2.731	4.539	6.645	11.46	5.565
	(0.0150)	(0.0277)	(0.0402)	(0.0240)	(0.0996)	(0.207)	(0.390)	(0.121)
$AES_{Trained,Academic}$	−3.177	−2.832	−3.024	−1.967	−4.216	−4.250	−8.991	−7.911
$AES_{Advanced,Academic}$	(0.0133)	(0.0161)	(0.0341)	(0.0194)	(0.105)	(0.101)	(0.309)	(0.237)
	6.810	8.636	6.525	8.594	5.657	13.73	13.69	14.72
	(0.0403)	(0.121)	(0.145)	(0.125)	(0.0995)	(0.248)	(0.421)	(0.368)

Note: 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 of coefficients are firm-level block-bootstrapped with 100 repetitions. Allen partial Elasticities of Substitution (AESs) are based on firms satisfying monotonicity and quasi-concavity conditions using the coefficients of the translog estimation and own input quantities. AESs are the average of the median AESs across firm-level block-bootstraps with 200 repetitions. Standard errors of AESs are based on these block-bootstraps. Industries grouped according NOGA 08 classification as in Figure 6. Small-sized firms have <50 employees, medium-sized firms between 50 and 249, and large-sized firms >250 employees.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

In subdividing the sample by industries and firm size, the number of observations shrinks, and the estimates become less precise. The number of firms satisfying the monotonicity and quasi-concavity conditions in the sub-samples is lower than in the baseline results reported in Table 4; this suggests that the inclusion of the triple and quadruple interactions is less adequate for identifying the production function in sub-samples.

Nevertheless, the elasticities reported in the bottom part of columns (2)–(8) show patterns similar to those from our baseline results. The size of the AESs is slightly higher, but the sign of the coefficients—which suggests either complementarity or substitutability—remains unchanged. Lower and Advanced workers are still found to be complementary, as are Trained and Academic workers. By contrast, all other pairwise combinations of the labor inputs suggest substitutability. In sum, the results of this robustness analysis presents elasticities that are qualitatively the same as our baseline estimations.

6.2 | Gross-output production function

As a second robustness check, we complement our value-added results by computing gross-output production function. Considering gross-output is relevant to alleviate concerns that the results are due to our choice of estimating a value-added translog production function estimated via OLS with firm fixed-effect.

Indeed, Gandhi et al. (2020) have shown that a nonparametric identification strategy for gross-output that can be employed even when additional sources of variation are not available. Concretely, they show that time-series variation in aggregate price indexes presents a potential source of variation which allow to solve the transmission bias. By so doing they show that OLS overestimates the flexible intermediate-input elasticities and underestimates the elasticities of capital and labor. Their identification strategy is particularly useful for cases in which time-series data on price variation or firm-specific prices are not available. As in the data set used in this article information on output-prices are available at firm level, we directly estimate gross-out production function following Rovigatti and Mollisi (2018). Table 6 shows the gross-output production function estimations for both the entire sample and the sub-samples of firms according to different characteristics.

The top part of column (1) reports the results of the production function estimation for the full sample. The coefficient on *Capital* (0.066) is about half that in the value-added estimation (0.123) reported in Table 4. The coefficients for the linear, quadratic, and interaction terms between the labor components are also lower than the value-added estimation, but show similar patterns in terms of relative magnitude. All of the coefficients are highly statistically significant. Because the interpretation of these coefficients is not straightforward, we focus—as in the case of value-added—on the AESs reported in the lower part of the table. An important point to note is that the number of firms satisfying the monotonicity and quasi-concavity conditions is slightly lower than in the value-added results (i.e., 3165 firms compared with 3243 firms), suggesting that the gross-output method identifies the production function less accurately.

The median values of the AES reported in the lower part of the Table 6 confirm the degrees of complementarity or substitution identified with the value-added method. In particular, the negative values for $AES_{Lower,Advanced}$ and $AES_{Trained,Academic}$ confirm that these two pairs of inputs are complementary in the firms' production processes. In contrast, the positive AESs confirm that firms at the median of the distribution have substitutability in four pairs, namely between Lower and Trained workers, Lower and Academic workers, Trained and Advanced

TABLE 6 Gross-output production function.

