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The Role of Specialized Knowledge and 'Know-How' for Firm Productivity: Evidence from the Equine Industry

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Abstract

Using matched employer–employee data, we investigate the influence of human capital inputs on firm productivity. Several variables are used to measure firms' access to skilled labor, such as their share of employees with occupation-specific education and experience in horse breeding and hippology and access to a local pool of skilled labour. The results show that occupation-specific training is associated with an average productivity premium of 11%, but there is significant heterogeneity in the extent that firms that can gain from workers with specialized training of relevance to the industry. The results have implications for policy and firms investment decisions.

Keywords: Human capital, Skills, Productivity, Equine industry
JEL classification: J24, D22, D24

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1 Introduction

Understanding the factors that drive productivity and efficiency in agriculture and related rural industries has long been an important goal (Hayami and Ruttan, 1970; Huffman, 1981; Sumner and Leiby, 1987; Martin et al. 1993; Goetz, 1993; Webber et al. 2009; Rizov and Walsh, 2011; Fuglie, 2017). A common argument is that, as agrarian industries have become more advanced technologically, human capital should play an important role in explaining why some firms are more productive than others (Reimers and Klasen, 2013; Nowak and Kijek, 2016). In theory, knowledge and skills are expected to provide firms with a competitive advantage and improve productivity through various channels and across different types of economic activity (Becker, 1964; Becker, 1983; Barney, 1991; Kramer, 1993). However, human capital can raise firm productivity differently, as labor can be more efficient for specific types of knowledge than for general (Becker, 1964; Gibbons and Waldman, 2004; Lazear, 2009). Workers with specific human capital, such as occupation- or firm-specific formal training and experience, should be more valuable to firms than those with general knowledge, as they possess tailored technological skills and intangible assets that allow them to work more efficiently (Kor and Mahoney, 2005; Raffiee and Coff, 2016).

Empirical research is consistent with these ideas. For instance, the review by Crook et al. (2011) shows that the knowledge characteristics of the workforce relates strongly to firm performance, especially when the knowledge is specific to firms. However, existing evidence on skill-related productivity gains adheres almost exclusively to firms in manufacturing and knowledge-intensive business services, and evidence from agriculture and related industries is limited. This is despite the fact that rural industries have become increasingly skill-based in recent decades with the introduction of new technology and complementary human capital.[2] But do rural firms benefit from expanding their employment share of knowledgeable workers, and if so, what type of formal training and experience matter for productivity? The answers to these questions are important, as they can support firms in making informed investment decisions regarding human resource management and up-skilling to strengthen long-term competitiveness.

This paper contributes with empirical evidence from a rural industry that is gaining global attention due to its contribution to rural and regional growth and an emerging experience-based rural economy (Rantamaki-Lahtinen and Vihinen, 2004; Jez et al. 2013; Heldt et al. 2018). Our focus on the equine industry has several additional reasons. The industry is labour-intensive and the knowledge characteristics of the workforce should have a relatively large influence on firm productivity (McManus et al. 2012; Roult et al. 2017). Furthermore,

[2] An increased focus on knowledge in rural production can also be witnessed in the Common Agricultural Policy (CAP 2023-27), with measures to support Knowledge Transfer (KT) and innovation systems (AKIS) to up-skill farmers and encourage innovation and long-term productivity (European Commission, 2022).

and as we show in this paper, the average firm in the industry has increased its employment share of workers with specific human capital, suggesting that firms are up-skilling. However, this is not uniform, and there is substantial heterogeneity within the industry, creating a very relevant setting for examining the human capital-productivity relationship. An additional interesting feature of the industry is the tendency for firms to cluster spatially, making access to both internal and external knowledge potentially important drivers of productivity.

In this paper, we perform the first population study on the role of general and specific human capital for firm productivity in the industry. We merge individual-level data on all Swedish registered employees with firm-level data on revenue, physical capital, worker qualities and additional inputs (2010-2022). We construct detailed firm-level measures of workforce characteristics using information on individuals' employment and education histories. Specifically, we measure total experience, education level and occupation-specific experience and education to proxy for general- and specific human capital. In addition, we measure worker qualities along other dimensions (e.g., age, gender) and use employment experience at a worker's current firm to proxy for firm-specific human capital. Our production function estimation relates Total Factor Productivity (TFP) to workforce qualities and employs several control function approaches to account for potential sources of endogeneity, such as simultaneity bias, rural labour market frictions, input quality and attrition (Ackerberg et al. 2015; Gandhi et al., 2020; Hu, Huang and Sasaki, 2020; Rovigatti and Mollisi, 2018).

Our main empirical finding is that firms can gain productivity from investing in workers with formal training of direct relevance to the industry, that is, in horse breeding and hippology. Averaging across firms in the industry, the productivity premium associated with specific human capital ranges between 11-13%. Knowledge diversity in the workforce can also raise productivity, but only if the knowledge has some degree of relatedness to agriculture and the equine industry. This supports the view that complementarities in workers' skill-sets can be an important resource for firms (Kramer, 1993; Boschma et al. 2009). The previous empirical literature has emphasized that the human capital-productivity relationship can vary significantly within industries due to differences in technology and skill-weigths (Rigby and Essletzbichler, 2006; Fox and Smeets, 2011). We classify the industry into its two main production orientations, horse breeding and horse racing and present estimates for each sector. We find an economically large and statistically significant coefficient on specific human capital, but only among firms specializing in horse racing. The largely insignificant results for general human capital suggest that investments in workers with specific skills are more strategic in nature for these firms.

This paper is not the first to examine the effects of human capital on firm productivity in a rural setting. In agriculture, a common finding is that general human capital, such as literacy and education level, is positively associated with agricultural productivity and

efficiency across countries, especially in more technologically advanced countries (Hayami and Ruttan, 1970; Reimers and Klasen, 2013). A positive effect of education on productivity is supported by micro-level evidence showing that farms operated by managers with higher education are more efficient (Asadullah and Rahman, 2009) and have higher TFP and labour productivity (Nowak and Kijek, 2016; Bjerke, 2016). A limitation of these studies is that several potentially important moderators of the human capital-productivity relationship have not been addressed, which limits the possibility of capturing the full effect of human capital. Specifically, a failure to account for both general and specific human capital accumulation in the long-term and among the entire workforce can lead to biased estimates (Crook et al. 2011). Furthermore, since rural firms face search costs in attracting and retaining workers with specialized skills (Rupasingha and Marre 2020), estimates can be biased if adjustment frictions in labour markets are left unaccounted for (e.g., Konings and Vanormelingen, 2015; Donovan and Schoellman, 2023). In fact, our results support such evidence as we find the output elasticities associated with specific-human capital to be biased when labour inputs are treated as freely adjustable inputs.

We depart from previous work and specify a production function that accounts for search frictions in rural labour markets and that relates TFP to several worker qualities. This is an important extension of the literature on human-capital-related productivity gains in agriculture, which has mainly focused on general human capital among managers (e.g., Nowak and Kijek, 2016). Most studies do also rely on the assumption that there exists a common agricultural production function (e.g., Reimers and Klasen, 2013), where in fact there is ample evidence that skill weights can vary significantly, even within narrowly defined industries (Orr, 2022; Cunningham et al., 2023). We contribute to the literature with evidence that the human capital-productivity relationship can vary significantly depending on the type of skills accumulated at rural firms and their production orientation.

2 Background and literature

The role of human capital inputs, such as experience and education, on firm productivity and growth has received a lot of attention in the literature. A positive return to human capital arises, for example, because educated workers have better managerial skills, are more likely to adopt new technologies and high-risk-return investments, and through knowledge spillovers (Cohen and Levinthal 1990; Andersson and Lööf, 2012; McGuirk et al., 2015; Akcigit et al., 2025). These arguments emerge from the resource-based theory of the firm (Barney, 1991) and the view that human capital plays a key role in determining workforce productivity (Becker, 1964; Becker, 1983). Human capital refers to the knowledge, skills, and abilities embodied in people and of particular importance are the skills acquired through formal education and experience. Workers can learn from experience and on-the-job training as they can obtain new

skills and develop previous ones while working (Arrow, 1962; Adhvaryu et al. 2023). They can also learn from education, and if the area in which workers have been formally trained is of direct relevance to a firm it plays a particularly important role for firm productivity (Crook et al., 2011). The idea is that for knowledge to be a valuable resource, it must be limited in supply and of direct relevance to a firm's economic activity to result in a lasting competitive advantage (Barney, 1991; Peteraf, 1993; Becker and Gerhart, 1996). Firms with workers who have valuable knowledge that cannot easily be duplicated or substituted will thus have a greater potential to raise productivity relative to their peers.

