Employees' Entrepreneurial Human Capital and Firm Performance

Braunerhjelm, Pontus; Lappi, Emma

Document Version
Final published version

Published in:
Research Policy

DOI:
10.1016/j.respol.2022.104703

Publication date:
2023

Citation for published version (APA):
Braunerhjelm, P., & Lappi, E. (2023). Employees' Entrepreneurial Human Capital and Firm Performance. *Research Policy*, *52*(2), Article 104703. https://doi.org/10.1016/j.respol.2022.104703

Research Policy 52 (2023) 104703

Contents lists available at ScienceDirect

Research Policy

journal homepage: www.elsevier.com/locate/respol

Employees' entrepreneurial human capital and firm performance

Pontus Braunerhjelm [a,b,c,*], Emma Lappi [d,e]

[a] *Professor in Entrepreneurship and International Business, Department of Industrial Economics and Management, KTH Royal Institute of Technology, INDEK, SE-100 44 Stockholm, Sweden*
[b] *Professor in Economics at Blekinge Institute of Technology, 371 79 Karlskrona, Sweden*
[c] *Swedish Entrepreneurship Forum, Saltmätargatan 9, SE-113 59 Stockholm, Sweden*
[d] *Department of Strategy and Innovation, Copenhagen Business School, DK-2000 Frederiksberg, Denmark*
[e] *Center for Entrepreneurship and Spatial Economics (CEnSe), Jönköping International Business School, P.O. Box 1026, SE-551 11 Jönköping, Sweden*

A R T I C L E I N F O

Keywords:
Human capital
Entrepreneurial experience
Productivity
Innovation

A B S T R A C T

We introduce a new measure of human capital, defined as employees' former involvement in entrepreneurship. Such entrepreneurial human capital (EHC) complements traditional human capital measures accumulated through work experience and education. Using detailed longitudinal register data, we track the previous years of entrepreneurial experience for the population of employees in Swedish private sector firms. We provide evidence that higher EHC among employees is associated with significantly higher levels of firm productivity. The baseline result implies that a 10 % increase in employees being former entrepreneurs increases firm-level productivity by 3.9 %. Additionally, we provide evidence that heterogeneity in employees' previous entrepreneurial experience (e.g., the reason for entering and exiting entrepreneurship, type of venture, length of entrepreneurial experiences, and relatedness of technology) influences the impact of EHC on productivity. The results are shown to be robust to various estimation techniques, alternative definitions of EHC, and other performance measures.

1. Introduction

Explaining productivity differences across firms has long been a key issue in industrial organization research. According to Bloom and Van Reenen (2007) and, more recently, the OECD (2015) and Foster et al. (2018), firms display considerable and increasing heterogeneity in productivity, and there is a long tail of low-productivity firms. The most common explanations for these differences have been a weaker diffusion of knowledge and slowing innovation, lower investments in physical and human capital, and measurement problems related to investments in intangible capital (Gordon, 2012; Andrews et al., 2015; Feldstein, 2017). Such deficiencies at the microeconomic level are likely to be mirrored by a faltering performance at the macroeconomic level, where knowledge and human capital have been claimed to be the decisive drivers of innovation, productivity, and growth (Romer, 1986, 1990; Aghion and Howitt, 1992).

The objective of this paper is to deepen our understanding of the underlying factors behind the observed heterogeneity in firm productivity. More precisely, a new type of human capital is introduced originating in employees' previous entrepreneurial experience, which is shown to influence firm-level performance. We argue that entrepreneurial human capital (EHC) captures a set of abilities and skills that are possessed or acquired by those who have started and managed a firm. To our knowledge, EHC has not been considered in previous empirical analyses, notwithstanding that there is a rich host of literature tracing employee human capital effects stemming from education and work experience on a variety of firm performance measures. Among those are improved decisions by management, extended diffusion and

* Corresponding author.
E-mail addresses: pontus.braunerhjelm@indek.kth.se (P. Braunerhjelm), Emma.Lappi@cbs.dk (E. Lappi).

https://doi.org/10.1016/j.respol.2022.104703
Received 3 November 2021; Received in revised form 29 September 2022; Accepted 28 November 2022
Available online 8 December 2022

exploitation of knowledge, enhanced innovation activities, more rapid learning-by-doing in general, and higher levels of absorptive capacity (Blakemore and Hoffman, 1989; Haltiwanger et al., 1999; Abowd et al., 1999).[1] However, competencies acquired during an employee's earlier engagement in entrepreneurship are absent from the analyses.

An adjacent research vein to ours examines whether there is a wage premium or a wage penalty associated with entrepreneurial experience (higher wages being an indication of higher productivity), where results are ambiguous.[2] The inconclusive results in the wage premium/productivity literature are likely to reflect a host of observable and unobservable factors, such as asymmetric information, as well as individual-specific (age, education, position in the firm, etc.) and firm-specific characteristics (labor force heterogeneity, capital intensity, technology intensity, etc.).

This study makes a contribution to the literature by extending and complementing previous findings in three specific ways. First, previous research infers a productivity effect by using an indirect measure (wages), while we estimate the direct effect of employees' entrepreneurial experience measured as the firms' share of employees formerly being entrepreneurs and the number of years in entrepreneurship. We then regress EHC primarily on productivity but also on sales and innovation. Second, whereas recent research has investigated the option value of having the possibility to switch back to employment (Dillon and Stanton, 2017), dynamic career choices, individual characteristics, and entrepreneurial income (Humphries, 2021), the timing of entrepreneurial endeavors and income effects (Mahieu et al., 2022; Merida and Rocha, 2021), we focus on the outcome at the firm level. Third, in addition to directly estimating how EHC affects firms' productivity, access to detailed data at the microlevel allows us to control for a large number of individual- and firm-specific factors, some of which are quite unique, such as employees' reason for exiting and entering their previous entrepreneurial endeavors, which have not been implemented in previous analyses. In addition, by providing a measure of entrepreneurial human capital that can be operationalized and explicitly integrated into the analysis of firm-level productivity, we also narrow the gap between the productivity and entrepreneurship research fields.

More broadly, there is a strand in the literature arguing that entrepreneurial experiences generate abilities and competencies that differ from those obtained through regular wage employment or education.[3] For instance, Minniti and Bygrave (2001) and Parker (2013) stress that entrepreneurs seem to gain human capital related to their entrepreneurial endeavors while operating their firms. Hence, employees' entrepreneurial experience may be an alternative channel to acquire and broaden the knowledge base that complements competencies originating in education and on-the-job learning. Such entrepreneurial experiences should not only widen and diversify the knowledge base of firms, but could also be expected to generate new and complementary networks from which the firm may benefit. Nevertheless, human capital related to entrepreneurial experiences is basically neglected in the previous literature that investigates the link between employee specifics and firm-level productivity.

Hence, we propose a new source of human capital that is specific to an individual's entrepreneurial experience but aggregated to the firm level. Such entrepreneurial human capital (EHC) is assumed to be at least partly transferrable when an individual switches from entrepreneurship to employment. The extent of the effect of EHC depends not only on the firm's ability to exploit and integrate employees' knowledge emanating from previous entrepreneurial endeavors but also on the new employees' ability to interact and diffuse their embodied knowledge (Cohen and Levinthal, 1990). Qian and Acs (2013) emphasize entrepreneurial absorptive capacity, i.e., the ability to recognize the value of new knowledge and how to exploit it for commercialization. Basically, the dynamics we propose imply that entrepreneurial capital embodied in former entrepreneurs is turned into intrapreneurial capabilities (Carrier, 1996; Braunerhjelm et al., 2018, 2020), which is expected to positively influence productivity.

We estimate firm-level production functions for private manufacturing and service sectors by using a longitudinal matched employee-employer register database for Sweden from 2009 to 2018. By tracing employees' previous entrepreneurial experience and calculating EHC for each firm, we contribute several new insights regarding skill composition and productivity. Most importantly, this new and complementary measure of human capital is shown to positively affect firm-level productivity. The findings are robust to different definitions of entrepreneurial experience and remain basically unaltered as we disaggregate EHC on different employee characteristics (educational levels, occupations, age cohorts, etc.). Similarly, altering the model specification or implementing alternative outcome measures does not influence the results in any decisive way. Finally, our results strongly suggest that the positive relationship can largely be attributed to learning effects and acquired skills, even though innate abilities also matter. The results carry implications at both the firm (e.g., recruitment strategies) and policy levels (e.g., mobility between occupations).

The remainder of this paper is organized as follows. Section 2 provides a discussion of earlier contributions regarding productivity, entrepreneurship experience, and human capital, which provides an intuitive explanation of why EHC can be expected to positively impact firm productivity. In Section 3, we motivate and describe the empirical approach and the data used. The main results are outlined in Section 4, while we present extensions and robustness tests in Section 5. In Section 6, we discuss the results and the possible underlying mechanisms in some detail. Finally, in Section 7, the managerial and policy implications of the results are elaborated upon, and suggestions for future research are presented.

2. Previous research: human capital and performance

2.1. Education, occupational experience, and individual characteristics

Human capital has long been key in explaining aggregate growth, as well as performance, at the individual and firm levels, but limited to the type and length of education or working experience (Mincer, 1958; Becker, 1962; Romer, 1990; Haltiwanger et al., 1999; Ilmakunnas et al., 2004; Fox and Smeets, 2011). At the firm level, one strand in the literature has focused on productivity and the skill dispersion of workers (Iranzo et al., 2008), while others have emphasized the relationship between productivity and the diversity of employees, measured by both ethnicity and education (Parrotta et al., 2014). Using a meta-approach, Unger et al. (2011) present compelling evidence for human capital having a positive effect on enterprise growth, profitability, and size.[4] Hence, a higher endowment of knowledge, measured as the level of education and work experience of employees and its diversification, tends to increase firms' productivity.

[1] Griliches (1957) first investigated how knowledge influences productivity across firms. For a more in-depth review on firm-level productivity, see Bartelsman and Doms (2000) and Syverson (2011). Mincer (1958) and Becker (1962) examined the relationship between human capital and income distribution.

[2] The first studies found a negative effect of previous entrepreneurship experiences, which however has been challenged in recent and more detailed empirical research (Evans and Leighton, 1989; Hamilton, 2000; Williams, 2000; Bruce and Schuetze, 2004; Hyytinen and Rouvinen, 2008; Kaiser and Malchow-Møller, 2011; Manso, 2016; Daly, 2015; Mahieu et al., 2021; Louigi and Broström, 2020; Lappi et al., 2022).

[3] Lazear (2004, 2005) stresses that entrepreneurs have a specific "jack-of-all-trades" ability. The occupational choice literature analyses the options of becoming an employee or an entrepreneur (Murphy et al., 1991; Banerjee and Newman, 1993). See also next section.

[4] Their analysis did however not include productivity effects.

Furthermore, previous contributions have shown how some key characteristics of certain personnel (founders/entrepreneurs) influence the achievements of firms, primarily the type of education (technical education having a positive effect) and sectors in which previous experience has been acquired (Colombo and Grilli, 2005; Grilli and Murtinu, 2018). Additionally, Mion and Opromolla (2014), studying internationalization, conclude that managers' previous experience in related industries positively influences firm performance and management wages. More recently, Bender et al. (2018) extended the analysis to include how observed as well as unobserved abilities of employees and management practices influence productivity. They conclude that a relatively small share of productivity is explained by the average employee compared to management and that managers' recruitment strategies and the design of incentive structures are important explanations of their productivity impact, i.e., it is mediated through employees. Overall, the literature provides robust empirical evidence that human capital and employee characteristics influence firm performance.

Regarding specific entrepreneurial skills, an early contribution was provided by Schultz (1980), who, following Arrow (1962), concluded that learning-by-doing takes place among entrepreneurs and is a way to develop specific skills and acquire specific knowledge. Schultz's approach shares some commonalities with the learning dynamics presented by Jovanovic (1982), arguing that those individuals who persist longer as entrepreneurs are more likely to acquire superior managerial ability, i.e., gain more human capital than those who exit early. A similar perspective is introduced by Nelson and Phelps (1966) and Otani (1996), claiming that there is a relationship between technical change within an economy and the supply of entrepreneurship, where entrepreneurial ability is a specific form of human capital acquired through experience. Thus, their proposed mechanism – albeit at the macro level – resembles the one we emphasize. However, we argue that EHC more generally increases the knowledge base, whereas Nelson and Phelps (1966) and Otani (1996) stressed that entrepreneurial experience facilitates the adoption of new technology, leading to enhanced productivity.[5] Iyigun and Owen (1998, 1999) allude to the same dynamics, stressing that entrepreneurs accumulate human capital through a work experience-intensive process that differs from the education-intensive human capital accumulation of employees.[6]

2.2. Entrepreneurial experience and earnings

The conventional wisdom, i.e., that spells of entrepreneurship are associated with a wage penalty, has been challenged in an emerging and recent strand of empirical research. The overall argument is that a more dynamic and nuanced perspective is required to grasp the consequences of switching between being an entrepreneur or an employee. Dillon and Stanton (2017) conclude that there is considerable mobility between occupations and that approximately 50 % of those who become entrepreneurs switch back to employment. Building on Daly (2015), they argue that there is an option value related to testing entrepreneurship, defined as the difference in earnings between having the possibility to return to employment or not. Examining lifetime earnings, they conclude that spells of entrepreneurship increase income, particularly for those individuals who, early on in their income earnings careers, learn about their entrepreneurial abilities.[7] Policies (either subsidies or flat taxes) that might speed up learning about the individual's ability are shown to have a negligible effect.

