What Makes a Good Entrepreneur?

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ABSTRACT

Which entrepreneur characteristics lead to the creation of highly productive firms? Based on a rich Swedish dataset, we evaluate a number of candidates, including various cognitive and noncognitive skills, in addition to physical characteristics and various demographic variables. When considered in isolation, many of these measures are associated with large and statistically significant effects on post-entry firm performance. However, when taken together, we find that noncognitive skills have the strongest effect upon performance, while the effect of cognitive skills is essentially zero. The verbal and logical component of cognitive skills has, however, a very strong association with performance, one that is even stronger than that of noncognitive skills.

Keywords: Entrepreneurship, Human Capital, Cognitive skills, Noncognitive skills,

Productivity

JEL: J24, J3, L26

1. INTRODUCTION

What makes a good entrepreneur? Given the importance of new-firm formation for economic growth (Schumpeter 1911), this is understandably a question of critical importance. It is also not a new one. For example, Hartog et al. (2010) report that entrepreneurs typically have higher cognitive and noncognitive abilities than wage workers. Adams et al. (2018) show the same holds when comparing CEOs and other employees. In turn, Levine and Rubinstein (2016) show that entrepreneurs with higher abilities tend to earn more.

Important as these results are, we believe they do not completely answer our opening question, which may be rephrased as; What entrepreneur characteristics lead to the creation of better firms, specifically, more productive firms? We argue, both conceptually and quantitatively, that this is a different question. First, the fact that the call for entrepreneurship attracts people with certain characteristics (e.g., cognitive skills) does not necessarily imply that those characteristics make for a productive firm (they do not, as we show empirically). Second, the correlation between an entrepreneur's personal success (e.g., earnings) and the success of the firm they found is positive but small, which again suggests that we are talking about two different research questions. In fact, we show that while there are common determinants of firm and entrepreneur success, there are also important differences.

Our goal in this paper is to explain the performance of newly founded firms. In addition to the common regressors used in productivity equations, we focus on various characteristics of the firm's founder. Our dataset is particularly apt for this purpose: Mandatory military draft test scores across eleven cohorts of Swedish men give us very detailed information about (male) entrepreneurs, including their cognitive and noncognitive skills. Based on a unique individual identifier, we then link these data to labor market records, which allows us to measure individual earnings as well as the identity of the firm each individual founds or works for — and a variety of firm performance measures.

We find that noncognitive skills are associated with an increase in firm productivity: a one-standard-deviation increase in noncognitive skills is associated with a 1.9 percent increase in a firm's total factor productivity (hereafter TFP), but cognitive skills are not. We dig deeper and decompose cognitive abilities into three different components: logical and verbal, spatial, and technical. We find that the absence of an effect when these three measures are aggregated hides considerable variation: The coefficients on logical and verbal skills, the components that are arguably closer to noncognitive skills, are positive and of similar size to the noncognitive abilities coefficient. By contrast, the coefficient on spatial skills, the one that is arguably closer to "pure" cognitive skills, has a negative coefficient, one that is both statistically significant and large in absolute value: a one-standard-deviation increase in spatial skills is associated with a 2.5 percent decrease in firm productivity. However, when we divide our sample into different types of firms, we find that cognitive abilities have a positive effect on the productivity of high-tech firms and a negative impact otherwise.

From an empirical and methodological point of view, we note that many entrepreneur characteristics, when considered separately, are positively correlated with firm performance — including, in fact, cognitive skills. However, when noncognitive skills are added, those effects disappear. In addition to noncognitive skills, there is one exception: entrepreneur height (but not strength or endurance) remains independently significant in the presence of other characteristics: a one-centimeter increase in height is associated with a 0.2 percent increase in firm productivity (or, equivalently, a one-inch increase in height is associated with a 0.5 percent increase in productivity).