Although economic theory suggests that firms can gain productivity profoundly from expanding their stock of workers with specific skills, combinations of workers with different skill sets have also been shown to facilitate firm productivity. Diversity in skills can provide informational and organizational advantages and improve firms' capacity to adopt new technologies (Penrose 2009, Østergaard et al., 2011). It can also generate knowledge spillover effects, given that workers' knowledge is not too cognitively different (Noteboom, 2000). The study by Boschma et al. (2009) show that it is not new employees per se that promote firm productivity, but their degree of cognitive complementarity in relation to the current workforce. This supports the view that there can exist productivity enhancing complementarities in workers' skill-sets, especially if firms perform many of their activities jointly (Kramer, 1993). The type of knowledge characteristics that matter most for firm productivity, however, is not clear as this has been shown to vary across and even within industries.

2.1 Literature comparison

Several studies have used longitudinal matched employer-employee data to examine output elasticities associated with workforce qualities with mixed results.[3] The study by Iranzo et al. (2008) uses data on Italian manufacturing firms with individual records on all their workers. They find a positive relationship between firm productivity and skill dispersion measured within occupational groups (production and non-production workers). Parrotta et al. (2014) use matched employer-employee data on Danish firms in manufacturing, retail, and business services and show mixed evidence regarding the role of diversity in education on firm productivity across industries. The study by Östbring and Lindgren (2013) on Swedish employer-employee data in knowledge-intensive business services (KIBS) finds that a high degree of related knowledge in the workforce has a positive effect on firm productivity, especially in labour-intensive KIBS. An additional finding in the literature is that firms with more internal knowledge and 'absorptive capacity' are better at exploiting and taking advantage of external knowledge (Cohen and Levinthal, 1990) and that there can exist productivity

[3] In this brief overview, we focus on studies that employ production function estimations and do not compare with studies that use wage regressions. Since we do not have access to wage data, this related perspective is out of the scope of the present study

enhancing interactions between the two (Crescenzi and Gagliardi, 2018).

One conclusion that can be drawn from these studies, and other similar studies, is that the implication of workers' skill sets for firm productivity is important, but the specific types of knowledge that matter for productivity can vary depending on industry specifics.[4] Another is that the existing evidence adheres almost exclusively to firms in manufacturing and KIBS and there is very little evidence from agriculture and related industries. As stated in the introduction, and as a motivation for this paper, we want to broaden the debate on how different forms of knowledge contribute to firm productivity in rural industries, which can be heavily reliant on specialized skills but are not formally classified as Knowledge Intensive (KI).

2.2 A rural industry perspective

In rural industries that are dominated by Small and Medium Size Enterprises (SMEs), the learning that is important to productivity can be tied to the specificity of input factors. Agriculture and related industries have become increasingly capital-intensive in recent decades, but the tasks performed by workers are still many times very labour-intensive (Van der Ploeg, 2023). Firms should therefore be well equipped to integrate specific skills and knowledge into their daily routines and productivity should be closely related to the knowledge characteristics of the workforce and firm (farm) managers. The knowledge that matters for rural SMEs is often described as a form of tacit, localized and experience-based knowledge (Asheim et al. 2003), that can be acquired through networks, industry experience, and the relevant formal training. Tacit knowledge is important for firms, as it can reduce transaction costs to enhance overall productivity (Malmberg and Maskell, 2002). Increasing the tacit knowledge base of a firm is also important to foster the technological change needed to raise firm productivity (Woods, 2019). The implication is that a significant portion of rural firm performance may be attributable to heterogeneity in workers skill-sets but also to localized knowledge externalities. Taking as our starting point the literature on sectorial differences in the human capital-productivity relationship, we focus our empirical application on the case of the equine industry.

2.3 The equine industry

While the overall performance of the agricultural sector in Europe has seen a declining trend in the past decades, the equine industry is growing. Recent statistics show that there are more than 6 million horses that graze on 6 million acres of permanent grasslands, and the

[4]Similar mixed results can be found in other studies on the human capital-productivity relationship (e.g., Black and Lynch, 1996; Fox and Smeets, 2011; Almeida and Carneiro, 2009; Konings and Vanormelingen, 2015; Serafinelli, 2019; Orr, 2022)

number of riders increases by around 5% each year.[5] Structural transformation in agriculture in combination with increased leisure is expected to reinforce these trends, which has led to a greater focus on the potential of the industry to contribute to rural and regional growth (Zesada et al. 2011; Lopez et al. 2019).[6].

The structure of the horse industry in an international context has been thoroughly explored by McManus et al. (2012), who especially points out the link between breeding and racing, and the complex relationships that exist between firms in the industry. The logic for the industry of horse racing is similar to professional sports, where expansion is driven by 'new money' coming in through the purchase of a horse put into professional training, i.e., firm output is the price money of racing. An increase in demand for horse racing, both the total number of horses bought and sold and the value of horses at the top-end of the market, has been described as resulting in a trickle-down of price increases through lower levels of the market. A large part of the business model to attract "new money" is the narrative that there is a higher probability that knowledgeable and experienced trainers earn higher prize money during a racing career than less knowledgeable. Input goods and services for success in horse racing are, apart from the horse itself, quality in factors feed, veterinary attention, training, stabling and other aside services like equine therapy and finally factors related to the trainer itself.

The logic of horse breeding is closely tied to agriculture as it requires similar types of input and facilities and builds on the knowledge and experience used to feed and raise other farm animals (McManus and Montoya, 2012). The output of horse breeding is naturally a foal, which is usually sold at auctions, either yearling sales or after some extra months of training. Taken together, breeding, racing, training and caring (including feed) for the horse are all labor- and knowledge-intensive activities (Asogwa et al. 2013; Lopez et al. 2019). Therefore, the human capital of relevance in the industry should be closely tied to the quality of trainers and breeders and the knowledge acquired through specific education and experience needed to perform well in horse-related activities. Furthermore, and as we show that firms specializing in horse racing have a higher degree of integration of specialized skills in their workforce, we anticipate that the importance of specific human capital for productivity at the firm level is especially important for these firms.

[5]The European Horse Network: Horses for Growth and Environment (2015)

[6]These trends are not distinctive features for the Swedish and European context, but are found in countries such as Australia, New Zeeland, the UK and the US (Pickering et al. 2009)

3 Data sources and variables

The employer-employee matched data used in this study originate from several population registries governed by Statistics Sweden. We combine information on firms and their employees using data from the Integration Database for Health Insurance and Labour Market Studies (LISA) and the business register (FEK).[7] Linking these registers, we obtain detailed information on all active firms, of which the most important is firm financial accounts (revenue, physical capital, intermediate inputs etc.) and employees education and employment histories. We use five-digit Swedish Standard Industrial Classification codes (SNI) to distinguish firms with horse breeding and horse racing as the main source of economic activity. We have classified the industry according to the European Industry Classification codes (NACE, similar to NAICS for U.S and SNI for Sweden) in two main industries, horse breeding (SNI 1430) and horse racing (SNI 93191). Data from three additional registers are sourced to obtain information on firm size in terms of land holdings (ownership), land in production (including land in rental agreements) and firms geographical location; The Property Tax Register (FTR), the Swedish AICS/LPIS data (the Land Parcel Identification System) and the Geographical database (GDB).[8]

The advantages of human capital typically develop over time in a path-dependent way, and there can exist a time lag that requires a long-term perspective to study the relationship between human capital and productivity (Crook et al. 2011). To provide time for human capital accumulation to take place within firms and for changes in productivity to materialize, we performed our production function estimation on data over a 13-year period (2010-2022). The data set used in the analysis is an unbalanced panel of an average of 1,049 and 1,886 firms in horse breeding and racing, respectively, which amounts to 19,392 observations. We restrict the sample to exclude multi-plant firms, which amounts to about 1% of all firms, resulting in an estimation sample of 19,181 observations, that is, all single-plant firms with more than one employee (counting the manager) for which information on revenue (gross-value of production) is available.

3.1 Measurement of general and specific human capital of relevance in the equine industry

The variables of main interest are constructed using information on educational qualifications among all workers belonging to a firm each year, employees and managers. The first measures occupation-specific human capital defined as the number of workers with education in horse breeding and hippology constructed using 3-digit Standard Classification of Education (SUN)

[7] These micro data identify all firms, plants and individuals (over age 16) in the Swedish economy since 1990.

[8] We use data on the amount of pasture in ownership and rental agreement as an additional input in our production function estimation, see section 5 and Table A4 in the Appendix for the details.

codes in the LISA register. SUN codes correspond to the International Standard Classification of Education (ISCED), and the 3-digit level is the most detailed, including information about the specific subject for each individual. We include two additional variables to measure occupation-related education defined as the number of workers with education in animal husbandry and agriculture (e.g., agronomy), respectively.[9] A key difference between our education measures is that the first is the most specific in terms of the type of training of relevance for the horse industry. A person with an education in horse breeding and hippology is skilled in how to train horses and riders, and they often work with horse care, feeding, and animal health issues. They also frequently act as advisors for horse farms and riding schools, and participate in research and development in the field (Asgowa et al. 2013). The remaining education qualifications provide skills in agronomy, agricultural science and the care of other farm and domestic animals. Whether these related qualifications are productivity-enhancing depends on whether firms can benefit from having workers with very specific or related skills.