Humphries (2021) elaborates on the lifetime earnings of different groups of entrepreneurs, sorted on the length of the entrepreneurial endeavor, time of entrance, education, labor market experiences, and the type of company. His specific focus is on the entrepreneurial outcome. Overall, he concludes that policies that augment skills have minor and short-lived effects, as do subsidies to increase entrepreneurship. Targeting younger cohorts is claimed to be the most efficient, while skills, education, and labor market experiences are important determinants of the types of entrepreneurs and their persistence levels.

An additional contribution to the literature is provided by Merida and Rocha (2021). They find that whether, and when, individuals enter entrepreneurship is decisive for lifetime earnings. Accordingly, for those experimenting with entrepreneurship soon after graduation and then returning to employment, there is a wage premium compared to those who never tried entrepreneurship. On the other hand, those switching to entrepreneurship later in their careers suffer a wage penalty if they return to employment. However, this does not seem to apply to those who have founded a growth-oriented firm or have been active in knowledge-intensive industries. Overall, the results imply that opportunity costs are lower for switches taking place early on in individuals' careers. Hence, they define boundary conditions for the option value of being able to switch to employment.

Additionally, Mahieu et al. (2022) investigate the income effect of switching between running a business and being employed.[8] Using Belgian data, they find a substantial and persistent wage penalty for returning to employment of approximately 27 %, contradicting Manso (2016), who claims that the wage discount is transitory. Further disaggregating the analysis, they conclude that previous performance as entrepreneurs is one determinant of the wage penalty. More importantly, however, is that former entrepreneurs, according to Mahieu et al. (2022), value independence and flexibility to a larger extent, which explains approximately 60 % of the wage penalty. For younger entrepreneurs, the wage penalty was shown to be basically nonexistent. On the other hand, Lappi et al. (2022) show how earnings after self-employment are largely dependent on education (or skills) and on the employer and industry-specific experience of the entrepreneur.[9] Overall, taking wages as an indication of productivity, the results are still ambiguous regarding the effects of switching between occupations.

2.3. Entrepreneurial experience and firm-level performance

There are several channels through which entrepreneurial experiences may influence firm-level performance. For instance, Baptista et al. (2012) underline how former entrepreneurs may provide employees with skills through supervisory and coordination tasks that can be

[5] This also relates to Beaudry and Francois (2010) analysis, showing that managerial skills associated with technology adaptation may lead to country-level differences in growth. At the regional level Audretsch and Keilbach (2004) links entrepreneurial capital, being a part of social capital that is defined as "those factors influencing and shaping an economy's milieu of agents in such a way as to be conducive to the creation of new firms." (p.419) to regional growth. Hence, entrepreneurship capital is measured indirectly.

[6] In their model individuals can only engage in one type of human capital accumulation with implications for entrepreneurial activities. Skill-biased technological change implies that professional human capital is more prevalent in richer economies while entrepreneurial human capital dominates in intermediate-income countries.

[7] Note that Daly (2015) and Louigi and Broström (2020) end up with opposite results, despite using the same methodological approach, with a treatment group that is matched against a control group. The former analysis concludes a negative effect of spells into entrepreneurship, whereas the latter finds no or positive effects.

[8] In a previous study on the same data Mahieu et al. (2021) find that the negative effects are driven by uncertainty about former entrepreneurs' productivity (particularly for those exiting entrepreneurs), smaller firms being employers, and those who belong to the high wage bracket.

[9] Lappi et al. (2022) show how the entry wages of the former entrepreneurs are not driven by imperfect information that can be alleviated by using referrals and how this differs across skill levels.

expected to impact productivity,[10] while Leibenstein (1968) emphasize that entrepreneurs, through leadership, motivation, crisis management, and risk-taking, influence firms' performance gradually. Such superior abilities related to supervision, coordination, and leadership are likely to be at least partially transferrable as individuals switch between entrepreneurship and employment. It also suggests that former entrepreneurs may be better managers, which could potentially influence firm performance. According to Agarwal et al. (2004), entrepreneurial experience is instrumental in developing complementary competencies within firms and generating increased value added. Since entrepreneurs are in a constant process of experimenting and learning, they acquire competencies that stretch over several functions and deviate from the typical employee or manager (Lazear, 2004; Foss and Klein, 2012).

Moreover, it has previously been shown that employees who change employers contribute new, sometimes industry specific knowledge. For instance, a positive effect on productivity has been established for firms hiring employees from multinational enterprises or R&D departments (Parrotta and Pozzoli, 2012; Stoyanov and Zubanov, 2012).[11] These findings suggest that experiences related to differences in the level of technology, or more industry-related compared to industry-unrelated technologies, could magnify firm performance (Mion and Opromolla, 2014). A former entrepreneur in a high-tech industry that becomes an employee may have better options to contribute new insights that influence productivity. However, the absorption capacity of such insights could depend on whether the previous entrepreneurial experience was accrued in a related or unrelated industry.

An alternative technology-driven mechanism would be that former entrepreneurs increase productivity by being more innovative. For example, Cirillo et al. (2014) find that inventors who join a spinout firm become "rejuvenated" and increase their inventive explorative activities. This might be paralleled by former entrepreneurs, i.e., they may continue, and even strengthen, their entrepreneurial and innovative efforts as they switch to becoming employees. However, as recent research has shown, both ends of the ability distribution – that is, high- and low-performing individuals – dominate in terms of who becomes a business owner (Andersson Joona and Wadensjö, 2013; Poschke, 2013; Humphries, 2021).[12] Hence, the proportion of high- versus low-performing individuals in firms hiring former entrepreneurs is likely to influence the potential for learning and knowledge diffusion and, thus, the effect of EHC.

A small subset of entrepreneurs has been shown to evolve into serial or portfolio entrepreneurs engaging in a large number of start-ups. This group of entrepreneurs also seems to outperform other new ventures, indicating that learning takes place (Gompers et al., 2006; Parker, 2013). Being involved in multiple entrepreneurial engagements over time consequently tends to enhance the ability to detect and exploit entrepreneurial opportunities, further strengthening high performers.[13] However, evidence has been provided that failures may also be a channel to acquire appropriate knowledge, as entrepreneurs transform failures into learning experiences (De Clercq and Sapienza, 2005).

Still, there are reasons to expect that the type of exit – mergers or/and acquisition versus close-downs/bankruptcy – may capture and form individuals' EHC (Bates, 1990). Similarly, the mode of entry can be expected to matter where individuals who are *pulled* into entrepreneurial endeavors because they perceive an opportunity are likely to differ in their effect on productivity compared to new ventures *pushed* to the market due to, for instance, unemployment. However, the distinction between different modes of entry and exit may be blurred, i.e., what seems to be a pushed venture may actually be a pulled one.

An alternative strand of the literature emphasizes certain individual-specific personality traits, i.e., risk attitudes and other psychological characteristics, and even genetic features, which arguably influence entrepreneurship rather than knowledge acquired through learning (Amit et al., 1993; Nicolaou and Shane, 2009). Hence, if employees who have been entrepreneurs in the past are innately more willing to undertake risk and are more innovative, this might show up in productivity improvements in the current firm. If such innate abilities drive entrepreneurs, the effect of employing former entrepreneurs can be expected to be independent of other characteristics associated with entrepreneurship, e.g., length of experience, learning, performance in the previous firm, education, etc. As pointed out by Eesley and Roberts (2012), the relationship between innate abilities and experience partly seems to depend on the context and degree of familiarity.

Knowledge may thus stem from different sources and be diffused through different channels. From the three strands of literature referred to above, we formulate the following overarching hypotheses: i) entrepreneurial experiences generate abilities and knowledge that complement formal education and work experience, which positively impacts firm-level productivity, and ii) the potentially positive effect of incorporating former entrepreneurs into firms' labor forces is moderated by heterogeneity in previous achievements, abilities/education, and experiences.

Hence, we expect EHC to constitute an important determinant of hitherto unobserved quality differences that could explain the heterogeneity in productivity across firms. Employees with previous experience in entrepreneurship can thus constitute a specific type of intangible capital, a production factor, in the firm that previously has been neglected. The next section will describe the model and empirical approach and unravel the individual- and firm-specific characteristics that will be implemented in the analysis.

3. Empirical design and data

3.1. The model and empirical estimation

We consider a conventional Cobb–Douglas production function for a given firm *j*, where we have labor-augmenting technology:

$$Y_j = K_j^{\beta_1}\left(A_j L_j^{\beta_2}\right) \tag{1}$$

Y refers to output, A is the technology term or the shift factor, K represents the stock of physical capital and L is labor. The β terms represent the elasticities of the respective inputs. The technology parameter is defined as:

$$A_j = exp\left\{\vartheta EHC_j + \gamma \boldsymbol{X} + \varphi_l + \varphi_k + \varphi_t\right\} \tag{2}$$

The *EHC* variable represents entrepreneurial human capital, $\boldsymbol{X}$ is a vector of other factors that influence the technology parameter, φ_l is the region (l) common shocks, φ_k denotes industry-specific (k) technology shocks, and φ_t captures the year-specific shocks. Inserting the technology parameter A_j into Eq. (1) and taking natural logarithms gives us the following expression for our regression analysis (which follows Marino et al., 2016; Parrotta and Pozzoli, 2012; Parrotta et al., 2014; Serafinelli, 2019):

$$y_{jt} = \alpha + \beta_1 k_{jt} + \beta_2 l_{jt} + \vartheta EHC_{jt} + \gamma \boldsymbol{X} + \varphi_l + \varphi_k + \varphi_t + \zeta_{jt} \tag{3}$$

The lowercase letters refer to the natural logarithm of the respective variables. The estimated ϑ coefficient captures how EHC influences productivity, which is our focal interest in the analysis. A conceivable

[10] This goes back to Casson (2003) and Say (1828), who argued that the entrepreneur contributes by efficiently coordinating factors of production, i.e., scarce resources.

[11] See also Distel et al. (2019) on export performance and Faleye et al. (2020) regarding the effects of having entrepreneurs as board members.

[12] This is mirrored by ambiguous results when examining the wage premium of individuals who exit entrepreneurship for wage employment referred to in the previous section.

[13] Moreover, according to Parker (2018) experience of previous entrepreneurship is a key explanatory factor of survival, together with education and age.

problem with estimating Eq. (3), specifically the ϑ-coefficient, is the possible and likely biases introduced due to the simultaneity (endogeneity) of inputs, i.e., firms adjust their labor with entrepreneurial experience nonrandomly. To solve for the endogeneity of input choices, including labor, we implement semiparametric estimation techniques as suggested by Olley and Pakes (1992) and Levinsohn and Petrin (2003).[14] These techniques, which we refer to as the OP and LP estimators, have been extensively used in the previous literature (Fox and Smeets, 2011; Parrotta et al., 2014; Serafinelli, 2019).