	(1)	(2) Manufacturing	(3)	(4) Services	(5)	(6)	(7)	(8)
	All firms	Low-tech	High-tech	Traditional	Modern	Small-sized	Medium-sized	Large-sized
Translog estimation								
Capital	0.0660***	0.0710***	0.0478*	0.0347	0.0385	0.0421*	0.0681*	0.0443
	(0.0121)	(0.0167)	(0.0254)	(0.0296)	(0.0758)	(0.0243)	(0.0358)	(0.0426)
Lower	0.110***	0.158***	0.0953***	0.108***	0.0158	0.129***	0.183***	0.0835***
	(0.00567)	(0.00719)	(0.00818)	(0.0126)	(0.0213)	(0.00919)	(0.0135)	(0.0136)
Trained	0.232***	0.230***	0.188***	0.228***	0.285***	0.278***	0.342***	0.187***
	(0.00820)	(0.0127)	(0.0158)	(0.0147)	(0.0200)	(0.0143)	(0.0210)	(0.0164)
Advanced	0.0904***	0.0741***	0.0700***	0.0802***	0.201***	0.118***	0.159***	0.0860***
	(0.00564)	(0.00858)	(0.0105)	(0.0131)	(0.0237)	(0.0106)	(0.0120)	(0.0176)
Academic	0.0934***	0.0403***	0.0687***	0.0893***	0.180***	0.116***	0.103***	0.0705***
	(0.00656)	(0.0105)	(0.00898)	(0.0159)	(0.0147)	(0.0159)	(0.0110)	(0.0119)
$Lower^2$	0.0820***	0.0854***	0.0672***	0.0980***	0.0944***	0.128***	0.131***	0.0371***
	(0.00595)	(0.0120)	(0.0126)	(0.0103)	(0.0219)	(0.0113)	(0.0184)	(0.00935)
$Trained^2$	0.0705***	0.0744***	0.0552***	0.0593***	0.0902**	0.0766***	0.0816***	0.0401**
	(0.00794)	(0.0162)	(0.0135)	(0.0136)	(0.0362)	(0.0167)	(0.0216)	(0.0158)
$Advanced^2$	0.0578***	0.0679***	0.0335**	0.0219	0.111***	0.0950***	0.116***	0.0170
	(0.0119)	(0.0123)	(0.0167)	(0.0176)	(0.0186)	(0.0185)	(0.0131)	(0.0292)
$Academic^2$	0.0463***	0.0333*	0.0171*	−0.0111	0.0981***	0.0628**	0.0894***	0.0303**
	(0.00789)	(0.0190)	(0.0102)	(0.0238)	(0.0171)	(0.0300)	(0.0181)	(0.0118)
Lower* trained	−0.0471***	−0.0723***	−0.0353***	−0.0548***	−0.0289	−0.0676***	−0.0881***	−0.00300
	(0.00473)	(0.00863)	(0.00883)	(0.00794)	(0.0212)	(0.0122)	(0.0158)	(0.0133)
Lower* advanced	−0.0232***	−0.0288***	−0.0344***	−0.0226**	−0.0176	−0.0480***	−0.0123	−0.0213*
	(0.00566)	(0.00777)	(0.0104)	(0.00886)	(0.0164)	(0.0100)	(0.0105)	(0.0112)

TABLE 6 (Continued)