Following the evidence that diversity in related skills can be important for firm productivity (Cunningham et al. 2023), we include a variable that measure the related knowledge diversity of the workforce calculated in the following:

$$H^e_{ijt} = -\sum_{e=1}^{r} p^e_{ijt} \ln p^e_{ijt} \tag{1}$$

where p^e_{ijt} measures the workforce share in educational type e of firm i at time t, where e denotes the three educational qualifications defined above (horse breeding and hippology, animal husbandry and general agricultural education). In our empirical application, we use both head count measures, employment shares and the diversity index to test hypotheses regarding the role of education specificity for firm productivity.

We include a set of additional worker qualities commonly associated with specific human capital. Occupation-specific experience is calculated using information on individual labour market histories and we create a firm-level variable that measures the accumulated number of years of industry experience (in horse breeding or horse racing) held collectively by all workers and managers belonging to a firm.[10] Similarly, we calculate a variable that measures firm-specific human capital defined as the accumulated number of years of tenure in the firm. Furthermore, and since specific human capital comprises managerial experience or 'entrepreneurial human capital' (Braunerhjelm and Lappi, 2023), which is highly relevant to SMEs (Shepherd and Wiklund, 2006), we include a variable that measures managerial

[9]The three educational qualifications are mutually exclusive. The correlations are shown in Table A1 in the Appendix.

[10]In calculating these variables, we use information on employment histories in the LISA register together with industry codes to track individuals' labour market experience (employment and self-employment) in horse breeding and horse racing from 1993 and onward.

experience in the workforce.[11] We also include a variable that measures education level (share of employees with higher education), which is a common proxy of general human capital (e.g., Fox and Smeets, 2011; Nowak and Kijek, 2016). We also control for the average age of employees and gender.

3.2 Summary statistics

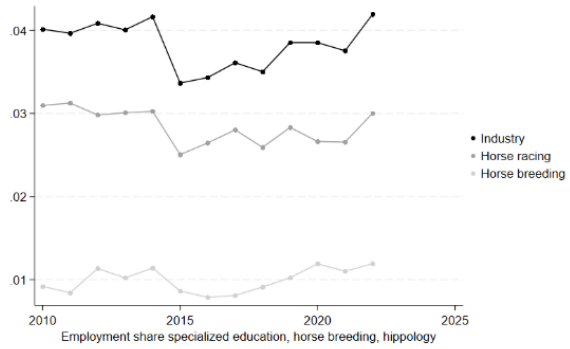
Table 1 shows the summary statistics of the common input factors included in the model (estimation sample), most of which follow standard definitions in the literature. Table A4 in the Appendix provides detailed variable definitions and data sources. The average firm in the industry has about one Full-Time Equivalent (FTE) employee, indicating that the industry is dominated by SMEs. There is large variation in the data as evidenced by the standard deviations of the amount of total labour and skilled labour employed in production. At industry level, the average employment share with specialized training in horse breeding and hippology is 4% with a standard deviation of 16%. Furthermore, an average firm specializing in horse breeding has an accumulated stock of experience in horse breeding of about 16 years and an accumulated stock of experience in horse racing of about 3 years. The stock is higher among firms in horse racing (18 years in horse racing and 6 years in horse breeding), suggesting that specialized experience is more important among these firms. Figure 1 shows trends of the main variables over our 13-year period of investigation split by sector (breeding and racing).

Table 1: Summary statistics: production factors and skilled labour (workers include managers). Mean values 2010-2022 with standard deviations in parentheses.

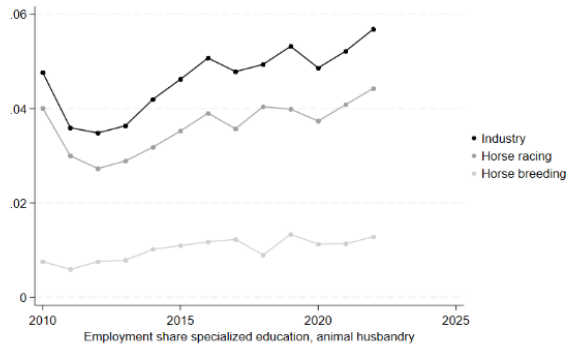
	Industry		Horse breeding		Horse racing	
Revenue	1518	(4454)	1680	(5027)	1436	(4122)
Intermediate inputs	1109	(4041)	1347	(4995)	978	(3240)
Capital	1346	(6871)	2222	(9589)	832	(4468)
Labour (FTE)	0.97	(3.32)	0.98	(3.88)	0.96	(2.93)
Land	3.48	(15.59)	6.38	(23.01)	1.78	(8.18)
Skilled labour						
Nr. workers spec. training (horse breeding, hippology)	0.13	(0.64)	0.11	(0.77)	0.14	(0.58)
Nr. workers spec. training (animal husbandry)	0.11	(0.45)	0.07	(0.37)	0.14	(0.50)
Nr. workers spec. training (agriculture)	0.11	(0.58)	0.15	(0.79)	0.10	(0.41)
Unskilled labour						
Nr. workers lack occupation-related training	2.05	(13.49)	1.67	(4.08)	2.16	(13.69)
Nr observations	19,181		7,158		12,116	
Nr firms	2,890		1,039		1,862	

Note: revenue (i.e., gross-output), intermediate inputs, and capital are displayed in thousand Swedish kronor KSEK (1 SEK approx. 0.090 USD) deflated using a producer input price index provided by the Swedish Board of Agriculture (2015=100). Labour is reported in Full Time Equivalent Employees (FTEs).

[11] The LISA register has availability from 1990. Due to changes in Swedish industry codes (SNI) we cannot accurately track work experience by sub-industry before 1993. We have also calculated the tenure separately for self-employment (managerial experience) and employment, as in Braunerhjelm and Lappi (2023), but this distinction did not add to the analysis and therefore we excluded these variables from the final model.



(a)



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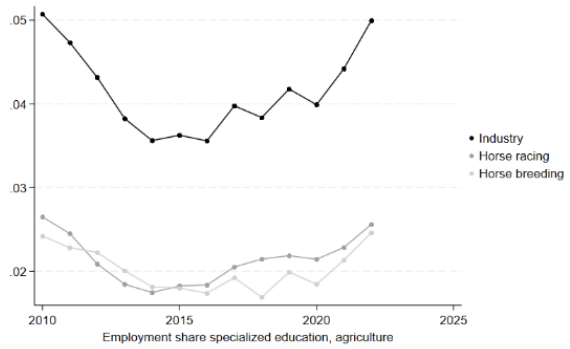

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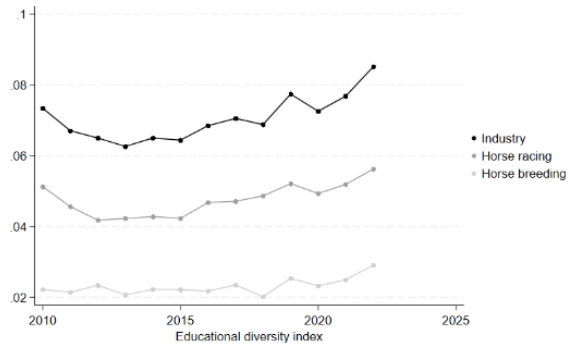


(d)

Figure 1: Employment share with specialized training 2010-2022

From Figure 1 we note that the share of workers with specialized training in horse breeding and hippolgy is increasing over time (panel a).[12] Employment shares of related education and related diversity are also rising and the standard deviations are large, suggesting variation in growth across firms. This shows that firms in the industry are up-skilling, but this is not uniform and there are large differences within the industry. Panels a-d show that the average firm specializing in horse racing has a workforce with more occupation-specific and occupation-related education than an average firm in breeding. The average firm has increased its share of workers with both occupation-specific and occupational-related education over time and that this is present in both production orientations.

3.3 Control variables

We include a set of labour market controls measured at the municipality level, which is the most disaggregated unit of local governance in Sweden (there are 290 municipalities). These variables are summarized in Table 2 and include two locational quotients that proxy for knowledge externalities, such as access to specialized suppliers and intermediate input, which are frequently hypothesized external sources of firm productivity (Malmberg and Maskell, 2002). These variables are computed by the number of firms in the two sectors (see Table A4). A variable that measures the supply of skilled labour in the municipality is included, defined as the stock of individuals with an education in horse breeding and hippology. This controls for that firms located in areas with a high supply of workers with the relevant skills are more likely to employ workers with such skills. Among the regional controls, we also include a variable that measures the wage sum to account for regional size and density, and proxy firms' access to thick markets and consumers with purchasing power. Fixed effects at the county level are used to account for time-invariant natural advantage and, lastly, we include controls for legal status of firms and landholdings to account for additional moderating effects related to firm size (Medase, 2020).

A limitation with the data is that they only report on firms established after 1986 (firms established before are given a value of 1986 regardless of establishment year). This prevents us from using a continuous measure of firm age in the production function estimation. Instead, we include age as a control that takes the value one if a firm is younger than 5 years. We also estimated separate models where we include the continuous measure of firm age together with a dummy variable denoting those firms for which age is unobservable prior to 1986.