The OP and LP estimators account for the correlation between unobserved productivity shocks and inputs by using investments or intermediate materials, where their inverse demand functions are proxies for the unobserved productivity shock. This means that the error term (ζ_{jt}) from Eq. (3) is defined as,

$$\zeta_{jt} = \omega_{jt} + \varepsilon_{jt}, \tag{4}$$

where ω_{jt} is the unobserved productivity shock, and ε_{jt} is the conventional error term, which exhibits the standard properties. The unobserved firm-specific productivity term can be solved by using the inverse demand function for intermediaries (in the LP method), which can then be used to derive the correct input elasticities. This means a stepwise procedure where the ω_{jt} term is estimated using materials and capital data, following a first-order Markov process.[15] The capital stock is assumed to be determined at *t-1* by the capital stock and investments in that period. Labor, on the other hand, is assumed to be flexible so that a profit-maximizing firm adjusts its labor after a productivity shock has occurred at time *t*. These assumptions imply that we use the current value of capital, the lagged values of the labor, EHC, and the control variables for the moment conditions of their estimated coefficients,

$$E\left[a_{jt}\middle|\begin{array}{c} k_{jt} \\ l_{jt-1} \\ EHC_{jt-1} \\ X_{t-1} \end{array}\right] = 0 \tag{5}$$

where the term a_{jt} captures the unobservables related to technological change or innovation of the productivity shock ω_{jt}.[16]

The difference between the traditionally used OP and LP methods is related to how to capture unobserved productivity shocks at the firm level. The OP estimator has been criticized because adjustment costs create lumpiness in the investment levels, and many firms report zero investments, meaning that they will be excluded from the analysis. Due to these shortcomings, the LP method instead uses intermediate inputs (materials) as a proxy for investment levels. For these reasons, we rely on the LP technique as our preferred estimator. However, more recently, Ackerberg et al. (2015) propose an alternative improved approach (AFC) since the OP and LP estimations may suffer from collinearity problems. As a robustness test, we also provide results for the ACF correction.[17]

3.2. Data

We use micro-level register data provided by Statistics Sweden (SCB) spanning from 1993 to 2018. The data cover the population of Swedish individuals and firms, which allows us to track employees' mobility in and out of entrepreneurship and match the individual records to the firm data. For the production function estimation, which corresponds to Eq. (3), we use observations for the time period of 2009 to 2018 to ensure that some accumulation of EHC has taken place across firms. Our prime outcome variable is productivity, measured as value-added. Capital is the firms' total tangible and intangible assets each year. All values are reported in Swedish Krona (SEK) and deflated with 2016 price levels.[18]

Our key variable is current employees who have been entrepreneurs in the past. There is no consensus in the literature regarding how to measure or define entrepreneurship; however, one frequently used variable is business ownership (Parker, 2018). We have information on the employment status of individuals defined as wage earners or whether they own a business.[19] According to Levine and Rubinstein (2016), incorporated and sole proprietors are inherently different, which leads us to focus on those individuals who own incorporated businesses.[20]

Using the longitudinal nature of the individual records going back to 1993, we distinguish between those employees who have previously been engaged in entrepreneurship and other employees. Furthermore, we can also calculate the number of years they have run a business before becoming employees. Hence, we have information at the firm level on both the count of employees who have formerly been entrepreneurs and the length of their experiences. In our baseline estimations, we do not impose any restrictions regarding former entrepreneurs' labor market status before being employed by the present firm.[21] Furthermore, we exclude current business owners with previous entrepreneurial experience from the analysis since our purpose is to include EHC emanating from employees within a firm.[22] Our main EHC measure is the share of employees with entrepreneurial experience in relation to the total number of employees.

The contribution of EHC may be related to traditional human capital variables, i.e., education and work experience. To account for such effects, we rerun the estimations where EHC has been distributed on employees with higher (tertiary level) and lower education. Since data from Statistics Sweden allow us to distinguish between the occupation of employees, we further separate between EHC in a management position (defined as operations managers, occupations requiring an advanced level of higher education, and occupations requiring higher education qualifications or their equivalent) and nonmanagers (defined as administration and customer services, other services, care work, shop sales, building and transport workers, and other more elementary functions). The occupational codes follow the international occupation standards (ISCO-88). Finally, we classify the EHC of employees into five different age cohorts and also examine whether tenure matters, defined as being employed for at least three years.

In the vector of covariates (***X***) in Eq. (3), we include a set of employee

[14] An alternative solution would be to implement fixed effects or instrumental variable estimations. However, these regression methods have been shown to work poorly with production functions (Griliches and Mairesse, 1998).

[15] Formally defined as $\omega_{jt} = s_t(k_{jt}, m_{jt})$, which is the inverse demand function (s_t) for intermediaries (m_{jt}).

[16] This stems from the solved expression of $a_{jt} = \omega_{jt} - g(\omega_{jt-1})$.

[17] Wooldridge (2009) has also proposed an estimation method for productions which uses the generalized method of moments estimation in a single step to correct for the endogeneity of input choices. The results of the Wooldridge estimation are not presented but can be provided on request.

[18] We exclude agricultural, forestry, fishing, public, and financial sector firms from the analysis due to their industry-specific characteristics, which makes it difficult to correctly estimate labor productivity.

[19] An individual is recorded as a business owner by Statistics Sweden if at least half of her income originates from a business she owns.

[20] Klapper et al. (2015) also show that incorporated businesses are more relevant for high-growth entrepreneurship. We test the robustness by also including sole proprietorship firms in the Section 5.1.

[21] Former entrepreneurs could thus be entrepreneurs, employed or unemployed before taking up their current position. As seen from the individual-level descriptive statistics in Appendix A (Table A1.2), employees with EHC seems to primarily enter from previous employment and have less experience of unemployment as compared to employees without EHC.

[22] We have also run regressions where the entrepreneurial experience of the current owner/founder is included, alternatively, for serial entrepreneurs. It decreases the coefficient of EHC somewhat but basically the results are unaltered. We argue that the numbers of years being an entrepreneur are more informative and about learning, rather than simply splitting up employees' EHC on serial entrepreneurs and other entrepreneurs. The regressions results are available upon request.

Table 1
Descriptive statistics.

Variables	Mean	St. dev.	Min	Max
Value added (in 1000 SEK)	6347	30,723	0.964	6,380,502
Capital (in 1000 SEK)	4660	97,573	0.001	33,448,294
Labor (number of employees)	9.938	27.048	2.000	3976
Materials (in 1000 SEK)	14,771	134,778	0.964	27,293,494
EHC	0.063	0.138	0.000	1.000
Highly educated employees	0.086	0.178	0.000	1.000
Male employees	0.489	0.327	0.000	1.000
Foreign employees	0.135	0.230	0.000	1.000
Age_1	0.222	0.236	0.000	1.000
Age_2	0.170	0.194	0.000	1.000
Age_3	0.164	0.193	0.000	1.000
Age_4	0.125	0.175	0.000	1.000
Firm age	8.430	8.630	0.000	32
Multinational	0.034	0.180	0.000	1.000
Number of firm-year observations	1,191,740			
Number of firms	368,993			

Notes: Values based on estimation period 2009–2018.

and firm characteristics that have previously been shown to influence firm-level productivity. To control for observable employee characteristics, we include the shares of all highly educated employees, which measures the level of human capital level and is a proxy for absorptive capacity (Nielsen, 2015) of the workforce (*Highly Educated Employees*), gender (share of *Male Employees*), and foreign-born employees (share of *Foreign Employees*)[23]. To further control for the age structure of the employees, we also include four age categories of current employees: employees <30 years old (Age_1) and age cohorts 30–39 (Age_2), 40–49 (Age_3), and 50–59 (Age_4). All categories are measured in relation to total employment in the firm.

At the firm level, we control for the age of the firm (*Firm age*), measured as the number of years since the firm started, and whether it belongs to a multinational group (*multinational*).[24] The latter is supposed to capture whether a firm has access to foreign capital and technology, measured as a dichotomous variable that takes on value one if the firm is a multinational corporation (and zero otherwise). Table 1 below summarizes the estimation sample. A correlation table with the covariates included in the estimations is provided in Appendix A (Table A1.1).

Altogether, the dataset comprises approximately 1.2 million observations for 370,000 firms over the years 2009 to 2018. In an average firm, 6.3 % of employees have been entrepreneurs in the past, with a standard deviation of 0.138. This suggests that the share of employees with entrepreneurial experience is relatively large.

A detailed description of the individual-level characteristics of employees with or without experience as entrepreneurs can be found in Appendix A (Table A1.2). The individual-level descriptive data show that employees who have entrepreneurial experience earn slightly more, are older and are more often managers. The average values for firm-year observations in Table 1 also reveal considerable variation in employees' entrepreneurship experience. If there is a selection of former entrepreneurs, it seems to be negative rather than positive since they are more frequently found in less productive and smaller firms, which are also less likely to be multinationals. The semiparametric estimation methods, however, deal with such unobserved firm-specific effects. We will also utilize employee heterogeneity to evaluate individual characteristics considered to be important for EHC and productivity.

We undertake a number of extensions and robustness tests by implementing data on alternative measures of performance outcome and EHC, different types of entrepreneurs, reasons for entering and exiting entrepreneurship, length of entrepreneurial experience versus innate ability, the importance of related and unrelated industries in which the entrepreneurial endeavor took place, and technology intensity.

4. Results

4.1. Main results

Table 2 contains our baseline specifications as described in Eq. (3). We include the OLS estimations in Columns 1 and 2 as references, although our main attention is directed toward the semiparametric estimation techniques implemented in Columns 3, 4, and 5.

The baseline results reveal a robust and positive relationship between having a larger share of employees with previous entrepreneurship experience and productivity. The elasticity of the share of previous entrepreneurs has a lower bound of 0.039 in Column 4 (our preferred estimator), implying that a 10 % increase in the share of former entrepreneurs in the firm's labor force generates a 3.9 % increase in productivity. Hence, having employees with an entrepreneurship background seems to augment and complement a firms' human capital, as captured by the more traditional measures, positively affecting productivity. Note that we cannot separate the direct human capital effect of entrepreneurial experience and the indirect effect stemming from individual knowledge spillovers to other employees. Both effects are captured by the estimated coefficients.

We can reject constant returns to capital and labor, as the elasticity of the capital is estimated to be 0.026 and the labor term 0.776 in our preferred LP estimations. All control variables included in the estimations are significant and have the expected signs. We find that older multinational firms are more productive. For the variables associated with the labor composition of the firm, a positive productivity impact is found for larger shares of educated, males and older employees, whereas a negative effect is reported for higher shares of foreign-born employees.

The unambiguous positive productivity impact of having EHC suggests that entrepreneurial experience stretches beyond the previous entrepreneurial venture and is transferred to the current firm. However, some of the previously referred literature found that those who switch from entrepreneurship to employment experience earning losses (Hyytinen and Rouvinen, 2008; Mahieu et al., 2021; Mahieu et al., 2022; Lappi et al., 2022; Lappi, 2022). Those analyses, however, focused on individual earnings where factors like lower bargaining power for former entrepreneurs, uncertainty and perceived risks associated with their capacity as employees, etc., systematically seem to lead to lower wage offerings. These could be expected to dissipate over time if their true productivity is shown to be comparable to other employees (Montgomery, 1991; Merida and Rocha, 2021).

To summarize, our baseline estimations show that having a higher share of former entrepreneurs as employees increases productivity, suggesting that they contribute complementary knowledge, abilities, and skills.

4.2. Robustness: alternative model and performance measures

We first test how robust our results are to an alternative model specification of EHC and to different outcome measures.[25] Theoretically, we modeled the EHC impact on productivity through the technology

[23] Highly educated employees are those with 3 or more years of tertiary education. The foreign-born employees are those who are born outside of Sweden

[24] The firm age variable refers to the establishment of the firm. However, the values are left truncated and do not go back further than 1986. The results are robust to adding a dummy variable capturing old Swedish firms.

[25] Table A1.3 in Appendix A estimates Eq. (3) separately for 1-digit industry codes, as well as small and large firms separately based on an employee threshold level of 50. The results show that there is considerable industry variation, where the positive relationship is driven by service sector firms and small firms.

Table 2
Main results.

Dependent variable: Ln(Value Added)	OLS (1)	OLS (2)	OP (3)	LP (4)	ACF (5)
k	0.076***	0.072***	0.060***	0.026***	0.082***
	(0.000)	(0.000)	(0.003)	(0.001)	(0.000)
l	1.033***	0.981***	0.922***	0.776***	0.991***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.000)
EHC	0.287***	0.082***	0.084***	0.039***	0.091***
	(0.005)	(0.005)	(0.010)	(0.007)	(0.000)
Highly educated employees		0.304***	0.350***	0.253***	0.314***
		(0.005)	(0.010)	(0.007)	(0.000)
Male employees		0.165***	0.162***	0.082***	0.174***
		(0.003)	(0.005)	(0.004)	(0.000)
Foreign employees		−0.269***	−0.234***	−0.121***	−0.260***
		(0.003)	(0.006)	(0.004)	(0.000)
Age_1		−0.162***	−0.165***	−0.179***	−0.152***
		(0.004)	(0.007)	(0.005)	(0.000)
Age_2		0.109***	0.111***	0.008	0.119***
		(0.004)	(0.008)	(0.006)	(0.000)
Age_3		0.205***	0.175***	0.076***	0.214***
		(0.004)	(0.008)	(0.005)	(0.000)
Age_4		0.130***	0.079***	0.024***	0.140***
		(0.004)	(0.009)	(0.006)	(0.000)
Firm age		0.009***	0.017***	0.007***	0.018***
		(0.000)	(0.003)	(0.000)	(0.000)
Multinational		0.260***	0.190***	0.140***	0.269***
		(0.004)	(0.008)	(0.007)	(0.000)
Industry FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Control variables	No	Yes	Yes	Yes	Yes
Observations	1,191,740	1,191,740	594,031	1,191,740	1,191,740
Firms	368,993	368,993	226,590	368,993	368,993
R-squared	0.755	0.768			

Notes: Robust standard errors in parentheses. For the Olley and Pakes (OP) and Levinsohn and Petrin (LP) estimations, bootstrapped standard errors with 300 replications are in parentheses. Models in Columns 1 and 2 include a constant term but are excluded from the table. The ACF method has bootstrapped standard errors with 50 replications due to the long computing time.