	(1)	(2) Manufacturing	(3)	(4) Services	(5)	(6)	(7)	(8)
	All firms	Low-tech	High-tech	Traditional	Modern	Small-sized	Medium-sized	Large-sized
Lower* academic	−0.0134***	−0.00504	−0.0201***	−0.0189*	−0.000854	−0.0493***	−0.0160*	−0.00674
	(0.00432)	(0.00814)	(0.00623)	(0.00999)	(0.0121)	(0.0120)	(0.00938)	(0.00781)
Trained* advanced	−0.0308***	−0.0288**	−0.0259*	−0.0243**	−0.0580***	−0.0737***	−0.0354**	0.00466
	(0.00799)	(0.0117)	(0.0140)	(0.0109)	(0.0222)	(0.0154)	(0.0148)	(0.00956)
Trained* academic	−0.0280***	−0.0110	−0.0213**	−0.0210	−0.0605***	−0.0667***	−0.0462***	−0.0333***
	(0.00598)	(0.00924)	(0.0105)	(0.0129)	(0.0128)	(0.0139)	(0.0124)	(0.00859)
Advanced* academic	−0.0166*	−0.0163	0.0130	0.0194	−0.0530***	−0.0424***	−0.0197**	0.00110
	(0.00918)	(0.0110)	(0.00896)	(0.0179)	(0.0130)	(0.0140)	(0.00868)	(0.0150)
N	7701	2725	1767	1959	1075	3405	3038	1258
N satisfying monotonicity and quasi-concavity	3165	1091	936	943	333	1192	1102	763
Allen elasticities of substitutions (AESs)								
$AES_{Lower,Trained}$	2.621	1.912	2.321	2.299	5.698	4.220	3.897	5.256
	(0.0147)	(0.0177)	(0.0280)	(0.0324)	(0.165)	(0.0364)	(0.0258)	(0.0791)
$AES_{Lower,Advanced}$	−2.531	−1.715	−2.108	−2.602	−5.784	−3.156	−2.793	−4.799
	(0.0140)	(0.0142)	(0.0288)	(0.0446)	(0.159)	(0.0222)	(0.0191)	(0.0850)
$AES_{Lower,Academic}$	2.859	1.983	2.386	4.303	5.523	3.665	2.362	4.254
	(0.0214)	(0.0385)	(0.0348)	(0.101)	(0.161)	(0.0468)	(0.0182)	(0.0848)
$AES_{Trained,Advanced}$	1.605	1.672	1.324	1.883	1.757	1.478	1.580	1.296
	(0.00754)	(0.0192)	(0.0141)	(0.0228)	(0.0211)	0.00908()	(0.0123)	(0.0130)
$AES_{Trained,Academic}$	−1.753	−1.794	−1.447	−2.712	−1.606	−1.674	−1.329	−1.149
	(0.0100)	(0.0224)	(0.0171)	(0.0394)	(0.0204)	(0.0196)	(0.00939)	(0.0145)

(Continues)

TABLE 6 (Continued)

	(1)	(2) Manufacturing	(3)	(4) Services	(5)	(6)	(7)	(8)
	All firms	**Low-tech**	**High-tech**	**Traditional**	**Modern**	**Small-sized**	**Medium-sized**	**Large-sized**
$AES_{Advanced,Academic}$	5.870	6.043	7.593	11.98	2.509	5.259	3.683	3.858
	(0.0628)	(0.121)	(0.146)	(0.186)	(0.0318)	(0.0738)	(0.0377)	(0.0784)
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Industry fixed effects	✓	✓	✓	✓	✓	✓	✓	✓

Note: Translog production functions estimated with Levinsohn–Petrin method. Dependent variable is the real gross-output. All variables in logs and demeaned to the (sub-)sample mean. Standard errors of coefficients are firm-level block-bootstrapped with 200 repetitions. Allen partial Elasticities of Substitution (AESs) are based on firms satisfying monotonicity and quasi-concavity conditions using the coefficients of the translog estimation and own input quantities. AESs are the average of the median AESs across firm-level block-bootstraps with 200 repetitions. Standard errors of AESs are based on these block-bootstraps. Industries grouped according NOGA 08 classification as in Figure 6. Small-sized firms have <50 employees, medium-sized firms between 50 and 249, and large-sized firms >250 employees.

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

workers, and Advanced and Academic workers. The magnitudes of the elasticities are very similar to those obtained using the value-added method, thus confirming the degree of substitutability/complementarity between labor inputs.

We now look at how the elasticities of substitution differ across firm characteristics. Columns (2)–(5) of Table 6 show the estimates of the gross output production function and the corresponding AESs by industry type, while columns (6)–(8) similarly show the results by firm size. Comparing these results with those of Table 4, we observe that the coefficients of the linear, quadratic, and simple interaction terms between the labor components are relatively smaller. None of the statistically significant coefficients change their sign, and the statistical precision remains relatively high. The number of firms satisfying the monotonicity and quasi-concavity conditions in the subsamples is also somewhat smaller than in the value-added case. Nevertheless, the elasticities reported in the bottom part of columns (2)–(8) show similar patterns to those obtained with the value-added method. The magnitude and signs of the AESs are also very similar. Overall, the results of this robustness test confirm the results obtained using the value-added method.