[12] Summary statistics and bivariate correlations regarding employments shares with occupations-specific and occupation-related education can be found in Table A2 and A3 in the Appendix.

Table 2: Summary statistics. Additional worker qualities and controls. Mean values 2010-2022 with standard deviations in parentheses.

	Industry		Horse breeding		Horse racing	
Tenure horse breeding	15.55	(21.22)	16.57	(22.28)	6.32	(2.61)
Tenure horse racing	10.21	(17.81)	2.50	(4.09)	18.51	(57.24)
Share female	53	(15)	53.80	(14.27)	52.45	(15.38)
Average age employees, managers	0.97	(3.32)	0.98	(3.88)	0.96	(2.93)
Share higher education	0.01	(0.04)	0.01	(0.05)	0.01	(0.04)
Legal firm	0.17	(0.38)	0.17	(0.38)	0.18	(0.38)
Young firm	0.38	(0.40)	0.40	(0.44)	0.36	(0.49)
Location quotient, breeding	0.299	(0.320)	0.302	(0.344)	0.193	(0.204)
Location quotient, racing	0.399	(0.400)	0.398	(0.401)	0.401	(0.339)
Skilled labour (municipality)	126.05	(148.96)	124.06	(148.22)	127.06	(148.97)
Wage sum (municipality) /10000	15649	(35723)	14544	(34002)	15954	(36200)
Nr observations	19,181		7,158		12,116	
Nr firms	2,890		1,039		1,862	

Note: municipal wage sum is displayed in ten thousand Swedish kronor deflated using CPI (2015=100).

4 Empirical model

Based on our research purpose, we use the following production function to specify the firm-level relationship between productivity and skilled labour:

$$y_{it} = \alpha + \gamma_l l_{it} + \gamma_k k_{it} + \gamma_m m_{it} + \omega_{it} + \eta_{it} \tag{2}$$

where y_{it} denote revenue (gross-output) of firm i at time t and l_{it} is a vector of variables that measure general and specific knowledge characteristics of the workforce. Capital and intermediate inputs are denoted k_{it} and m_{it} and the production function relates output to inputs and efficiency A, such that $\ln A_{it} = \alpha + \epsilon_{it}$ where $\epsilon_{it} = \omega_{it} + \eta_{it}$.[13] The production function has the two usual unobservable terms η_{ijt} and ω_{ijt}. The first is a residual, and the second is the productivity of the firm, assumed to follow a first-order Markov process. Although the first is assumed to be uncorrelated with firms' period t input choices, the second can affect such choices and give rise to simultaneity bias (Marshak and Andrews, 1944). To address this, and following standard assumptions in this literature, we use firms intermediate inputs to define the following control function (Levinsohn and Petrin, 2003):[14]

$$\omega_{ijt} = h_t(k_{ijt}, m_{ijt}) \tag{3}$$

[13] We follow the denotations used in this literature (e.g., Ackerberg et al. 2015) and use lowercase letters denote the log of a variable.

[14] Inputs are assumed either variable (intermediates) or quasi-fixed (capital) and capital accumulation follows a law of motion such that firms capital stock in t is determined by the investments made in *t-1*. Demand for intermediate inputs is monotonic in ω_{ijt}.

substituted into the production function (Eq. (2)) provides the first-stage equation in our two-stage control function estimation:

$$y_{it} = \gamma_l l_{it} + \phi_t(k_{it}, m_{it}) + \epsilon_{it} \tag{4}$$

where $\phi_t(\cdot) = \alpha + \gamma_k k_{it} + \gamma_m m_{it} + \omega_{it}(k_{it}, m_{it})$.

In our empirical application, we estimate this first-stage equation using OLS and a third-order polynomial approximation using k_{it} and m_{it} in place of $\varphi(\cdot)$. We specify the following moment conditions:[15]

$$\mathbb{E}[\epsilon_{it} + \xi_{it} \mid k_{it}, m_{i,,t-1}] = 0 \tag{5}$$

and calculate TFP as a residual using the production function estimates:

$$\text{TFP}_{it} = \widehat{\epsilon_t + \xi_t} = y_{it} - \hat{\gamma}_l l_{it} - \gamma_k' k_{it} - \gamma_m' m_{it} - \mathbb{E}(\widehat{\omega_t \mid \omega_{t-1}}) \tag{6}$$

where $\hat{\omega}_{it} = \hat{\phi}_{it} - \gamma_k' k_{it} - \gamma_m' m_{it}$.

A potential limitation of this approach for our purpose is that the labor coefficient may be biased in the first-stage estimation if there exist adjustment frictions, such as hiring, firing, and search costs, that prevent firms from changing labor inputs in response to changes in ξ_{it} (Bond and Söderbom, 2005; Ackerberg et al. 2015). Such adjustment frictions are likely present in a context such as Sweden, which is governed by collective agreements and strict labor market legislation. Adjustment frictions associated with labour are also likely to be particularly evident in rural labour markets as firms often face significant search costs in attracting and retaining workers with relevant skills, especially if the skills in demand are highly specialized (Rupasingha and Marre, 2020).[16] To adjust for potential endogeneity resulting from labour market frictions, we apply the correction proposed by Ackerberg et al. (2015).

The main adjustment is that labour is included as an argument in the control function and that the first-stage estimation serves only to generate an estimate of $\phi_t'(k_{it}, m_{it}, l_{it})$. Based on the Markov chain assumption, we estimate the input coefficients in the following second

[15]The alternative approach to use firms demand for investments as in Olley and Pakes (1995) is not an option for us as firms in our data frequently report zero investment, which would exclude a large number of firms in the analysis. Nearly all firms in our data report positive values on intermediate inputs and we therefore build on the approach by Levinsohn and Petrin (2003).

[16]In Sweden, employees are generally well protected against dismissal due to employment protection legislation. Such labour market regulations and search frictions are not distinctive features only for the Swedish context, but are found in labour markets and rural industries in several countries (Konings and Vanormelingen, 2015; Donovan and Schoellman, 2023).

stage estimation:

$$y_{it} = \alpha + \gamma_l l_{it} + \gamma_k k_{it} + \gamma_m m_{it} + g(\phi'_{t-1} - \alpha - \gamma_k k_{i,t-1} - \gamma_m m_{i,t-1} - \gamma_{it} l_{i,t-1}) + \xi_{it} + \eta_{it} \quad (7)$$

using the following moment conditions to obtain the coefficients for labor and capital:

$$\mathbb{E}\left[\phi'_{ijt}\begin{pmatrix} k_{it} \\ l_{it-1} \end{pmatrix}\right] = 0. \quad (8)$$

Implied TFP can then be calculated in the usual way as a residual using the estimates of the adjusted production function. A further extension of our model is that we use the approach proposed by Hu, Huang and Sasaki (2020) to evaluate the presence of measurement error in intermediate inputs.[17] Following the literature on skill-related productivity gains (Parrotta et al. 2014; Braunerhielm and Lappi, 2023), we estimate the production function where labour qualities enter the model as headcount measures, we also estimate the following extended version where human capital variables are measured as labour shares:

$$TFP_{it} = \zeta_0 + \zeta_1\, gen_hc_{it} + \zeta_2\, spec_hc_{it} + \zeta_3 C_{it} + r_{it} + \tau + \upsilon_i + x_{it} \quad (9)$$

where TFP_{it} denote a revenue-based estimate of TFP of firm i at time t (described above) and gen_hc_{it} and $spec_hc_{it}$ denote vectors of variables that measure general and specific knowledge characteristics of the workforce as employment shares. Additional worker qualities and common input factors are included in C_{it} and the associated productivity premiums are $\zeta_1 - \zeta_3$. The model includes time (τ), regional (r_{it}) and firm fixed-effects (υ_t) and ϵ_{it} is an error term.

Even with the inclusion of local labor market controls, fixed effects at the firm and county level, it is difficult to rule out that the choice of firms to employ skilled labour is endogenously determined. Firms could have sorted themselves into areas with a high supply of workers with the relevant skills, making it difficult to establish a causal link. Another concern is that results may be driven by less productive firms exiting the industry, causing selection issues related to panel attrition. We perform several robustness tests to address such selection issues. First, we employ a two-stage Instrumental Variable (IV) approach where we instrument the skill variables with indices that measure the pre-existing stock of labour with specialized training of relevance in the industry at the level of LA:s. More details on this estimation strategy and the validity of the instrument can be found in Section 5.3, and similarly computed labour supply instruments can be found in Parrotta et al. (2014) and Mohammadi et al. (2017). Second, and to account for selection issues related to firm exits, we re-estimate all models

[17] This implies including a least two intermediate inputs in the estimation. More information on this estimation and the intermediate inputs considered can be found in Section 5.

using the attrition correction proposed by Rovigatti and Mollisi (2018), which accounts for firms' probability of survival over the investigation period.