*** $p < 0.01$.

parameter (Eq. (1)). An alternative way to model employees is simply to divide the total stock of labor between employees with and without previous entrepreneurial experience[26]. This means that we estimate the following equation:

$$y_{jt} = \alpha + \beta_1 k_{jt} + \beta_2 l_{NEHCjt} + \beta_3 l_{EHCjt} + \vartheta EHC_{jt} + \zeta_{jt}, \tag{6}$$

where the difference compared to Eq. (3) is that we explicitly separate the stock of employees without and with EHC (l_{NEHC} and l_{EHC}), expressed in natural logarithms. Eq. (6) is estimated with the LP method, implementing the same controls as previously. This allows for more direct comparisons between the marginal effect of employees with and without entrepreneurial experience.

We also include different performance variables as our outcome variable. Instead of estimating the production functions with value-added as the dependent variable, we include labor productivity as an alternative productivity measure. Theoretically, this means that we divide our production function by labor, which results in the following:

$$\frac{Y_{jt}}{L_{jt}} = \frac{K_j^{\beta_1}\left(A_{jt}L_{jt}{}^{\beta_2}\right)}{L_{jt}} = A_{jt}K_{jt}^{\beta_1}L_{jt}^{\delta} \tag{7}$$

The only difference this modification leads to is that the labor elasticity is now calculated as $\delta = \beta - 1$ from the estimated parameter. The estimation is thus identical to Eq. (3), with the exception that the natural logarithm of value added per labor is the dependent variable.

We implement two additional outcome measures. First, we rerun Eq. (3) using ordinary least squares estimation with sales of the firms (in natural logarithms) as the dependent variable. We use a simple linear model to show a plausible correlation between EHC and the alternative performance measure. Thus, the results should be interpreted as correlational and not causal. Second, we examine the relationship between EHC and innovation, approximated by total factor productivity (TFP). Here, we implement a reduced form where we calculate the total factor productivity (TFP) of a firm in two steps. We start by regressing capital and labor inputs on value-added using the LP estimator to calculate TFP (the residual). We do this separately for 1-digit industries. In the next step, we analyze whether EHC is related to TFP at the firm level. We implement the same set of covariates in this second step, including industry, region, and year fixed effects.[27] Since TFP is frequently used as a proxy for innovation but also more generally as reflecting technological change, a positive effect would indicate that firms with former entrepreneurs as employees have a higher innovative capacity and are better at adopting new and productivity-enhancing technologies (Beaudry and Francois, 2010; Hall, 2011). The results and the implemented estimators are presented in Table 3.

[26] Formally this implies that our production function is now in the form: $Y_{jt} = A_{jt}K_{jt}^{\beta_1}L_{NEHC}^{\beta_2}L_{EHC}^{\beta_3}$. Where L_{NEHCjt} and L_{EHCjt} denote the stocks of labor for employee without and with EHC experience, respectively.

[27] Estimating these production functions separately for the 1-digit industry codes systematically controls for differences in the technology level and takes into account output and input demands at an aggregate level. These first-step estimations are not presented but are available on request from the authors.

Table 3
Robustness: alternative performance measures.

Dependent variable:	ln(Value Added) (1)	ln(Value Added per Labor) (2)	ln(Sales) (3)	ln(TFP) (4)
l_{NEHC}	0.791*** (0.002)			
l_{EHC}	0.206*** (0.002)			
EHC		0.039*** (0.007)	0.138*** (0.005)	0.088*** (0.005)
Industry FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
Observations	1,191,740	1,191,740	1,191,740	1,191,740
Firms	368,993	368,993	368,993	368,993
R2			0.759	0.346
Method	LP	LP	OLS	OLS

Notes: Robust standard errors in parentheses. Control variables include firm age, whether the firm is a multinational corporation, the share of highly educated employees, the share of male employees, and the share of foreign-born employees, and the four different employee-age categories. All estimations include capital and labor terms. Estimations also include region, 2-digit industry, and year-fixed effects.
*** $p < 0.01$.

As expected, the results from Column 1 indicate that the stock of labor with EHC positively influences productivity even though the magnitude is smaller than that of labor without EHC. For the latter category, the skill base resides in education and work experience. Hence, by combining the two types of labor, firms can come closer to constant or increasing returns to scale, i.e., it is productivity increasing.

The results suggest a complementary relationship between employees with and without EHC, where both contribute to the value-added produced in the firm, likely through different channels due to various types of competencies and abilities. There are several plausible reasons for the observed differences in the magnitude of productivity effects. There may be some optimal proportion of the two types of employees that are required to fully exploit the productivity potential of former entrepreneurs, which firms adjust over time. Alternatively, the two types of employees may impact each other's productivity through transfers of knowledge that take place in complex and intractable ways (compare Bender et al., 2018). Unfortunately, our data preclude any deeper analysis of the exact mechanisms behind these differences. Rather, we settle with the observation that EHC remains a highly significant factor for firm productivity.

In Columns 2 and 3, the alternative performance measures confirm a robust positive impact of former entrepreneurs who have switched to employment. The EHC coefficients for labor productivity are identical to the results from our baseline estimations. The sales estimations (Columns 3) are qualitatively similar but should be cautiously interpreted, as they are included for reference, and there are likely to be endogeneity problems present in this model.[28] In addition, the TFP estimations suggest that EHC increases innovation and technological adoption, broadly defined. Again, some cautiousness is warranted with regard to the causal effects. Even though the input choices of capital and labor are corrected for endogeneity, the second step estimation (Column 4) is estimated through ordinary least squares and thus provides correlational evidence.[29]

Table 4
Robustness: entrepreneurship definition.

Dependent variable: Ln(Value Added)	(1)	(2)	(3)	(4)
EHC^{Recent}	0.040*** (0.007)			
$EHC^{(Recent\text{-}10)}$		0.052*** (0.008)		
$EHC^{(Sole\text{-}Proprietor)}$			−0.193*** (0.006)	−0.201*** (0.006)
$EHC^{Incorporated}$				0.064*** (0.007)

Notes: Levinsohn and Petrin (LP) estimations with bootstrapped standard errors with 300 replications in parentheses. Control variables include firm age, whether the firm is a multinational corporation, the share of highly educated employees, the share of male employees, and the share of foreign-born employees, and the four different employee-age categories. All estimations include capital and labor terms. Estimations also include region, 2-digit industry, and year-fixed effects. Entrepreneurial human capital is measured as the share of employees with entrepreneurial experience.
*** $p < 0.01$.

5. Extensions and additional robustness tests

5.1. Alternative definitions of entrepreneurship

Next, we examine how robust our results are to different definitions of entrepreneurship. In our baseline estimations, the definition of an employee qualifying as a formerly entrepreneur required at least one year of entrepreneurial experience going back to 1993. However, this might result in us overestimating the number of employees with EHC, i.e., experiences going back in time might not have any long-standing productivity effects. We, therefore, limit experiences to more recent times, starting from 2000 and onward (Table 4, Column 1). However, even with this restriction, the impact of entrepreneurial experience on current productivity may be overestimated. Hence, we include EHC from a rolling window of only the last 10 years of entrepreneurial experience of individuals before becoming an employee. This more restrictive EHC measure is included in Column 2, Table 4.[30]

Finally, we introduce two types of entrepreneurs by separating the self-employed and those with incorporated businesses. According to previous findings, the latter type should better capture genuine entrepreneurship (Levine and Rubinstein, 2016). Hence, we expect divergent productivity effects of ECH from sole proprietors compared to entrepreneurs with incorporated businesses.

The results convey that when we limit entrepreneurial experience to more recent times, the results are unchanged (Columns 1 and 2). Furthermore, implementing a 10-year rolling window suggests that our baseline estimates are actually downward biased. Hence, the time

[28] We tried to use past values of regional entrepreneurship levels of the same industry as an instrument for the demand for former entrepreneurs, i.e., our EHC variable, but these 2SLS estimations produced unreliable estimates. This was likely driven by regional entrepreneurship rates being highly constant throughout the years leading to little variation and being correlated with current productivity of firms.

[29] Furthermore, we run two alternative robustness tests to our specification. First, we estimate our baseline model by including the lagged value of productivity as an additional explanatory variable to account for any path dependency but also as an alternative way to control for selection. Second, we lagged all the independent variables of one period to further evaluate possible effects related to timing. The results from these alternative specifications are in line with our main model. In addition, we have also checked whether the financial crisis (2008/2009) affects our results by estimating different time periods (2004–2018 and 2004–2008). We find no evidence that our results are confined to the chosen time of our analysis. The results can be provided by the authors on request.

[30] For additional definitions of EHC, see Appendix B (Table B1.1). Irrespective of definition the positive impact of EHC on productivity remains.

differences with regard to when the EHC was obtained do not influence the results in any substantial way.

Regarding different types of entrepreneurial ventures, the results are reported in Columns 3 and 4. EHC emanating from sole proprietorship has a negative effect on productivity, in contrast to the strongly positive effect when EHC stems from incorporated businesses. This holds irrespective of whether our baseline EHC measure (incorporated businesses) is included in the estimations or not (Column 4). This finding corroborates previous literature, which differentiates the effects of sole proprietors from incorporated business owners.[31]

5.2. Heterogeneity in former entrepreneurs' knowledge base

To further evaluate the robustness of our findings, we extend the baseline regressions by examining whether the effect of entrepreneurial experience is associated with the level of education of former entrepreneurs. As has been shown previously, more highly educated employees tend to have a stronger impact on productivity (Haltiwanger et al., 1999), which can also be expected to apply to EHC. We, therefore, differentiate between two groups of employees with EHC: the first is defined as those with three or more years of tertiary education, and the second is those with lower formal education. The individual's education level is defined at the time of employment, not when they were engaged in entrepreneurship.

In addition, we also separate EHC among employees who are currently hired as managers and those in other occupations (nonmanagers). Managers and nonmanagers can be expected to have different tasks and skills within a firm, implying that the two groups' respective impacts on firm productivity may differ. We complement educational levels with the position in the firm of employees with EHC since managers have more decision-making power than nonmanagers. The latter category may, however, influence productivity through everyday business improvements (Leibenstein, 1968). This particular aspect has not received much empirical attention in previous research, with Syverson (2011) and Bender et al. (2018) being exceptions.

According to the individual-level descriptive statistics (see Appendix A, Table A1.2), employees who have been entrepreneurs are, on average, older and earn more. To test whether our results are simply driven by age (i.e., experience), we construct five age groups ranging from below 30 years old and those in the age brackets 30–39, 40–49, 50–59, and older than 60. If age is driving the results, the highest EHC impact should pertain only to the oldest age cohort.

Distributing employees with EHC to different age cohorts does not, however, capture possible tenure effects. We, therefore, also examine whether the positive impact of EHC comes from employees who are recently hired in the firm or those who have been in the firm for a longer time, defined as three years or more. [32]

The results show that the educational level of EHC does not seem to have a strong impact on firm-level productivity (Table 5, Column 1). The coefficients for higher- and lower-educated former entrepreneurs are almost identical, but the significance is higher for the lower-educated. Similarly, even though the result in Column 2 reveals a larger positive relationship of EHC for employees in managerial positions than for nonmanagerial employees, the difference is not statistically significant.[33] Thus, when the position of EHC is included, we cannot separate the effects of managers and nonmanagers on productivity, in contrast to Bender et al. (2018), who allot most of the impact on managers.

Table 5
Robustness: employee characteristics.

Dependent variable: Ln(Value Added)	(1)	(2)	(3)	(4)
$EHC^{(Higher\ Educated)}$	0.035*			
	(0.021)			
$EHC^{(Lower\ Educated)}$	0.038***			
	(0.007)			
$EHC^{Managers}$		0.098***		
		(0.016)		
$EHC^{(Non\text{-}Managers)}$		0.082***		
		(0.008)		
$EHC^{(<30)}$			0.138***	
			(0.027)	
$EHC^{(30–39)}$			0.011	
			(0.016)	
$EHC^{(40–49)}$			0.060***	
			(0.013)	
$EHC^{(50–59)}$			0.116***	
			(0.012)	
$EHC^{(\geq 60)}$			−0.062***	
			(0.015)	
$EHC^{(Tenure<3years)}$				−0.194***
				(0.010)
$EHC^{(Tenure\geq 3years)}$				0.161***
				(0.008)
Industry FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
Observations	1,191,740	1,191,740	1,191,740	1,191,740
Firms	368,993	368,993	368,993	368,993

Notes: Levinsohn and Petrin (LP) estimations with bootstrapped standard errors with 300 replications in parentheses. Controls variables include firm age, whether the firm is a multinational corporation, the share of highly educated employees, the share of male employees, and the share of foreign-born employees, and the four different employee-age categories. All estimations include capital and labor terms. Estimations also include region, 2-digit industry, and year-fixed effects. Entrepreneurial human capital is measured as former entrepreneurs as a share of employees.