7 | CONCLUSION

This article show the existence of complementarities among workers with different types of education in affecting 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 have 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 could assume, particularly for countries in which the workforce is highly heterogeneous in education and a high proportion of workers have a VET education.

Using Swiss firm-level panel data covering the period from 2005 to 2015, we show that complementarities among workers are high when differences in types of education are large without being too high. Indeed, we find complementarity between workers with no post-secondary education (Lower) and workers with a tertiary professional education (Advanced); we also find it between workers with an upper secondary VET (Trained) and workers with a tertiary academic education (Academic). By contrast, all other pairwise combinations of these four education groups show substitutability. Specifically, our results suggest that firms can make a relatively easy substitution of 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. From a managerial perspective, these results highlight the importance of having a skill mix as it is beneficial in terms of firm productivity.

In terms of firm characteristics, the results are surprisingly similar for both low-tech and high-tech industries. Depending on the combination of workers, service industries—particularly innovative ones—exhibit higher substitutability and complementarity. The significance of both vertical education diversity, represented in the Swiss context by the significant number of VET workers with secondary education, and horizontal diversity at the tertiary level (Advanced vs. Academic) is highlighted by the findings. From a policy perspective, these results stress the relevance of VET in the Swiss education system as a provider of key workers at the upper secondary level, but also as a point of access to further advanced education.

This article fills the gap in the literature by showing that complementarities among workers with different types of education affect firm productivity. We add to previous studies by providing a fine-grained differentiation also at the tertiary level, where we distinguish between workers with a university education and workers with a tertiary professional education. In doing so, we are able to complement studies such as that of Backes-Gellner et al. (2017), in which they show the existence of positive spillovers between upper secondary VET workers and tertiary educated workers, by showing that the complementarity is particularly high between upper secondary VET workers and workers with a tertiary university education, while lower with workers with a tertiary professional education.

This article has several limitations that pave the way for future research. First, theoretical considerations suggest a U-shaped relationship between skills distance and substitutability. However, we link this prediction to our empirical hypotheses based on assumptions that should be verified by future research. Concretely, we locate the four worker groups in a hypothetical skill space that differentiates between theoretical and practical skills. We test the plausibility of this skills distance based on data for Swiss workers that allows to approximate skills by the share of workers in skilled occupations. The empirical results are consistent with the hypothesized pattern of complementarity and substitutability. However, the primary aim of this article does not consist of measuring skills empirically. Therefore, the indirect approximation of skill distances cannot confirm the location of workers in the skills space. Future research should validate these results based on an empirical framework that defines and measures skills distances directly.

A second limitation is the use of survey data, which may suffer from measurement error. Future research should confirm our results using administrative data that allow for a more detailed differentiation of worker groups. Furthermore, the survey structure does not give us worker-level information such as labor market experience or possible skills mismatch. Being able to control for these characteristics could allow us to refine the degree of complementarity or substitution. Similarly, also information on the structure of the firm (e.g. hierarchies and frequency of interaction between different workers) would allow to refine the patterns of complementarities taking into account the actual tasks and roles within the firms. This would be particularly relevant for testing the robustness of the results in medium and large firms, where, for example, academic workers may be in managerial positions and never interact directly with lower educated workers on the production line.

A methodological limitation is that the elasticities represent average treatment effects given the actual composition of the workforce. Implications may differ for specific occupations, educational groups, and tasks. From a methodological perspective, future research should also consider further extensions of the Levinsohn–Petrin approach, such as that developed by Ackerberg et al. (2015).

Finally, a valuable extension of this article could be to broaden the focus to the concept of the innovation value chain. Our study only analyzes total value added and gross output as output variables of firms. However, future research could focus on other objectives of the innovation value chain. Specifically, one can consider as alternatives the output of the production function as a measure of R&D intensity—which captures the knowledge creation process of firms—or the share of sales generated by innovative products—which measures the ability to transform knowledge into innovation.

AUTHOR CONTRIBUTIONS

Thomas Bolli and Filippo Pusterla wrote, read, and approved the final manuscript.