5 Regression results

5.1 Industry level

Table 3 displays the results from our production function estimations and Table 4 displays the results where we relate implied TFP to additional workers qualities measured as employment shares (equation 9). All estimations include a sector control equal to one if a firm is specialized in horse breeding. From Table 3, we can compare the estimates generated by the different specifications, i.e., the standard methods OLS and LP (Lenvinsohn and Petrin, 2003) and the adjusted version (Ackerberg et al. 2015), (henceforth ACF) and evaluate the importance of simultaneity bias and labor market frictions in this industry. We report as well the results where we use the robust option proposed by Hu et al. (2020) (hencefort HHS) to evaluate the presence of measurement error in intermediate inputs.

The results show that labor and intermediate inputs are most important in explaining firm productivity and that the different approaches generate output elasticities that are different qualitatively. In particular, OLS and LP are indicated to overestimate the output elasticity of intermediate and labour inputs and ACF and HHS are shown to generate more consistent estimates, as indicated by the lower standard errors. This supports the theory that an upward bias in variable inputs arises when contemporaneous input choice and adjustment frictions are left unaccounted for (e.g., Ackerber et al. 2015).[18] This difference can be seen from the plotted Kernel densities (Figure 2). Since the ACF elasticities are indicated to be more precisely estimated, this is our preferred specification.

Results (Table 3) indicate that skilled labour (measured as log headcounts of workers with education in either horse breeding and hippology, animal husbandry or agriculture) is associated with a higher productivity premium than is unskilled labour (the log of the number of workers that lack occupation-related education). The results also show that occupation-specific educational qualifications are associated with a higher elasticity $(0.331; p < 0.05)$ than are occupation-related $(0.157, 0.139; p < 0.05)$. These results are most in line with the view that firms should invest in workers with formal training specific to the occupation i.e., in horse breeding and hippology. Overall, we find reasonable estimates of the gross-output production function while simultaneously correcting for simultaneity bias, labour market frictions and measurement error. Intermediate inputs are associated with the highest elasticity,

[18] The differences between the estimates of labour and intermediate inputs are statistically significant across the different methods as evidenced by chi-square statistics and associated p-values, we can reject the null of equal coefficients at 5% confidence level.

with an average of about 0.8 (ACF).[19] In Table 3, we also report a Wald test on the sum of the coefficients for each productivity estimator where the null is Constant Returns to Scale (CRS). All estimators, but the HHS, return a p-value where we can reject the null, i.e., the revenue-based production function for this industry does not exhibit CRS. The sum of the elasticities suggests that firms in the industry cannot scale inputs to increase efficiency. The result that intermediate inputs are the predominant source of productivity growth, exceeding the contributions of both capital and labour, is consistent with studies focusing on related industries, such as agriculture (e.g., Skevas, 2023).

Table 3: Production function estimations at industry level.

	Pooled sample, horse breeding and horse racing						
	OLS		LP		ACF		HHS
Log capital	0.009	0.018	0.072*	0.067*	0.025*	0.021*	0.022*
	(0.008)	(0.008)	(0.019)	(0.012)	(0.003)	(0.009)	(0.012)
Log labour	0.361*		0.326*		0.301*		
	(0.018)		(0.035)		(0.005)		
Log intermediate inputs	0.983*	0.983*	0.817*	0.866*	0.811*	0.801*	0.802*
	(0.007)	(0.007)	(0.026)	(0.023)	(0.005)	(0.005)	(0.009)
Log labour with spec. training		0.362*		0.341*		0.331*	0.330*
(horse breeding, hippology)		(0.047)		(0.043)		(0.002)	(0.007)
Log labour with spec. training		0.188*		0.186*		0.157*	0.158*
(animal husbandry)		(0.062)		(0.060)		(0.003)	(0.009)
Log labour with spec. training		0.171*		0.234*		0.139*	0.125*
(agriculture)		(0.058)		(0.055)		(0.002)	(0.007)
Log unskilled labour		-0.226*		-0.219*		-0.257*	-0.254*
		(0.037)		(0.039)		(0.002)	(0.009)
R-square	0.679	0.674					
Wald test CRS (p-value)			152.75	87.02	21446	35361	1.506
			(0.00)	(0.00)	(0.00)	(0.00)	(0.09)
Nr observations	19,181		19,181	19,181	19,181	19,181	19,181
Nr firms	2,890		2,890	2,890	2,890	2,890	

Note: LP and ACF are estimated with bootstrapped standard errors using 500 replications. OLS estimations are performed with robust standard errors clustered at firm-level. All estimations control for firm age. The second intermediate input considered in the HHS specification is the amount of pasture employed in production each year. This additional input is sourced from the Land Parcel Identification System (LPIS).
* indicates statistical significance at the 5% level or lower.

[19] We have also tested educational diversity indices that measure overall diversity (across all educational subjects) and unrelated educational diversity (across all non-agricultural and non-horse related educational subject), but these estimates where always insignificant and was dropped from the final model.

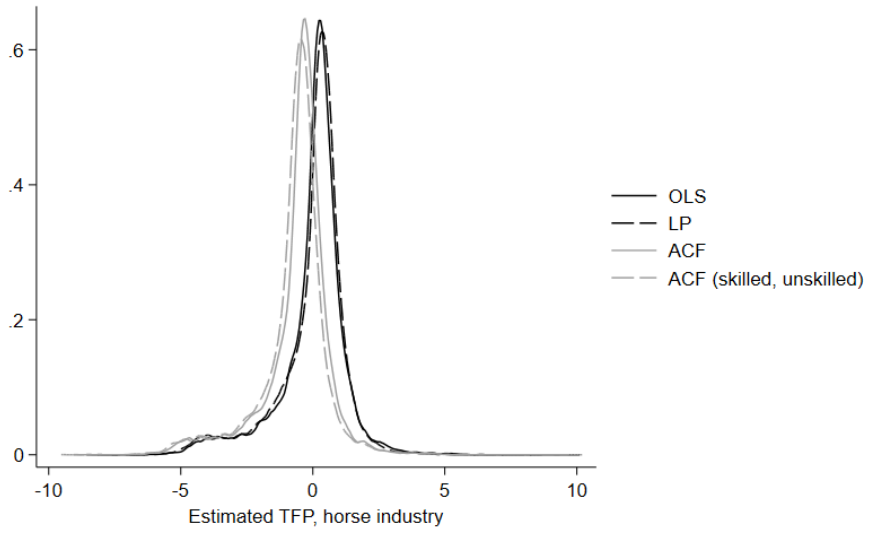


Figure 2: Kernel density of firm TFP at industry level calculated from different production function estimations with skilled and unskilled labour.

Table 4 shows the results where we relate implied TFP generated by the ACF method to additional firm, workforce, and labour market characteristics. Column 1 displays the results where we consider a between estimator, and the remaining columns show the results where we control for time-invariant firm-specific effects. The first two columns include workforce characteristics in terms of employment shares separating between the three educational types, and the last column displays the results where we include the Shannon index of related educational diversity (equation 1).

Results show that, when the educational variables are evaluated separately as shares and with the inclusion of firm-fixed effects (column 2), only the qualifications in horse breeding and hippology are positively related to productivity. In addition, when the model is estimated with the diversity index (column 3), there is a positive relationship between related educational diversity and productivity. These results may suggest two things. The first is that occupation-specific education is associated with an average productivity premium of about the size of 11% across firms in the industry. The second is that firms can benefit from combining workers with related skills. These industry-level results are again more in line with the view that firms in the equine industry can benefit from investing in workers with formal training relevant to the industry.[20]

Results (column 3) show that occupation-specific education is associated with a higher productivity premium than experience in horse breeding and horse racing, respectively. This suggests that specific human capital acquired via formal training is relatively more impor-

[20]These differences are statistically significant at the 5% level.

tant in explaining firm productivity than that acquired via labour market experience.[21] These results are quite consistent with previous studies based on employer-employee matched data showing positive and significant associations between human capital inputs and firm productivity, which are often found ranging between 1% and 17% in other industries (e.g., Pischke, 2001; Frazis and Loewenstein, 2005).

Additional labor qualities measured as education level (general human capital), seniority (average age of employees), and gender (share of female workers) are either insignificant or negatively associated with firm productivity.[22] The coefficient that denotes the local clustering of firms in horse breeding is positive and significant. This could suggest that firms in the industry can benefit from access to external knowledge and specialized suppliers (breeders) and intermediate inputs. This might also capture a combination of learning, sharing, and matching mechanisms of co-location or simply localized natural advantage that augment firm productivity. It is important to note that the specifications considered thus far are unable to disentangle the underlying mechanisms. A causal link between skilled labour and productivity is difficult to establish due to various sorting mechanisms. We return to this in Section 5.3 where we address the endogeneity of skilled labour in a causal effect analysis using an IV strategy.

[21] The null of equal coefficient can be rejected at 5% level (Chi-squre $120.21, p < 0.05$).

[22] We have tried alternative educational diversity measures that account for overall diversity (across all educational types) and these are insignificant in all estimations.