*** $p < 0.01$.

* $p < 0.1$.

On the other hand, the age distribution of employees with EHC shows some distinct differences (Column 3). There is a particularly pronounced effect for employees who are either young or at the later stages of their career, i.e., aged 50 to 59. This partly contrasts with the findings in Table 2, where, taking all employees into account, it was shown that the age cohort younger than 30 years negatively affected firms' productivity. Hence, our results suggest that even entrepreneurial experience acquired at a young age generates skills that positively influence firm productivity. At the opposite end of the age distribution, the results indicate that depreciation of EHC may occur since those aged 60 or above have a negative effect on productivity, which might serve as a boundary condition to our main findings.[34] Finally, it is shown that tenure (>3 years) is important for EHC to influence firms' productivity, indicating that it takes time to integrate and diffuse knowledge from previous entrepreneurs (Column 4, Table 5). These results are in line with the individual-level findings by Merida and Rocha (2021), who report short-term penalties but long-term wage premiums.

Overall, controlling for heterogeneity in former entrepreneurs' knowledge base does not influence our baseline results in any major way. Rather, EHC is shown to consistently have a positive effect on firms' productivity.

[31] Similar results are presented by Humphries (2021).

[32] Detailed descriptive statistics of all the alternative EHC measures as presented in Table A1.4 in Appendix A.

[33] The coefficients for the managers and nonmanagers are twice as large as in our main specification, which is driven by the fact that the occupational data is missing for many individuals as it is based on a random sample of individuals, i.e., it does not cover the whole population in a systematic manner.

[34] The coefficients of the EHC age groups are all significantly different form each other with the exceptions of the groups $EHC^{<30}$ and $EHC^{50–59}$.

5.3. Related industries and technology differences

Next, we consider whether the estimated positive effect of EHC on firms' productivity is driven by technology factors. It may be the case that EHC is industry specific, implying that the positive impact of EHC is dependent on whether a former entrepreneur is employed in a related industry. We, therefore, examine whether the positive impact of EHC varies with experience gained in related or unrelated industries, i.e., is it general entrepreneurial experience that matters or is it more industry specific. We define related industry experience as belonging to the same 2-digit industry code, while the rest of the industries are seen as unrelated.

Since relatedness does not take the level of technology into account, we continue by analyzing how previous entrepreneurship emanating from high- or low-technology sectors influences productivity. It seems reasonable to expect that experience in more advanced technological industries could result in larger productivity effects. We consequently classify entrepreneurial experience based on the Eurostat definition of technology intensities.[35]

We find that industry-specific knowledge is important. In fact, entrepreneurial experience from other industries is shown to exert a negative impact on productivity (Column 1, Table 6). This corroborates findings by Kaiser and Malchow-Møller (2011) but contradicts the results in Mahieu et al. (2022). On the other hand, we find modest differences associated with technology level (Column 2), i.e., the impact of entrepreneurs previously active in more technology-intensive industries is not significantly larger compared to those having experience from low-technology segments. Overall, we provide evidence that industry-specific knowledge is important to attain productivity improvements based on EHC, whereas there is no evidence that the impact of EHC is associated with different technology levels.

Table 6
Robustness: industry relatedness and technology differences.

Dependent variable:	ln(Value Added) (1)	ln(Value Added) (2)
$EHC^{(Same\ Industry)}$	0.113***	
	(0.008)	
$EHC^{(Different\ Industry)}$	−0.100***	
	(0.011)	
$EHC^{(High\ Tech)}$		0.039***
		(0.015)
$EHC^{(Low\ Tech)}$		0.026***
		(0.007)
Industry FE	Yes	Yes
Region FE	Yes	Yes
Year FE	Yes	Yes
Control variables	Yes	Yes
Observations	1,191,740	1,191,740
Firms	368,993	368,993

Notes: Robust standard errors in parentheses. Control variables include firm age, whether the firm is a multinational corporation, the share of highly educated employees, the share of male employees, and the share of foreign-born employees, and the four different employee-age categories. All estimations include capital and labor terms. Estimations also include region, 2-digit industry, and year-fixed effects.
*** $p < 0.01$.

5.4. Heterogeneity in entrepreneurial experience

To further excavate into the underlying mechanism of EHC's impact on firm productivity, we separate successful and less successful previous entrepreneurial endeavors. To account for such differences, we employ multiple complementary definitions of success related to the following characteristics of former entrepreneurial ventures: i) the firm had employees, ii) persistence or time of survival, iii) level of entrepreneurial income, iv) modes of entry, and v) modes of exit.

Some entrepreneurs may run growing and successful firms with many employees, whereas others can be characterized as subsistence entrepreneurs. As a first measure, we approximate previous entrepreneurial success by separating between employees who were formerly either self-employed (*Own-Account*) or had employees (*Employer*). In addition to being an indication of entrepreneurial success, having employees also implies an opportunity to acquire more diverse managerial skills. As an alternative measure, we divide EHC emanating from five or more years of entrepreneurship experience (*Long Persistence*) and those with less (*Shorter Persistence*). This variable could also be seen as a proxy for entrepreneurial success through survival. An additional indication of a successful entrepreneurial endeavors is to evaluate the income entrepreneurs have generated as entrepreneurs. We include this measure by calculating the average annual income (wages) that the individuals obtained as business owners and separate between EHC belonging to the top 50th-percentile (*High Income*) and the bottom 50th-percentile (*Low Income*).

Finally, we account for the underlying decision for individual entry and exit to and from entrepreneurship. These are unlikely to be random decisions, and according to Amit and Muller (1995), individuals' experiences differ depending on whether they are forced into entrepreneurship or enter voluntarily. Those who choose entrepreneurship are likely to have better-performing businesses. To account for such self-selection into entrepreneurship (Wennberg et al., 2010), we divide the employees with EHC into three different groups. First, we differentiate between individuals who were employed before they started a firm (*Pulled*) and those who were unemployed (*Pushed*). We also have a third category (*Other*) representing university graduates, migrants, and those for whom information on pre-entry activities is missing. The expectation is that those who started a firm due to perceived opportunities (*Pulled*) should exert a more distinct positive effect on firm productivity.

Similarly, the reason to exit can provide information on the success of an entrepreneurial venture. Some may have been pushed out from the market filing for bankruptcy, while others exit the market because of mergers and acquisitions. To account for the divergent exit routes, we differentiate between three types of exits: those firms that closed down for unknown reasons where bankruptcies can be assumed to be prevalent (*Closed Down*), exits due to mergers or acquisitions (*Merg&Aq*); and exits where the firm remains in the market (*Not Closed Down*) (but we do not know the exact reason).[36]

The results presented in Table 7 reveal that EHC acquired through successful entrepreneurial endeavors, as captured by the reason for entering (pulled) and exiting (merged, acquired, or firm still exists), the type of firm (with employees), and entrepreneurial income, are crucial determinants of EHC's influence on firm productivity. Higher entrepreneurial income is shown to have a particularly distinct effect compared to our baseline result. In addition, persistence, i.e., longer

[35] High-technology manufacturing industries include manufacturers of basic pharmaceutical products, pharmaceutical preparations, and computer, electronic and optical products. In the service sector, knowledge-intensive industries are classified as providers of services related to water and air transport, law and accounting, activities of head offices, management consultancy, sound recording and music publishing, programming, and broadcasting, telecommunications, computer programming, consultancy, information, scientific research and development, and financial and insurance activities.

[36] For instance, even if the entrepreneur exits there might be co-owners who continue to run the business, or the entrepreneur simply sells the business. Unfortunately, we cannot identify whether they continue as part-time entrepreneurs in these firms. If so, it is likely to be a limited phenomenon, given that such behavior has not identified in the previous literature on exit strategies (see, e.g., DeTienne et al., 2015).

Table 7
Results: entrepreneurship success and skills.

Dependent variable: Ln(Value Added)	(1)	(2)	(3)	(4)	(5)
$EHC^{Employer}$	0.075***				
	(0.007)				
$EHC^{(Own\text{-}Account)}$	−0.121***				
	(0.014)				
$EHC^{(Longer\ Persistence)}$		0.065***			
		(0.010)			
$EHC^{(Shorter\ Persistence)}$		0.018**			
		(0.009)			
$EHC^{(High\ Income)}$			0.235***		
			(0.010)		
$EHC^{(Low\ Income)}$			−0.165***		
			(0.009)		
EHC^{Pulled}				0.056***	
				(0.008)	
EHC^{Pushed}				−0.005	
				(0.013)	
EHC^{Other}				−0.100***	
				(0.018)	
$EHC^{(Closed\ Down)}$					−0.104***
					(0.013)
$EHC^{(Merg\&Aq)}$					0.072***
					(0.016)
$EHC^{(Not\ Closed\ Down)}$					0.062***
					(0.008)
Industry FE		Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes
Observations	1,191,740	1,191,740	1,191,740	1,191,740	1,191,740
Firms	368,993	368,993	368,993	368,993	368,993

Notes: Levinsohn and Petrin (LP) estimations with bootstrapped standard errors with 300 replications in parentheses. Control variables include firm age, whether the firm is a multinational corporation, the share of highly educated employees, the share of male employees, and the share of foreign-born employees, and the four different employee-age categories. All estimations include capital and labor terms. Estimations also include region, 2-digit industry, and year-fixed effects. Entrepreneurial human capital is measured as the share of employees with entrepreneurial experience.
*** $p < 0.01$.
** $p < 0.05$.

entrepreneurial spells, exerts a considerably stronger impact than shorter spells, indicating that learning takes place and that EHC is not solely determined by innate abilities (regarding entrepreneurial learning, see also Appendix B).[37]

Hence, not all kinds of entrepreneurial experience matter for firm performance, and the mechanism through which EHC works seems to primarily be by deploying knowledge acquired through previous successful entrepreneurship.

6. Discussion: explaining the mechanisms through which EHC works

We have shown that EHC positively impacts firm-level productivity and that the effect is robust to several modifications of the baseline model. However, as we refine our model to also account for additional characteristics of previous entrepreneurs and their businesses, a more nuanced picture emerges. These insights provide information about the underlying mechanisms that make EHC important for firm productivity.

First, the above results clearly suggest that EHC acquired through successful entrepreneurial endeavors is driving out results. In addition, implementing several alternative time-related variables, the results show that longer entrepreneurial spells are associated with a larger impact on productivity, implying that learning takes place. However, we also found that success is likely to be associated with some innate ability, which cannot be ruled out. One interpretation is that the combination of learning and innate abilities generates EHC that primarily impacts firms' productivity. This is further confirmed by the fact that the youngest cohort of former entrepreneurs switching to employment (<30 years) is shown to exert a positive and strongly significant effect on productivity. A more detailed explanation concerning the composition of a firm's knowledge base seems to be an important task for future research.

Second, enlarging firms' knowledge pool to include EHC is likely to facilitate the absorption of new or relevant knowledge that can be exploited by firms. Absorption capacity is basically about recognizing the value of external knowledge and assimilating it for commercial applications (Cohen and Levinthal, 1990).[38] Nevertheless, we provide evidence that the absorption of new and complementary knowledge embodied in employees takes time, i.e., a positive effect of EHC requires some tenure (at least three years) and may thus be costly (Rider et al., 2019).[39] Moreover, distinct differences are observed between entrepreneurial experience gathered in related and unrelated production, where the former has a positive and strongly significant effect, whereas the latter is negatively associated with firms' productivity. Hence, knowledge that is more "distant" and less recognizable is either harder to diffuse and absorb or inappropriate for the firm. On the other hand, no difference was observed between EHC accumulated in high-tech or low-tech industries, indicating that sorting between firms' technological

[37] Income from entrepreneurship might not be a perfect measure of ability. However, it falls outside the scope of the current study to examine alternative measures, e.g., wealth or cognitive skills of individuals.

[38] See Chapparro et al. (2020) for a survey on absorptive capacity and entrepreneurial efforts. Nielsen (2015) claims that absorption capacity increases with the level of education, which may pertain also to experience.

[39] Humphries (2021) claim that knowledge transfers are more easily accomplished in the white-collar sector as compared to the blue-collar sector, and that sector-specific knowledge is more valuable.

needs and EHC is effective.

Third, drawing on the insights provided by the resource-based approach to firm performance (Barney, 1991), EHC can be seen as contributing with an additional ability that strengthens firms' overall capability. Firm-level resources can be defined as a bundle of different knowledge and competencies, complementing and reinforcing each other. Abilities typically associated with entrepreneurs, e.g., self-efficacy, adaptability, and opportunity recognition (Alvarez and Busenitz, 2001; Ayala and Manzano, 2014), are supposedly embodied in EHC. As firms access such competencies, it can be expected to enrich the knowledge mix in a way that positively influences firm outcomes.