ACKNOWLEDGMENTS

We are grateful for comments from Uschi Backes-Gellner, Mehdi Farsi, Pierre Mohnen, Stefan Wolter, and seminar and conference participants at KOF-Leading House "Economics of Education, Firm Behaviour and Training Policies" Workshop, KOF Brown Bag Seminar, University of Neuchâtel Economic Seminar, 4th LEER Conference on Economics of Education, 2018 Congress of the Swiss Society of Economics and Statistics, and the SASE's 30th Annual Meeting. We would also like to express our gratitude to the editor and thank two anonymous referees for valuable suggestions. Open access funding provided by Eidgenossische Technische Hochschule Zurich.

FUNDING INFORMATION

This study is partly funded by the Swiss State Secretariat for Education, Research, and Innovation.

CONFLICT OF INTEREST STATEMENT

No potential conflict of interest is reported by the authors.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the KOF Swiss Economic Institute. Purchase terms do not allow authors sharing these data.

ETHICS STATEMENT

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How to cite this article: Bolli, T. & Pusterla, F. (2023) Complementarities among types of education in affecting firms' productivity. *LABOUR*, 1–38. Available from: https://doi.org/10.1111/labr.12256

APPENDIX

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

	(1) All firms	(2) Manufacturing	(3)	(4) Services	(5)	(6) Small-sized	(7) Medium-sized	(8) Large-sized
		Low-tech	High-tech	Traditional	Modern			
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)

TABLE A1 (Continued)

	(1) All firms	(2) Manufacturing	(3)	(4) Services	(5)	(6) Small-sized	(7) Medium-sized	(8) Large-sized
		Low-tech	High-tech	Traditional	Modern			
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	3931	1522	890	613	526	626	1126	1031
Quasi-concavity								
Allen elasticities of substitutions (AES)								
$AES_{Lower,Trained}$	2.641	1.627	2.818	4.605	8.011	3.461	2.571	3.501
	(0.0125)	(0.0129)	(0.0473)	(0.139)	(0.242)	(0.0431)	(0.0196)	(0.0838)
$AES_{Lower,Advanced}$	−2.700	−1.588	−2.728	−3.719	−7.951	−2.483	−2.132	−4.189
	(0.0154)	(0.0143)	(0.0435)	(0.118)	(0.217)	(0.0378)	(0.0175)	(0.107)
$AES_{Lower,Academic}$	2.919	2.365	2.908	5.921	5.641	1.986	2.058	4.062
	(0.0152)	(0.0526)	(0.0465)	(0.197)	(0.159)	(0.0283)	(0.0272)	(0.115)

(Continues)

TABLE A1 (Continued)

	(1) All firms	(2) Manufacturing	(3)	(4) Services	(5)	(6) Small-sized	(7) Medium-sized	(8) Large-sized
		Low-tech	High-tech	Traditional	Modern			
$AES_{Trained,Advanced}$	1.620	1.401	1.345	1.465	1.322	1.691	1.363	1.742
	(0.00545)	(0.0148)	(0.0163)	(0.0353)	(0.0200)	(0.0134)	(0.0130)	(0.0704)
$AES_{Trained,Academic}$	−1.749	−1.995	−1.490	−2.147	−0.915	−1.314	−1.364	−1.761
	(0.0114)	(0.0410)	(0.0213)	(0.0597)	(0.0131)	(0.0109)	(0.0200)	(0.0820)
$AES_{Advanced,Academic}$	5.125	10.07	4.601	6.018	2.832	3.890	4.818	6.010
	(0.036)	(0.278)	(0.0634)	(0.354)	(0.0493)	(0.0500)	(0.0918)	(0.222)
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Firm fixed effects	✓	✓	✓	✓	✓	✓	✓	✓

Note: Firm-level translog production functions estimated with Levinsohn–Petrin method with firm fixed effects (FE LP). All variables in logs and demeaned to the (sub-)sample mean. Standard errors of coefficients are firm-level block-bootstrapped with 100 repetitions. Allen partial elasticities of substitution (AESs) are the median across firms satisfying monotonicity and quasi-concavity conditions and calculated using the coefficients of the translog estimation and the own input quantities. Standard errors of AESs are based on these block-bootstraps. Industries are grouped according NOGA08 classification as in Figure 6. Small-sized firms have <50 employees, medium-sized firms have between 50 and 249 employees, and large-sized firms have >250 employees.

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.