Table 4: Productivity estimates at industry level with labour shares of occupational-specific educational qualifications. Pooled sample (breeding and racing)

Dependent variable: log TFP (ACF)	I (between)	II (between)	III (within)
Share spec. training horse breeding, hippology	0.126*	0.115*	-
	(0.052)	(0.009)	
Share spec. training animal husbandry	0.071	0.011	-
	(0.063)	(0.065)	
Share spec. training agriculture	0.223*	0.088	-
	(0.070)	(0.072)	
Educational diversity	-	-	0.171*
			(0.061)
Tenure, horse breeding	0.087*	0.033	0.035*
	(0.016)	(0.021)	(0.021)
Tenure, horse racing	0.073*	0.047*	0.048*
	(0.014)	(0.017)	(0.017)
Share higher education	0.009	0.010	0.010
	(0.010)	(0.022)	(0.021)
Share female	-0.153*	-0.154*	-0.150*
	(0.039)	(0.049)	(0.049)
Log average age employees, managers	-0.547*	-0.029	0.027
	(0.053)	(0.066)	(0.065)
Log land	0.077*	0.047*	0.047*
	(0.016)	(0.023)	(0.023)
Legal firm	0.130*	-	-
	(0.047)		
Location quotient, horse breeding	-0.062*	-0.087*	-0.087*
	(0.019)	(0.036)	(0.036)
Location quotient, horse racing	0.021	0.014	0.014
	(0.029)	(0.043)	(0.043)
Skilled labour (municipality)	0.027*	0.006	0.006
	(0.001)	(0.007)	(0.007)
Log wage sum (municipality)	-0.002	-0.004	-0.005
	(0.027)	(0.051)	(0.051)
Constant	1.503*	0.326*	0.312*
	(0.332)	(0.099)	(0.098)
R square	0.171	0.098	0.101
Nr observations	19,181	19,181	19,181
Nr firms	2,890	2,890	2,890

Note: robust standard errors in parenthesis clustered at firm level. All estimations include year and county dummies and a dummy to indicate sub-industry. * indicates statistical significance at the 5% level or lower.

5.2 Intra-industry heterogeneity

Table 5 and 6 show the results in which we use our estimation strategy to perform estimations on sub-samples of firms that specialize in horse breeding and horse racing. This allows us to account for technology choice and obtain a more nuanced picture of the association between workforce characteristics and firm productivity in the industry. Results (Table 5) show that

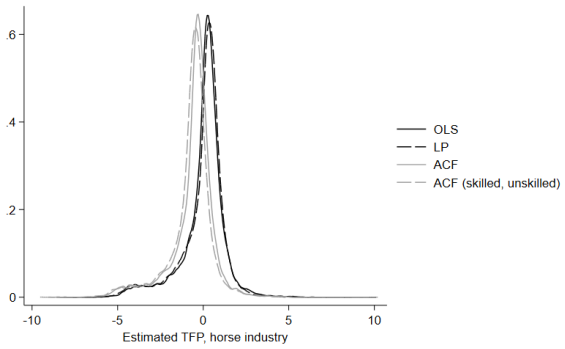
the intra-industry estimations are broadly in line with the industry-level results (Table 4), but with some notable differences regarding factor intensities. Both capital and skilled labour seems to be relatively more important inputs in horse racing compared to horse breeding, while intermediate inputs seems to be about equally important. This is a reasonable result considering that firms that specialize in racing are more dependent on specific human capital than those that specialize in horse breeding (McManus and Montoya, 2012). Evaluations of the presence of simultaneity bias and adjustment frictions do also support a more nuanced picture than the industry-level findings.

The different approaches generate elasticities that differ in ways predicted by theory in that traditional estimates (OLS, LP) are indicated to overestimate the output elasticity of intermediate inputs (Figure 3). Furthermore, the ACF method is indicated to generate elasticities much larger than those estimated in the OLS and LP regressions, most notably in horse racing and w.r.t. to workers with occupation-specific education. This suggests the existence of adjustment frictions and that firms cannot freely adjust their use of workers with specific training in horses. Thus, it appears that labour adjustment costs have differential influence in the two sectors. The results also suggest that specialized education is associated with a much higher productivity premium in horse racing compared to horse breeding (this difference is statistically significant at the 5% level with a Chi-square statistic of 141.2 ($p < 0.05$).

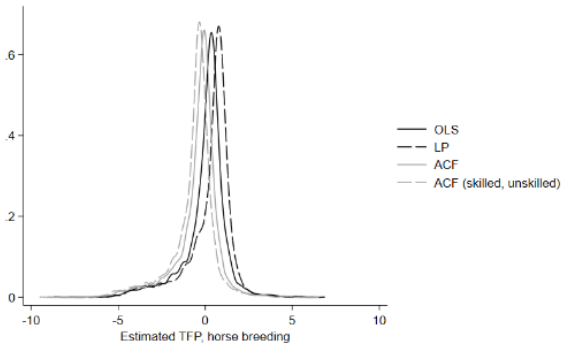
Table 5: Gross output estimates at intra-industry level with different control function approaches.

	Horse breeding				Horse racing			
	OLS	LP	ACF	HHS	OLS	LP	ACF	HHS
Capital	0.028*	0.010*	0.012*	0.012*	0.010*	0.078*	0.048*	0.049*
	(0.010)	(0.005)	(0.004)	(0.005)	(0.005)	(0.018)	(0.002)	(0.002)
Intermediate inputs	1.058*	0.837*	0.789*	0.788*	0.998*	0.854*	0.850*	0.850*
	(0.027)	(0.034)	(0.009)	(0.007)	(0.010)	(0.028)	(0.009)	(0.010)
Log labour with spec. training	0.255*	0.243*	0.103*	0.103*	0.477*	0.294*	0.456*	0.455*
(horse breeding, hippology)	(0.099)	(0.092)	(0.006)	(0.007)	(0.053)	(0.048)	(0.003)	(0.004)
Log labour with spec. training	0.254	0.049	0.029	0.022	0.281*	0.179*	0.275*	0.275*
(animal husbandry)	(0.223)	(0.125)	(0.031)	(0.032)	(0.064)	(0.062)	(0.003)	(0.007)
Log labour with spec. training	0.250*	0.247*	0.156*	0.155*	0.340*	0.267*	0.361*	0.360*
(agriculture)	(0.098)	(0.095)	(0.002)	(0.004)	(0.054)	(0.066)	(0.005)	(0.009)
Unskilled labour	0.073	0.082	0.057*	0.056*	-0.320*	-0.361*	-0.310*	-0.311*
	(0.070)	(0.074)	(0.006)	(0.005)	(0.041)	(0.049)	(0.003)	(0.005)
R-square	0.683			0.674				
Wald test CRS		29.02	2257.10	1899.79		34.44	52202	67023
(p-value)		(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)
Nr observations	7,158	7,158	7,158	7,158	12,116	12,116	12,116	12,116
Nr firms	1,039	1,039	1,039	1,039	1,862	1,862	1,862	1,862

Note: OLS estimations are performed with robust standard errors clustered at firm level, LP and ACF with bootstrapped standard errors using 500 replications. All estimations include controls for firm age.
* indicates statistical significance at the 5% level or lower.



(a)



(b)

Figure 3: Kernel density of firm TFP at sub-industry level calculated from different production function estimations.

Results from the extended productivity analysis (Table 6) show that we can confirm the important role played by labour market experience in breeding and racing for firm productivity in both sectors. However, occupation-related education is again only significant in horse racing when we estimate the model across firms. In particular, when the models are estimated without firm-fixed effects, there is a positive relation between all three educational qualifications and productivity in horse racing (Column 4,5). The coefficient on agricultural education is the largest, which supports earlier evidence on the productivity-enhancing potential of agricultural schooling (Bjerke, 2016). When we instead evaluate the change that occurs within firms, it is only occupation-specific education that remains significant. Similarly to the above, the positive association between educational diversity and TFP can only be confirmed among firms specializing in horse racing (Column 6). These results could suggest that there exists significant variation within the firm that is correlated with the possibility of the firms to employ and maintain a skilled labour force. Firms that employ more skilled workers may simply have managers who are more able, but this may also be related to firm size. It could be the case that both level and diversity in skills are more beneficial to larger firms as they have organizational routines, resources and financial strength that makes them better equipped to employ and sustain a workforce with specialized knowledge.

Table 6: Productivity estimates at intra-industry level with labour shares of occupational-specific educational qualifications.