Moreover, learning that takes place at a different level within an organization tends to strengthen the aggregate (firm) level (Reagan et al., 2005). We have shown how EHC positively influences firm-level productivity even when distributed on different levels of education and positions within firms. A conceivable explanation is that such multilevel diffusion of knowledge enhances organizational learning and a firms' performance (Levine and Argote, 2020). Having a diversified knowledge pool may also be associated with signaling effects that attract more inflows of human capital and other assets (Distel et al., 2019; Haeussler et al., 2014), further strengthening the resource base of the firm.

From a broader perspective, the labor and productivity veins of economic research have shown that formal education and work experience contribute to abilities that complement and reinforce the overall knowledge pool and performance of a firm. Parallel to those findings, several studies in the entrepreneurship field have stressed the specific abilities of entrepreneurs and how these can leverage a firms' productivity (as referred to in Section 2). There have, however, been few attempts to include such entrepreneurial abilities in a comprehensive empirical analysis, primarily due to a lack of appropriate data. By implementing EHC, which parallels work experience, our results confirm the importance of a diversified knowledge base and suggest conceivable mechanisms through which EHC is likely to impact firms' productivity. Hence, this provides a link that better integrates the research fields of productivity and entrepreneurship.

7. Conclusion

The purpose of this paper is to examine whether an employee's previous engagement in entrepreneurship, or what we refer to as entrepreneurial human capital (EHC), influences firm-level productivity. To that end, we construct a measure of EHC at the firm level, which we use in the empirical analysis. Overall, our contribution extends and complements previous findings in three particularly connected research areas: how spells into entrepreneurship affect wages and lifetime earnings, how characteristics of entrepreneurs and managers influence a firms' performance, and the effects of higher levels of education and work experiences among employees on the outcome at the firm level. Overall, a new and complementary form of human capital for firms is identified that previously has been unobserved.

Irrespective of the estimation technique and alternative measures of EHC, as well as taking individual- and firm-specific characteristics into account, the results show a robust and relatively large positive impact of EHC on firm productivity. Our baseline result implies that a 10 % increase in entrepreneurial experience among employees increases productivity by 3.9 %. We find that the positive effect of EHC pertains to both higher- and lower-educated, younger and somewhat older age cohorts but seems to depreciate with the oldest cohorts. The results remain as other performance variables are implemented, e.g., labor productivity, sales, and innovation (broadly defined through TFP). In addition, we provide evidence that the effect varies with regard to the specific experience and length of previous entrepreneurship. We reject that entrepreneurial ability is exclusively innate. Additionally, tenure in the firm in which the former entrepreneur is employed is shown to be important for the positive effects of EHC. Hence, the two broadly framed hypotheses are supported.

The results contain several relevant insights at the firm and policy levels. As the above analysis shows, hiring previous entrepreneurs can be highly beneficial for a firm since it seems to augment and diversify its pool of human capital and significantly affect productivity and other performance variables. However, the outcome is likely to depend on the specific experience of the entrepreneurs who become employees, results that echo some of the previous findings, e.g., effects vary with the age and duration of an entrepreneurial spell, education, and type of entrepreneurial endeavor. These previous studies have, however, examined individual earnings effects and not firm-level productivity (Dillon and Stanton, 2017; Mahieu et al., 2022; Merida and Rocha, 2021). Our results imply that firms considering hiring individuals with entrepreneurial experience need to carefully consider their entrepreneurial background in terms of reasons to enter and exit entrepreneurship, the type of firms, which sector they were active in, etc. Entrepreneurs may also develop preferences that are not compatible with being employed (Åsterbro and Thompson, 2011), which may adversely affect firms' performance. Moreover, the potential benefits are likely to materialize after a period. Thus, hiring former entrepreneurs should be seen as a medium- to long-term strategy to enhance productivity.

Harvesting the benefits of hiring employees with EHC is related to the absorption capacity of the employing firm. The difficulties and costs attached to the transfer of knowledge have long been documented (Polanyi, 1967; Mansfield, 1991). Our results confirm that there seem to be costs related to the diffusion of knowledge connected to the time and proximity of knowledge bases.

Despite these caveats, there seem to be considerable gains to be made at the firm level from hiring employees with EHC. As a side effect of broadening the knowledge base of firms, it is also likely to increase a firm's absorption capacity over time. Previous studies have stressed the importance of enhancing absorption capacity at the firm level to exploit knowledge spillovers and enhance performance (Escribano et al., 2009). For example, Cassiman and Veugelers (2002) underline the importance of firms strategically considering their absorption capacity. By employing individuals with former entrepreneurial experience, the potential for internal corporate entrepreneurship can also be expected to increase, which has been shown to positively affect firm performance (Simsek and Heavey, 2011).

We have identified a microeconomic mechanism of productivity that also has implications for aggregate growth. This is in line with previous assertions by Nelson and Phelps (1966). More precisely, we present a distinct link between entrepreneurship experience, mobility across occupations, and productivity. The link mainly operates via human capital accumulation through entrepreneurship, which is transferrable across firms as an entrepreneur shifts occupation and becomes an employee. Therefore, it could be argued that the government should pursue policies that facilitate individuals' mobility and learning about their abilities (Vereshchagina and Hopenhayn, 2009). Potentially, this would benefit sorting between occupations and generate a more efficient allocation of competencies, thereby promoting growth. Alternatively, governments could undertake measures to upgrade entrepreneurial or other skills to alleviate growth deterring shortages of certain knowledge factors, e.g., a lack of entrepreneurs.

The design of policies thus becomes imperative. Several studies conclude that tax relief or subsidies are inefficient and costly policies with negligible effects on entrepreneurship (Dillon and Stanton, 2017; Humphries, 2021). If such policies are initiated, targeting younger and high-performing individuals seems to generate the most beneficial outcomes. However, other policy initiatives to stimulate entrepreneurship may be more cost-efficient, e.g., related to education (Bergmann et al., 2018), innovations (Bloom et al., 2019), facilitating interactions with entrepreneurs (Lerner and Malmendier, 2011), and labor market policies (Kaiser et al., 2015; Braunerhjelm et al., 2016).

To conclude, both at the management level and policy level, we present arguments for why entrepreneurial experience should be acknowledged in building competitive firms and promoting productivity and growth. Nevertheless, our analysis also has several limitations. The level of aggregation used and the methods chosen imply that we cannot pin down the exact mechanism of how knowledge associated with EHC is diffused and utilized within a firm. Similarly, the proportions of the respective knowledge base among employees – education, work experience, and EHC – are likely to influence the outcome of firms. Threshold effects might appear, where for instance, additional EHC has no or even negative effects on firm-level productivity. A related issue concerns the impact on external channels of having more EHC, i.e., whether it contributes to expanding the customer base, improving networks conducive to innovativeness, etc. Finally, fully comprehending the relationship between innate and acquired entrepreneurial ability requires further analyses.

A crucial task for future research should thus be to better understand how knowledge related to EHC is exploited within firms and through which channels. Even though there is consensus regarding the importance of upgrading and accumulating knowledge to build competitive firms and growth-oriented societies, our understanding of how knowledge flows within and between individuals and firms and the type of knowledge that matters are still limited. Finally, since similar data are available for a number of other countries, we encourage colleagues to replicate our analysis and to further excavate the mechanisms through which EHC may influence performance at the individual, firm, and regional levels.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

CRediT authorship contribution statement

Pontus Braunerhjelm: has had the major responsibility for conceptualizing, writing, reviewing, theoretical analysis and editing. Emma Lappi: has had the major responsibility for the empirical analyses, data, and the empirical construct of EHC. Empirical and analytical refinements are based on close cooperation between authors.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Acknowledgments

We are very grateful for the highly constructive and valuable comments given by two anonymous referees. We have also benefited from important feedback from Jolanda Hessels, Alexander Kritikos, Maurice Kugler, Maria Minnitti, Kristina Nyström, Martin Olsson, and Tomas Åsterbro and participants at the Academy of Management (paper development workshop "Knowledge Contexts of Entrepreneurship, Preentry Capabilities, and New Ventures' Outcomes"), the DRUID 2021 and the 18th Joseph A. Schumpeter Conference 2021.

Appendix A. Tables

Table A1.1
Correlation matrix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Capital (K)	1.000											
(2) Labor (L)	0.173	1.000										
(3) EHC	−0.002	−0.035	1.000									
(4) Highly educated employees	0.033	0.083	0.103	1.000								
(5) Male employees	0.022	0.113	0.151	−0.028	1.000							
(6) Foreign-born employees	−0.005	0.025	−0.048	0.090	0.117	1.000						
(7) Age_1	−0.012	0.054	−0.120	−0.089	0.117	−0.003	1.000					
(8) Age_2	0.005	0.078	0.007	0.210	0.199	0.193	−0.150	1.000				
(9) Age_3	0.021	0.081	0.124	0.129	0.208	0.099	−0.254	−0.097	1.000			
(10) Age_4	0.023	0.062	0.190	0.059	0.181	0.014	−0.249	−0.163	−0.035	1.000		
(11) Firm age	0.021	0.127	0.057	−0.052	0.065	−0.206	−0.198	−0.080	0.063	0.154	1.000	
(12) Multinational	0.051	0.197	−0.010	0.165	0.088	0.006	−0.038	0.085	0.119	0.075	0.044	1.000

Notes: Correlations are based on 1,191,740 firm-year observations corresponding to a total number of 368,993 firms. EHC is measured as the share of former entrepreneurs among employees.

Table A1.2
Detailed individual-level descriptive statistics of employees.

Variables	Employees with EHC	Employees without EHC
Individual-level characteristics		
Earnings (in SEK)	397,395	312,821
Age	49.37	38.95
Years of schooling	12.00	11.98
Years of entrepreneurship experience	4.835	0
Years of sole proprietor experience	0.815	0.254
Years of wage employment experience	14.17	14.33
Years of unemployment experience	0.542	1.076
Managers	0.191	0.0378
Male	0.731	0.647
Married	0.587	0.356
Children	0.535	0.534

(*continued on next page*)

Table A1.2 (*continued*)

Variables	Employees with EHC	Employees without EHC
Foreign born	0.0889	0.171
Metropolitan	0.520	0.514
Value added (in SEK and thousands)	27,700	66,489
Capital (in SEK and thousands)	1.561e+07	5.805e+07
Size of firm (in employees)	37.40	93.69
Share of former entrepreneurs employees	0.212	0.0417
Highly educated employees	0.144	0.133
Male employees	0.642	0.611
Foreign born employees	0.120	0.158
Age_1	0.210	0.267
Age_2	0.210	0.220
Age_3	0.228	0.216
Age_4	0.183	0.160
Firm age	11.26	11.68
Multinational	0.0740	0.146
Individual-year observations	587,374	10,126,458
Unique individuals	154,867	2,484,568

Notes: Previous experience measures, i.e., entrepreneurship, sole-proprietorship, wage employment, and unemployment experiences for individuals, are based on data extending back to 1993; otherwise, all values for the estimation period covering the years from 2009 to 2018. All values are mean values.

Table A1.3
Results: industry and firm size.

Dependent variable: Ln(Value Added)	Manufacturing			Services						Small firms L < 50	Large firms L ≥ 50
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
l	0.030***	0.045***	0.037***	0.030***	0.025***	0.013***	0.025***	0.020***	0.005	0.026***	0.021*
	(0.005)	(0.005)	(0.005)	(0.001)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.001)	(0.012)
k	0.762***	0.719***	0.777***	0.770***	0.728***	0.775***	0.852***	0.831***	0.811***	0.783***	0.792***
	(0.009)	(0.009)	(0.011)	(0.002)	(0.005)	(0.008)	(0.006)	(0.005)	(0.009)	(0.002)	(0.019)
EHC	0.046	0.038	−0.077*	0.031***	0.128***	0.033	−0.022	0.035	0.242***	0.042***	0.083
	(0.034)	(0.027)	(0.040)	(0.008)	(0.024)	(0.025)	(0.021)	(0.026)	(0.040)	(0.007)	(0.134)
Observations	40,066	73,501	29,119	559,074	139,347	86,692	114,184	100,298	49,459	1,162,093	29,647
Firms	9902	14,646	7410	159,262	63,941	27,096	39,960	33,525	18,631	363,999	7581
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Levinsohn and Petrin (LP) estimations with bootstrapped standard errors with 300 replications in parentheses. Control variables include firm age, whether the firm is a multinational corporation, the share of highly educated employees, the share of male employees, and the share of foreign-born employees, and the four different employee-age categories. All estimations include capital and labor terms. Estimations also include region, 2-digit industry, and year-fixed effects. Divisions are based on 1-digit SNI industry codes, i.e., from 1 to 9, where the first 3 are in the manufacturing sector, and the others are in the service sector. The column number corresponds to the 1-digit SNI code. SNI 1 includes manufacturing of food, beverages, tobacco, textiles, wearing apparel, leather, wood, paper, coke, and petroleum products, and printing and reproduction of recorded media. SNI 2 includes the manufacturing of chemical, pharmaceutical, rubber, plastic, other nonmetallic, mineral, metal, computer, electronic, and optical products, electrical equipment and machinery, and motor vehicles. SNI 3 includes manufacturing of other transport equipment and furniture, repair and installation of machinery, and supply of electricity, water, sewage, and waste services. SNI 4 includes construction, wholesale, and retail trade. SNI 5 includes water and air transport, warehouse activities, postal activities, accommodation, food and beverage service activities, as well as publishing and motion picture production. SNI 6 includes programming, telecommunications, consultancy, information service, finance, insurance, real estate, and legal activities. SNI 7 includes activities of head offices, architectural and engineering, scientific research and development, advertising and market research, veterinary services, rental and employment activities, and travel agency services. SNI 8 includes security and investigation, buildings and landscape office administration, public administration, education, human health residential care, and social work activities. SNI 9 includes arts and entertainment, cultural, gambling, and sports activities, as well as activities of membership organizations, personal service and household activities, and activities of extraterritorial organizations and bodies. Entrepreneurial human capital is measured as the share of previous entrepreneurs among employees.

*** $p < 0.01$.

* $p < 0.1$.

Table A1.4
Descriptive statistics of EHC.

Variables	Mean	St. dev.	Min	Max
Share former entrepreneurs among employees	0.063	0.138	0.000	1.000
Total years of entrepreneurial experience	2.364	5.973	0.000	282.000
Years of entrepreneurial experience per employee	0.318	0.941	0.000	25.000
Years of entrepreneurial experience per former entrepreneur	1.436	3.053	0.000	25.000
EHC	0.054	0.130	0.000	1.000
$EHC^{(Sole\text{-}Proprietor)}$	0.070	0.138	0.000	1.000
EHC^{Pulled}	0.045	0.117	0.000	1.000
EHC^{Pushed}	0.019	0.075	0.000	1.000
EHC^{Other}	0.006	0.042	0.000	1.000

(*continued on next page*)

Table A1.4 (*continued*)

Variables	Mean	St. dev.	Min	Max
$EHC^{Closed\ Down}$	0.018	0.071	0.000	1.000
$EHC^{(Merg\&Aq)}$	0.012	0.056	0.000	1.000
$EHC^{(Not\ Closed\ Down)}$	0.049	0.124	0.000	1.000
$EHC^{(Higher\ Educated)}$	0.009	0.055	0.000	1.000
$EHC^{(Lower\ Educated)}$	0.053	0.126	0.000	1.000
$EHC^{Managers}$	0.009	0.049	0.000	1.000
$EHC^{(Non\text{-}Managers)}$	0.041	0.112	0.000	1.000
$EHC^{(<30)}$	0.003	0.026	0.000	1.000
$EHC^{(30–39)}$	0.009	0.049	0.000	1.000
$EHC^{(40–49)}$	0.017	0.070	0.000	1.000
$EHC^{(50–59)}$	0.019	0.076	0.000	1.000
$EHC^{(\geq 60)}$	0.015	0.069	0.000	1.000
$EHC^{(Tenure<3\ years)}$	0.023	0.082	0.000	1.000
$EHC^{(Tenure\geq 3\ years)}$	0.039	0.114	0.000	1.000
$EHC^{(Longer\ Persistence)}$	0.026	0.091	0.000	1.000
$EHC^{(Shorter\ Persistence)}$	0.036	0.103	0.000	1.000
$EHC^{Employer}$	0.054	0.128	0.000	1.000
$EHC^{(Own\text{-}Account)}$	0.014	0.067	0.000	1.000
$EHC^{(Same\ Industry)}$	0.038	0.112	0.000	1.000
$EHC^{(Different\ Industry)}$	0.025	0.082	0.000	1.000
$EHC^{(High\ Tech)}$	0.013	0.068	0.000	1.000
$EHC^{(Low\ Tech)}$	0.053	0.126	0.000	1.000

Notes: Values are based on the estimation sample of 1,191,740 firm-year observations corresponding to a total of 368,993 firms.

Table A1.5
Correlation matrix with different entrepreneurial human capital measures.

	(1)	(2)	(3)	(4)
(1) Share of employees who are former entrepreneurs	1.000			
(2) Total stock of entrepreneurial capital	0.470	1.000		
(3) Entrepreneurial human capital per employee	0.768	0.611	1.000	
(4) Entrepreneurial human capital per former entrepreneur	0.541	0.777	0.745	1.000

Notes: Correlations are based on 1,191,740 firm-year observations corresponding to a total of 368,993 firms.

Appendix B. Alternative measures and innate abilities

As individual data goes back to 1993, we are able to disentangle the length of each employee's former experience in entrepreneurship. This means that we can assess whether the positive effect of EHC is possibly driven by innate and individual-specific abilities or rather by learning-by-doing effects. In Table B1.1, we have included our results from the baseline regression (Table 2) as a reference estimate (entrepreneur for at least a year, Column 1). We then elaborate with modified definitions of the EHC variable to primarily capture the length, measured as the number of years that firms' employees have of entrepreneurial experience. In Column 2, EHC is measured as the natural logarithm of all entrepreneurial years among the employees, while Column 3 implements EHC defined as entrepreneurial years per employee (also in natural logarithms), modified to entrepreneurial years per former entrepreneur in Column 4.[40]

Table B1.1
Alternative measures of EHC.

Dependent variable: Ln(Value Added)	From Table 2 (1)	(2)	(3)	(4)
EHC	0.039***	0.002**	0.016***	0.002**
	(0.007)	(0.001)	(0.002)	(0.001)
Industry FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
Observations	1,191,740	1,191,740	1,191,740	1,191,740
Firms	368,993	368,993	368,993	368,993

Notes: Levinsohn and Petrin (LP) estimations with bootstrapped standard errors with 300 replications in parentheses. Control variables include firm age, whether the firm is a multinational corporation, the share of highly educated employees, the share of male employees, and the share of foreign-born employees, and the four different employee-age categories. All estimations include capital and labor terms. Estimations also include region, 2-digit industry, and year-fixed effects. Entrepreneurial human capital is measured as former entrepreneurs as a share of employees (Column 1), the natural logarithm of total previous entrepreneurial years (Column 2), the natural logarithm of entrepreneurial years per employee (Column 3), and the natural logarithm of years of entrepreneurship experience per former entrepreneur (Column 4).
*** $p < 0.01$.
** $p < 0.05$.

[40] As shown in the Appendix A (Table A1.5), the correlation between the four different EHC measures is relatively high.

As evident, all the estimated EHC coefficients are positively related to productivity irrespective of specification. Note that the significance of entrepreneurial years per entrepreneur indicates stronger diffusion effects from more experienced entrepreneurs. We thus conclude that EHC-capital is not only an innate ability, but rather individuals seem to gain human capital that can be attributed to entrepreneurial learning (Jovanovic, 1982; Minniti and Bygrave, 2001). Entrepreneurs acquire knowledge and learn during their entrepreneurial endeavors since each additional year results in higher productivity. For instance, the elasticity of EHC in Column 2 implies that a 1 % increase in total entrepreneurial years in a firm results in a 0.2 % increase in productivity annually.

References

Abowd, J.M., Kramarz, F., Margolis, D.N., 1999. High wage workers and high wage firms. Econometrica 67 (2), 251–333.

Ackerberg, D.A., Caves, K., Frazer, G., 2015. Identification properties of recent production function estimators. Econometrica 83 (6), 2411–2451.

Agarwal, R., Echambadi, R., Franco, A.M., Sarkar, M., 2004. Knowledge transfer through inheritance: spin-out generation, development, and survival. Acad. Manag. J. 47, 501–522.

Aghion, P., Howitt, P., 1992. A model of growth through creative destruction. Econometrica 60, 323–335.

Alvarez, S., Busenitz, L., 2001. The entrepreneurship of resource-based theory. J. Manag. 27 (6), 755–775.

Amit, R., Muller, E., 1995. "Push" and "pull" entrepreneurship. J. Small Bus. Entrep. 12, 64–80.

Amit, R., Glosten, L., Muller, E., 1993. Challenges to theory development in entrepreneurship research. J. Manag. Stud. 30, 815–834.

Andersson Joona, P., Wadensjö, E., 2013. The best and the brightest or the least successful? Self-employment entry among male wage-earners in Sweden. Small Bus. Econ. 40 (1), 155–172.

Andrews, D., Criscuolo, C., Gal, P.N., 2015. Frontier Firms, Technology Diffusion and Public Policy. ISSN: 24139424 (online).

Arrow, K.J., 1962. Economic welfare and the allocation of resources for invention. In: Nelson, R.R. (Ed.), The Rate and Direction of Inventive Activity. Princeton University Press, Princeton, NJ, pp. 609–626.

Åsterbro, T., Thompson, P., 2011. Entrepreneurs, jacks of all trades or hobos? Res. Policy 40 (5), 637–649.

Audretsch, D., Keilbach, M., 2004. Does entrepreneurship capital matter? Enterp. Theory Pract. 28 (5), 419–430.

Ayala, J.-C., Manzano, G., 2014. The resilience of the entrepreneur. Influence on the success of the business. A longitudinal analysis. J. Econ. Psychol. 42, 126–135.

Banerjee, A.V., Newman, A.F., 1993. Occupational choice and the process of development. J. Polit. Econ. 101 (2), 274–298.

Baptista, R., Lima, F., Torres Preto, M., 2012. How former business owners fare in the labor market? Job assignment and earnings. Eur. Econ. Rev. 56 (2), 263–276.

Barney, J., 1991. Firm resources and sustained competitive advantage. J. Manag. 17, 99–120.

Bartelsman, E.J., Doms, M., 2000. Understanding productivity: lessons from longitudinal microdata. J. Econ. Lit. 38 (3), 569–594.

Bates, T., 1990. Entrepreneur human capital inputs and small business longevity. Rev. Econ. Stat. 72 (4), 551–559.

Beaudry, P., Francois, P., 2010. Managerial skills acquisition and the theory of economic development. Rev. Econ. Stud. 77 (1), 90–126.

Becker, G., 1962. Investment in human capital: a theoretical analysis. J. Polit. Econ. 70 (5), 9–49.

Bender, S., Bloom, N., Card, D., Van Reenen, J., Wolter, S., 2018. Management practices, workforce selection, and productivity. J. Labor Econ. 36 (S1), S371–S409.

Bergmann, H., Geissler, M., Hundt, C., Grave, B., 2018. The climate for entrepreneurshipat higher education institutions. Res. Policy 47 (4), 700–716.

Blakemore, A.E., Hoffman, D.L., 1989. Seniority rules and productivity: an empirical test. Economica 56, 359–371.

Bloom, N., Van Reenen, J., 2007. Measuring and explaining management practices across firms and Countries*. Q. J. Econ. 122 (4), 1351–1408.

Bloom, N., Van Reenen, J., Williams, H., 2019. A toolkit of policies to promote innovation. J. Econ. Perspect. 33 (3), 163–184.

Braunerhjelm, P., Ding, D., Thulin, P., 2016. Labour as a knowledge carrier – how increased mobility influences entrepreneurship. J. Technol. Transf. 41, 1308–1326.

Braunerhjelm, P., Ding, D., Thulin, P., 2018. The knowledge spillover theory of intrapreneurship. Small Bus. Econ. 51 (1), 1–30.

Braunerhjelm, P., Ding, D., Thulin, P., 2020. Labour market mobility, knowledge diffusion and innovation. Eur. Econ. Rev. 123 online version.

Bruce, D., Schuetze, H.J., 2004. The labor market consequences of experience in self-employment. Labour Econ. 11 (5), 575–598.

Carrier, C., 1996. Intrapreneurship in small businesses: an exploratory study. Enterp. Theory Pract. 21 (1), 5–20.

Cassiman, B., Veugelers, R., 2002. R&D cooperation and spillovers: some empirical evidence from Belgium. Am. Econ. Rev. 92 (4), 1169–1184.

Casson, M., 2003. The Entrepreneur: An Economic Theory, Second edition. Edward Elgar, Cheltenham.

Chapparro, X., Kozesinski, R., Junior, A., 2020. Absorptive capacity in startups: a systematic literature review. J. Entrep. Manag. Innov. 17 (1), 59–95.

Cirillo, B., Brusoni, S., Valentini, G., 2014. The rejuvenation of inventors through corporate spinouts. Organ. Sci. 25 (6), 1764–1784.

Cohen, W.M., Levinthal, D.A., 1990. Absorptive capacity: a new perspective on learning and innovation. Adm. Sci. Q. 35 (1), 128–152.

Colombo, M.G., Grilli, L., 2005. Founders' human capital and the growth of new technology-based firms: a competence-based view. Res. Policy 34 (6), 795–816.