	Horse breeding			Horse racing		
Dependent variable: log TFP (ACF)	I	II	III	IV	V	VI
Share spec. training	0.140	0.166	-	0.121*	0.110*	-
(horse breeding, hippology)	(0.099)	(0.101)		(0.059)	(0.023)	
Share spec. training	0.015	0.025	-	0.153*	0.018	-
(animal husbandry)	(0.017)	(0.107)		(0.080)	(0.081)	
Share spec. training	0.039	0.078	-	0.418*	0.129	-
(agriculture)	(0.096)	(0.100)		(0.097)	(0.088)	
Educational diversity	-	-	0.098*	-	-	0.190*
			(0.047)			(0.041)
Tenure, horse racing	0.024	0.041	0.086	0.070*	0.015*	0.017*
	(0.058)	(0.049)	(0.075)	(0.016)	(0.009)	(0.009)
Tenure horse breeding	0.130*	0.084*	0.086*	0.026	0.010*	0.009
	(0.020)	(0.022)	(0.022)	(0.069)	(0.001)	(0.085)
Share higher education	0.003	0.009	0.007	0.004	0.003	0.003
	(0.004)	(0.011)	(0.008)	(0.005)	(0.004)	(0.004)
Share female	-0.173*	-0.208*	-0.207*	-0.164*	-0.118*	-0.111
	(0.060)	(0.082)	(0.082)	(0.049)	(0.061)	(0.061)
Log average age	-0.395*	-0.141	-0.140	-0.637*	0.164	0.158
(employees, managers)	(0.083)	(0.097)	(0.096)	(0.070)	(0.089)	(0.099)
Log land	0.074*	0.042	0.042	0.070*	0.047	0.048
	(0.019)	(0.027)	(0.027)	(0.027)	(0.037)	(0.037)
Legal firm	0.102	-	-	0.113*	-	-
	(0.079)			(0.057)		
Location quotient, horse breeding	-0.011*	-0.094*	-0.094*	0.032*	0.023*	0.020*
	(0.043)	(0.052)	(0.051)	(0.009)	(0.001)	(0.001)
Location quotient, horse racing	0.012	0.064	0.066	0.039	-0.003	-0.004
	(0.056)	(0.089)	(0.087)	(0.035)	(0.050)	(0.056)
Log skilled labour (municipality)	0.060	0.026	0.025	0.010*	0.049	0.037
	(0.055)	(0.088)	(0.087)	(0.001)	(0.044)	(0.065)
Log wage sum (municipality)	0.030*	0.109	-0.111	-0.007	0.038*	0.034*
	(0.003)	(0.089)	(0.089)	(0.035)	(0.009)	(0.009)
R square	0.101	0.077	0.078	0.162	0.076	0.079
Nr observations	7,158	7,158	7,158	12,116	12.116	12,116
Nr firms	1,039	1,039	1,039	1,862	1,862	1,858

Note: robust standard errors in parenthesis clustered at firm level. All estimations include year and county dummies. Specification I & IV (between), II, III, V & VI (within)
*indicates statistical significance at 5% level or lower.

To investigate the moderating role of firm size, we re-estimate the model including the size of firms' capital stock. The results are very similar, but the magnitude of the educational variables decreases slightly (see Table A3). We also evaluate if there is any change in the results when we consider only larger firms. Bearing in mind that firms in the industry are small, we have limited possibilities to divide firms into multiple size groups. Therefore, we consider the subsample of firms that have a minimum of 3 FTEs (counting the manager(s)). The results (Table 7) show that the coefficient of occupation-specific educational diversity is larger in magnitude among larger firms (0.273) compared to the average across firms (0.215), but again only significant in horse racing. We can therefore conclude that firms specializing in horse racing are more likely to benefit from combinations of workers with specialized training in horse breeding and hippology and that this is likely to increase with firm size.

Table 7: Productivity estimates at intra-industry level with labour shares of occupational-specific educational qualifications, firms with at least 3 Full Time Equivalent employees.

	≥ 3FTE			
Dependent variable: log TFP (ACF)	Horse breeding		Horse racing	
	I(between)	II(within)	III(between)	IV(within)
Share spec. training	0.260		0.098*	
(horse breeding, hippology)	(0.202)		(0.009)	
Share spec. training	0.050		0.054	
(animal husbandry)	(0.097)		(0.049)	
Share spec. training	0.009		0.044**	
(agriculture)	(0.010)		(0.023)	
Educational diversity		0.232		0.202*
		(0.174)		(0.084)
Tenure horse breeding	0.050*	0.051*	0.043*	0.044*
	(0.010)	(0.010)	(0.007)	(0.007)
Tenure horse racing	0.089	0.088	0.037	0.035
	(0.063)	(0.062)	(0.029)	(0.027)
R square	0.121	0.121	0.139	0.144
Nr observations	1,459	1,459	4,401	4,401
Nr firms	295	295	702	702

Note: robust standard errors in parenthesis clustered at firm level. All estimations include year and county dummies and the firm, worker and labour market variables included in the main model.
*indicates statistical significance at 5% level or lower.

Taken together, we find robust evidence of a positive correlation between increased specialization in labor types and productivity among firms specializing in horse racing. These results could suggest that firms that invest in workers with specialized training in horses improve their productivity, perhaps via higher absorptive capacity and adoption of productivity-enhancing technologies and training methods and ways of doing business. This is a reasonable explanation given the common interpretation of TFP as a proxy for technological progress (Solow, 1957). Below, we try to address the causal link between skilled labour and firm productivity.

Another robust finding is that co-location can be important. This can be seen from the coefficient denoting local clustering of firms in horse breeding, which is positively associated with productivity among firms in racing. The reason why positive co-location might occur is that firms in racing can benefit from access to specialized horse suppliers and related inputs, which may lead them to increase efficiency. This could also be related to transport cost, which was Marshall's main explanation for the productivity advantages of co-location. Yet, this positive association may not only be attributed to the advantages of co-location, but can correlate with factors that we cannot observe in the registry data, such as inter-firm networks. Since the main focus of this study is on firms' access to internal knowledge, we do not attempt to disentangle the nature of this spillover.

5.3 Sensitivity analysis

Several robustness checks are used to validate the main results. First, we employ a 2-stage least square model (2SLS) to estimate equation 9 for the sub-set of firms specializing in horse racing. In this estimation we instrument the Shannon index of educational diversity in the following first-stage estimation:

$$div_edu_{it} = \zeta_0 + \zeta_1 \mathrm{LA}_{(i,k,t|1993)} + \zeta_2 \mathrm{tenure}_{it} + \zeta_{cj} C_{it} + \tau + r_{it} + x_{it} \tag{10}$$

where the instrument $\mathrm{LA}_{(i,k,t|1993)}$ is computed as the predicted stock of skilled labour in local labour market k at time t based on the stock observed in 1993. Specifically, it measures the stock of workers with occupation-related education in the active workforce computed w.r.t. educational qualifications in horse breeding and hippology.[23] Local labour markets (LA) are defined by Statistics Sweden based on observed commuting flows between municipalities, as such, they account for that the size of individuals' actual labour market and that workers can move beyond municipal borders. Our assumption is that pre-existing supply of skilled labour at the level of LA:s may be not correlated with a firm's current demand for skilled workers and productivity, if measured with a long time lag (in our case a minimum of 17 years and a maximum of 29 years). The instrument is significantly correlated with our index of educational diversity (17.9% $p < 0.001$) and is uncorrelated with TFP (2.1%, n.s.) conforming to the exclusion restrictions.[24] The F-statistics of the first stage is larger than 50 suggesting that the instrument is strong. The first and second stage results are presented in Table 8 and they are largely supportive of the main findings.

[23] The predicted value is used in the estimation of equation 9 in place of the diversity index.

[24] Summary statistics regarding the instrument and additional information on how the national stock of workers with this type of specialized education has evolved over time can be found in the Appendix (Table A6).

Table 8: First and second stage IV results for the sub-sample of firms specializing in horse racing.

	Horse racing
Dependent variable (first stage): occupation-specific skills diversity H^e_{ijt}	
Predicted stock of skilled labour in local labour market I^h_{iJc}	0.027*
	(0.003)
Constant	0.046*
	(0.003)
Firm, worker and labour market controls	Yes
F-value	52.75
R square	0.101
Nr observations	11,624
Nr firms	1,850
Dependent variable (second stage): log TFP (ACF)	
Educational diversity (predicted)	0.091*
	(0.004)
Constant	0.096*
	(0.021)
Firm, worker and labour market controls	Yes
Nr observations	11,624
Nr firms	1,850

Note: robust standard errors in parenthesis clustered at the LA level. All estimations include year and county dummies and the firm, worker and labour market variables included in the main model (Table 6), see Appendix for details.
* indicate statistical significance at the 5% level or lower.

As a second robustness check, we re-estimate all production functions using the ACF method with the attrition correction proposed by Rovigatti and Mollisi (2018). The results of the subsequent productivity analysis are displayed in Table A7 in the Appendix showing that the main results are very similar.

6 Conclusions

This study is related to a growing literature that focuses on the potential role played by human capital in strengthening firm productivity among rural SMEs (Goetz, 1993; Webber et al., 2009; Reimers and Klasen, 2013; Nowak and Kijek, 2016; Bjerke, 2016). We contribute to this literature with evidence from the equine industry that exemplifies a rural industry where specialized skills is a key part of the production process, but which is not formally classified as a KI industry. Through our industry approach, we hope to further broaden the debate on how different forms of skills and knowledge contribute to firm productivity in light of a growing knowledge-based rural economy (Naldi et al. 2015). Overall, there have been very few studies that focus on how general and specific human capital characteristics

among the workforce influence productivity among firms that have their main base in the rural economy, and this is the first study focusing specifically on the equine industry. Given the labour intensive nature of the work, we hypothesize that a high degree of occupation-specific training (measured as educational qualifications) can promote firm productivity in the industry.