Daly, M., 2015. The long term returns of attempting self-employment with regular employment as a fall back option. Labour Econ. 35, 26–52.

De Clercq, D., Sapienza, H.J., 2005. When do venture capital firms learn from their portfolio companies? Enterp. Theory Pract. 29 (4), 517–535.

DeTienne, D.R., McKelvie, A., Chandler, G.N., 2015. Making sense of entrepreneurial exit strategies: a typology and test. J. Bus. Ventur. 30 (2), 255–272.

Dillon, E., Stanton, C., 2017. Self.Employment Dynamics and the Returns to Entrepreneurship, NBER WP 23168. NBER, Cambridge, Ma.

Distel, A.P., Sofka, W., de Faria, P., Preto, M.T., Ribeiro, A.S., 2019. Dynamic capabilities for hire – how former host-country entrepreneurs as MNC subsidiary managers affect performance. J. Int. Bus. Stud. 1–32.

Eesley, C.E., Roberts, E.B., 2012. Are you experienced or are you talented? When does innate talent versus experience explain entrepreneurial performance. Strateg. Entrep. J. 6, 207–219.

Escribano, A., Fosfuri, A., Tribó, J.A., 2009. Managing external knowledge flows: the moderating role of absorptive capacity. Res. Policy 38 (1), 96–105.

Evans, D.S., Leighton, L.S., 1989. Some empirical aspects of entrepreneurship. Am. Econ. Rev. 79 (3), 519–535.

Faleye, O., Kung, W., Parwada, J.T., Tian, G.Y., 2020. Are entrepreneurs special? Evidence from board appointments. J. Bus. Ventur. https://doi.org/10.1016/j.jbusvent.2020.106003.

Feldstein, M., 2017. Underestimating the real growth of GDP, personal income, and productivity. J. Econ. Perspect. 31 (2), 145–164.

Foss, N.J., Klein, P.G., 2012. Organizing Entrepreneurial Judgment: A New Approach to the Firm. Cambridge University Press, Cambridge, UK.

Foster, L., Grim, C., Haltiwanger, J.C., Wolf, Z., 2018. Innovation, Productivity Dispersion, and Productivity Growth, NBER WP 24420. NBER.

Fox, J.T., Smeets, V., 2011. Does input quality drive measuerd differences in firm productivity. Int. Econ. Rev. 52 (4), 961–989.

Gompers, P., Kovner, A., Lerner, J., Scharfstein, D., 2006. Skill vs. Luck in Entrepreneurship and Venture Capital: Evidence From Serial Entrepreneurs. NBER WP 12592, NBER.

Gordon, R.J., 2012. Is US Economic Growth Over? Faltering Innovation Confronts the Six Headwinds. NBER WP 18315, NBER.

Griliches, Z., 1957. Specification bias in estimates of production functions. J. Farm Econ. 39 (1), 8–20.

Griliches, Z., Mairesse, J., 1998. Production functions: the search for identification. In: Econometrics and Economic Theory in the Twentieth Century: The Ragnar Frisch Centennial Symposium. Cambridge University Press, Cambridge.

Grilli, L., Murtinu, S., 2018. Selective subsidies, entrepreneurial founders' human capital, and access to R&D alliances. Res. Policy 47 (10), 1945–1963.

Haeussler, C., Harhoff, D., Mueller, E., 2014. How patenting informs VC investors—the case of biotechnology. Res. Policy 43 (8), 1649–1659.

Hall, B., 2011. Using productivity growth as an innovation indicator. In: Report for the High Level Panel on Measuring Innovation. DG Research, European Commission.

Haltiwanger, J.C., Lane, J.I., Spletzer, J.R., 1999. Productivity differences across employers: the roles of employer size, age, and human capital. Am. Econ. Rev. 89 (2), 94–98.

Hamilton, B., 2000. Does entrepreneurship pay? An empirical analysis of the returns to self-employment. J. Polit. Econ. 108 (3), 604–631.

Humphries, J., 2021. The Causes and Consequences of Self-employment Over the Life Cycle, Mimeo. University of Chicago, Chicago.

Hyytinen, A., Rouvinen, P., 2008. The labour market consequences of self-employment spells: European evidence. Labour Econ. 15 (2), 246–271.

Ilmakunnas, P., Maliranta, M., Vainiomäki, J., 2004. The roles of employer and employee characteristics for plant productivity. J. Prod. Anal. 21 (3), 249–276.

Iranzo, S., Schivardi, F., Tosetti, E., 2008. Skill dispersion and firm productivity: an analysis with employer&employee matched data. J. Labor Econ. 26 (2), 247–285.

Iyigun, M.F., Owen, A.L., 1998. Risk, entrepreneurship, and human-capital accumulation. Am. Econ. Rev. 88 (2), 454–457.

Iyigun, M.F., Owen, A.L., 1999. Entrepreneurs, professionals, and growth. J. Econ. Growth 4 (2), 213–232.

Jovanovic, B., 1982. Selection and the evolution of industry. Econometrica 50, 649–670.

Kaiser, U., Malchow-Møller, N., 2011. Is self-employment really a bad experience?: The effects of previous self-employment on subsequent wage-employment wages. J. Bus. Ventur. 26 (5), 572–588.

Kaiser, U., Kongsted, H., Ronde, T., 2015. Does the mobility of R&D labor increase innovation? J. Econ. Behav. Organ. 110, 91–105.

Klapper, L., Love, I., Randall, D., 2015. New firm registration and the business cycle. Int. Entrep. Manag. J. 11 (2), 287–306.

Lappi, E., 2022. Help from the past—coworker ties and entry wages after self-employment. Small Bus. Econ. https://doi.org/10.1007/s11187-022-00652-3.

Lappi, E., Eklund, J., Klaesson, J., 2022. Does education matter for the earnings of former entrepreneurs? Longitudinal evidence using entry and exit dynamics. J. Evol. Econ. 32, 827–865.

Lazear, E., 2004. Balanced skills and entrepreneurship. Am. Econ. Rev. 94 (2), 208–211.

Lazear, E., 2005. Entrepreneurship. J. Labor Econ. 23 (4), 649–680.

Leibenstein, H., 1968. Entrepreneurship and development. Am. Econ. Rev. 58 (2), 72–83.

Lerner, J., Malmendier, U., 2011. With a Little Help From my (Random) Friends: Success and Failure in Post-business School Entrepreneurship, NBER WP 16918. NBER, cambridge, Ma.

Levine, J., Argote, L., 2020. Group and organizational learning: past, present and future. In: Argote, L., Levine, J. (Eds.), The Oxford Handbook of Group and Organizational Learning. Oxford University Press, New York.

Levine, R., Rubinstein, Y., 2016. Smart and illicit: who becomes an entrepreneur and do they earn more?*. Q. J. Econ. 132 (2), 963–1018.

Levinsohn, J., Petrin, A., 2003. Estimating production functions using inputs to control for unobservables. Rev. Econ. Stud. 70 (2), 317–341.

Louigi, M., Broström, A., 2020. The Labor Market Value of Experience from Temporary Self-Employment. CESIS Working Paper No. 484 KTH Royal Institute of Technology.

Mahieu, J., Melillo, F., Reichstein, T., Thompson, P., 2021. Shooting stars? Uncertainty in hiring entrepreneurs. Strateg. Entrep. J. 15 (4), 526–567.

Mahieu, J., Melillo, F., Thompson, P., 2022. The long-term consequences of entrepreneurship: earnings trajectories of former entrepreneurs. Strateg. Manag. J. 43 (2), 213–236.

Mansfield, E., 1991. Academic research and industrial innovation. Res. Policy 20 (1), 1–12.

Manso, G., 2016. Experimentation and the returns to entrepreneurship. Rev. Financ. Stud. 29, 2319–2340.

Marino, M., Parrotta, P., Pozzoli, D., 2016. Educational diversity and knowledge transfers via inter-firm labor mobility. J. Econ. Behav. Organ. 123 (Supplement C), 168–183.

Merida, A., Rocha, V., 2021. It's about time: the timing of entrepreneurial experience and the career dynamics of university graduates. Res. Policy 50, 1–13.

Mincer, J., 1958. Investment in human capital and personal income distribution. J. Polit. Econ. 66 (4), 281–302.

Minniti, M., Bygrave, W., 2001. A dynamic model of entrepreneurial learning. Enterp. Theory Pract. 25 (3), 5–16.

Mion, G., Opromolla, O.D., 2014. Managers' mobility, trade performance, and wages. J. Int. Econ. 94 (1), 85–101.

Montgomery, J.D., 1991. Social networks and labor-market outcomes: toward an economic analysis. Am. Econ. Rev. 81 (5), 1408–1418.

Murphy, K.M., Shleifer, A., Vishny, R.W., 1991. The allocation of talent: implications for growth*. Q. J. Econ. 106 (2), 503–530.

Nelson, R.R., Phelps, E.S., 1966. Investment in humans, technological diffusion, and economic growth. Am. Econ. Rev. 56 (1/2), 69–75.

Nicolaou, N., Shane, S., 2009. Can genetic factors influence the likelihood of engaging in entrepreneurial activity? J. Bus. Ventur. 24 (1), 1–22.

Nielsen, K., 2015. Human capital and new venture performance: the industry choice anf performance of academic entrepreneurs. J. Technol. Transf. 40 (3), 453–474.

OECD, 2015. The Future of Productivity. DSTI/IND1, OECD, Paris.

Olley, S.G., Pakes, A., 1992. The Dynamics of Productivity in the Telecommunications Equipment Industry. NBER WP 3977, NBER.

Otani, K., 1996. A human capital approach to entrepreneurial capacity. Economica 63 (250), 273–289.

Parker, S.C., 2013. Do serial entrepreneurs run successively better-performing businesses? J. Bus. Ventur. 28 (5), 652–666.

Parker, S.C., 2018. The Economics of Entrepreneurship. Cambridge University Press.

Parrotta, P., Pozzoli, D., 2012. The effect of learning by hiring on productivity. RAND J. Econ. 43 (1), 167–185.

Parrotta, P., Pozzoli, D., Pytlikova, M., 2014. Labor diversity and firm productivity. Eur. Econ. Rev. 66 (Supplement C), 144–179.

Polanyi, M., 1967. The Tacit Dimension. Routledge & K. Paul, London, England.

Poschke, M., 2013. Who becomes an entrepreneur? Labor market prospects and occupational choice. J. Econ. Dyn. Control. 37 (3), 693–710.

Qian, H., Acs, Z.J., 2013. An absorptive capacity theory of knowledge spillover entrepreneurship. Small Bus. Econ. 40, 185–193.

Reagan, R., Argote, L., Brooks, D., 2005. Individual experience and experience working together: predicting learning ratse from kmowing what to do and knowing who knows what. Manag. Sci. 51, 869–881.

Rider, C.I., Thompson, P., Kacperczyk, A., Tåg, J., 2019. Experience and entrepreneurship: a career transition perspective. Int. Labour Rev. 72 (5), 1149–1181.

Romer, P.M., 1986. Increasing returns and long-run growth. J. Polit. Econ. 94 (5), 1002–1037.

Romer, P.M., 1990. Endogenous technological change. J. Polit. Econ. 98 (5, Part 2), S71–S102.

Say, J.B., 1828. Cours Complet d'Economie Politique Practique. Paris.

Schultz, T.W., 1980. Investment in entrepreneurial ability. Scand. J. Econ. 82 (4), 437–448.

Serafinelli, M., 2019. "Good" firms, worker flows, and local productivity. J. Labor Econ. 37 (3), 747–792.

Simsek, Z., Heavey, C., 2011. The mediating role of knowledge-based capital for corporate entrepreneurship effects on performance: a study of small- to medium-sized firms. Strateg. Entrep. J. 5 (1), 81–100.

Stoyanov, A., Zubanov, N., 2012. Productivity spillovers across firms through worker mobility. Am. Econ. J. Appl. Econ. 4 (2), 168–198.

Syverson, C., 2011. What determines productivity? J. Econ. Lit. 49 (2), 326–365.

Unger, J.M., Rauch, A., Frese, M., Rosenbusch, N., 2011. Human capital and entrepreneurial success: a meta-analytical review. J. Bus. Ventur. 26 (3), 341–358.

Vereshchagina, G., Hopenhayn, H., 2009. Risk taking by entrepreneurs. Am. Econ. Rev. 99 (5), 1808–1830.

Wennberg, K., Wiklund, J., DeTienne, D.R., Cardon, M.S., 2010. Reconceptualizing entrepreneurial exit: divergent exit routes and their drivers. J. Bus. Ventur. 25 (4), 361–375.

Williams, D.R., 2000. Consequences of self-employment for women and men in the United States. Labour Econ. 7 (5), 665–687.

Wooldridge, J.M., 2009. On estimating firm-level production functions using proxy variables to control for unobservables. Econ. Lett. 104 (3), 112–114.