With employer-employee matched data for all active firms and their employees (2010-2022) we can precisely measure educational qualifications and labour market experience of all workers and managers belonging to a firm. Thus, we expand previous research by focusing on occupation-specific training and by including the entire workforce of a firm, rather than focusing on managers (e.g., Sumner and Leiby, 1987; Asadullah and Rahman, 2009; Nowak and Kijek, 2016). We estimate a gross output production function to obtain a consistent estimate of firm TFP, which means that we do not have to resort to the unrealistic assumption that intermediate inputs are separable from primary inputs, such as labour and capital, which is usually not the case (Christensen, 1975; Gandhi et al. 2020). The results show that firms in the industry can derive productivity gains from having workers with training specifically aimed at a profession in the industry, but this knowledge effect mainly arises among firms specializing in horse racing. Although our results are robust to a number of control function approaches that correct for simultaneity bias, labour market frictions and the endogeneity of skilled labour via IV estimations, this study is not without caveats. One limitation is that we lack data to examine other dimensions of firms absorptive capacity commonly considered in this literature, such as exports, R&D and network activities. Our data make it possible to observe firms that export, but this constitutes only a small fraction (less than 1% of all firms in the industry). Aware that we cannot fully capture the construct of absorptive capacity, we believe that our focus on the characteristics of the workforce is the most relevant given that labor is one of the most important inputs in the industry (McManus et al. 2012). We also do not have access to data to account for differences in the quality of education in our analysis, which would have been a useful extension. Therefore, our results may actually underestimate the influence of the studied educational qualifications on firm productivity.

The positive impact of specialized training in horse breeding and hippology on firm productivity supports the view that specific knowledge acquired through formal training is a key factor in enhancing productivity in the industry. This is important information for firms and can support them to make informed labour investment decisions when it comes to matching workers with different skills. From a policy perspective, our results exemplify how to support productivity in an industry that is gaining interest in policy circles due to its significant contributions to rural and regional economies, its low-intensive nature and biodiversity enhancing use of permanents grasslands (Jez et al., 2013).

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Appendix

Table A1: Correlation matrix. Skilled and unskilled labour measured as headcounts.

	1.	2.	3.
1. Workers with specialized training in horse breeding and hippology			
2. Workers with specialized training in animal husbandry	0.333		
3. Workers with specialized training in agriculture	0.540	0.261	
4. Unskilled workers	0.174	0.154	0.302

Table A2: Summary statistics. Additional worker qualities and controls. Average values 2010-2022. Mean values and standard deviations in parentheses.

	Industry		Horse breeding		Horse racing	
Share specialized training horse breeding, hippology	0.04	(0.16)	0.03	(0.13)	0.05	(0.17)
Share specialized training animal husbandry	0.05	(0.18)	0.02	(0.14)	0.06	(0.21)
Share specialized training agriculture	0.04	(0.18)	0.04	(0.18)	0.03	(0.15)
Educational diversity	0.06	(0.18)	0.05	(0.17)	0.08	(0.19)
Nr observations	19,181		7,158		12,116	
Nr firms	2,890		1,039		1,862	

Note: municipal wage sum is displayed in ten thousand Swedish kronor KSEK (1 SEK 0.090 USD) deflated using a consumer price index provided by Statistics Sweden (2015=100).

Table A3: Correlation matrix. Skilled unskilled labour measured as employment shares.

	1.	2.	3.
1. Share specialized training horse breeding and hippology			
2. Share specialized training animal husbandry	-0.026		
3. Share specialized training agriculture	-0.033	-0.035	
4. Educational diversity index	0.479	0.590	0.546

Table A4: Detailed variable definitions.

Variable	Definition
Gross output	Total sales in KSEK.
Intermediate inputs	Value of intermediate inputs in KSEK.
Labour	Number of Full Time Equivalent employees including manager(s).
Capital	Value of material and immaterial assets (machinery, buildings, and land) in KSEK.
Share specialized training, horse breeding, hippology	Share of workforce with education in horse breeding and animal husbandry constructed using Standard Classification of Education (SUN) codes (621f).
Share specialized training, animal husbandry	Share of workforce with education in animal husbandry (SUN 621e, 621g).
Share specialized training, agriculture	Share of workforce with education in agriculture, such as agronomy (SUN 620x, 621a-621d, 621x).
Educational diversity	Equation 10.
Tenure breeding	Accumulated years of experience (employment and self-employment) in horse breeding among workers (incl. manager(s)) measured from 1993.
Tenure racing	Accumulated years of experience (employment and self-employment) in horse racing among workers (incl. manager(s)) measured from 1993.
Land	Number of hectares of agricultural land (pasture, arable) in ownership or rental agreement.
Young firm	Equals one if less than 5 years since establishment.
Legal status	Equals one if the firm is registered as a legal company. The base is sole proprietorships and trading companies.
Share female	Share of employees (incl. manager(s)) that are female.
Share higher education	Employment share (incl. manager(s)) with a bachelor degree or above regardless of type of education.
Average age employees	Average age of employees (incl. manager(s)).
Locational quotient, horse breeding	Location quotient: The share of firms in horse breeding in municipality divided by the share of firms in horse breeding in the national total. Excluding the focal firm.
Locational quotient, horse racing	Location quotient: The share of firms in horse racing in municipality divided by the share of firms in horse racing in the national total. Excluding the focal firm.
Skilled labour (municipality)	The stock of individuals in local labour market (LA) with an education in horse breeding and hippology.
Wage sum (municipality)	Real wage sum in municipality measured in 10,000 KSEK.

Table A5: Productivity estimates at intra-industry level with labour shares of occupational-specific educational qualifications. Including a control for firms' capital stock.

	Horse breeding		Horse racing	
Dependent variable: log TFP (ACF)	Within		Within	
Share specialized training horse breeding, hippology	0.166		0.109***	
	(0.101)		(0.022)	
Share specialized training, animal husbandry	0.025		0.013	
	(0.107)		(0.080)	
Share specialized training, agriculture	0.078		0.126	
	(0.100)		(0.084)	
Educational diversity		0.097		0.188***
		(0.077)		(0.040)
Tenure, horse racing	0.041	0.085	0.014**	0.017***
	(0.049)	(0.074)	(0.009)	(0.008)
Tenure horse breeding	0.084***	0.085***	0.010*	0.005
	(0.022)	(0.022)	(0.001)	(0.076)
Share higher education	0.009	0.004	0.002	0.002
	(0.011)	(0.008)	(0.004)	(0.004)
Share female	-0.208***	-0.204***	-0.116**	-0.114*
	(0.082)	(0.080)	(0.060)	(0.061)
Average age employees	-0.141	-0.141	0.165*	0.159*
	(0.097)	(0.094)	(0.088)	(0.088)
Land	0.042	0.040	0.044	0.045
	(0.027)	(0.025)	(0.037)	(0.037)
Capital	0.022***	0.021***	0.030***	0.031***
	(0.007)	(0.006)	(0.008)	(0.008)
Labour market controls	Yes	Yes	Yes	Yes
R square	0.077	0.079	0.077	0.080
Nr observations	7,158	7,158	12.116	12,116
Nr firms	1,039	1,039	1,862	1,858

Note: robust standard errors in parenthesis clustered at firm level. All estimations include year and county dummies and the municipality level controls included in the baseline model (Table 6).
*** $p < 0.01, **p < 0.05, *p < 0.10$

Table A6: Table A6. Summary statistics IV. Mean values and standard deviations in parentheses.

	Horse racing	
Index skilled labour (LA)	1.057	(0.64)
Skilled labour in municipality 1990	29.96	(26.76)
Skilled labour in municipality at t	126.92	(148.90)
Skilled labour in LA 1990	281.92	(311.03)
Skilled labour in LA at t	1,290.83	(1,523.19)

Table A7: Productivity estimates at intra-industry level with labour shares of occupational-specific educational qualifications.

	Horse breeding		Horse racing	
Dependent variable:				
(ACF with the attrition option in Rovigatti and Mollisi 2018)				
Share specialized training, horse breeding, hippology	0.163		0.112*	
	(0.103)		(0.022)	
Share specialized training, animal husbandry	0.026		0.017	
	(0.108)		(0.084)	
Share specialized training, agriculture	0.079		0.123	
	(0.102)		(0.089)	
Educational diversity		0.099*		0.191*
		(0.044)		(0.040)
R square	0.079	0.081		0.077
0.082				
Nr observations	7,158	7,158	12.116	12,116
Nr firms	1,039	1,039	1,862	1,858

Note: robust standard errors in parenthesis clustered at firm level. All estimations include year and county dummies and the firm, worker and labour market variables included in the main model (Table 6).
* denote significance at the 5% level or lower.