Our paper relates to an extensive literature on entrepreneurship and entrepreneur characteristics. Perhaps closest to our analysis are Adams et al. (2018) and Levine and Rubinstein (2016). Adams et al. (2018) pose the question, "Are CEOs born leaders?" which they address using Swedish data similar to ours. They show that "the median large-company CEO belongs to the top 5% of the population in the combination of [] three traits, [namely] cognitive and noncognitive skills and height." This is consistent with our finding regarding the comparison between entrepreneurs and the general population. We go beyond the selection issue and look at the effect of entrepreneur characteristics on post-entry performance. We also use more granular data regarding cognitive abilities and show that such granularity makes a difference in estimation.

Levine and Rubinstein (2016) work with US data. They show that "those who become incorporated business owners [] tend to be more educated and—as teenagers—score higher on learning aptitude tests, exhibit greater self-esteem, reveal stronger sentiments of controlling their futures, and engage in more illicit activities than others." They also show that entrepreneurs "experience a material increase in earnings." Since the correlation between entrepreneur earnings and firm performance is small (though positive), one may ask whether the estimated effects for earnings extend to firm performance. We find that, while in our sample, the correlation between earnings and productivity is no more than 0.22, the same qualitative results hold for both variables.

In addition to the above two papers, our work is related to recent literature documenting the rising importance of noncognitive skills in the labor market (Acemoglu & Autor 2011, Deming 2017, Edin et al., 2022, Heckman & Rubinstein 2001). One possible rationale for this trend is that, as globalization and automatization render cognitive skills more easily tradable, social and other soft skills play increasingly an important role in occupational sorting and wage setting. It is not obvious whether and how this intuition extends to entrepreneurs and CEOs. Our paper offers evidence in this regard.

Our paper is also related to the economics literature on the relationship between entrepreneurs or CEO characteristics and firm productivity. The theoretical literature (Lucas 1978, Jovanovic 1982) has long assumed that firm performance depends on the entrepreneur's ability. Recent empirical evidence shows that the quality of management matters (Bender et al., 2018, Bloom & van Reenen 2007). For all of the progress in this direction, total factor productivity (TFP) is still largely a black box: a residual from production function estimation that is not accounted for by input levels and related variables. Our research contributes to this literature by opening the black box with detailed data on the entrepreneur characteristics as determinants of TFP.

The rest of the paper is organized as follows. Section 2 provides an overview of the data and discusses the empirical estimations. In Section 3, we present and discuss the results of our main empirical model as well as a series of extensions and robustness tests. Section 4 concludes the paper.

2. DATA AND DESCRIPTIVE STATISTICS

2.1. Employee-Employer Data

The data we work with is provided and maintained by Statistics Sweden (SCB), which covers the population of Swedish individuals and firms combined from different registers where all identifiers are anonymized. We use information on the labor market accounts of individuals from the *Longitudinell integrationsdatabas för sjukförsäkrings-och arbetsmarknadsstudier* (LISA) database. The individual records include information on the labor market status, earnings, occupation, and several other individual variables, such as age and household characteristics, all at a yearly level. The records include all individuals above 16 years old who reside in Sweden at the end of each year. We also make use of information about the labor market experience and educational attainment of each individual's biological father. We use information from the Multigenerational Register (*flergenerationsregistret*) to connect each man to his father's unique identifier.

The labor market status of an individual is defined as a function of the person's occupation and primary source of income in November of each year. We use this information to identify who is an entrepreneur and who is an employee: Entrepreneurs are defined as those who own an incorporated business from which they derive at least half of their income. In a robustness check, we run similar regressions for sole proprietorships. Results for noncognitive ability are similar, although smaller in magnitude and estimated with less precision.

The firm-level information on entrepreneurial ventures is derived from two registers, *Företagsdatabasen* (FDB) and *Registren för Företagens och arbetsställenas dynamik* (FAD), which include accounting information and centralized firm registries. Based on unique firm-level identifiers, also at the individual level, we match individuals to the businesses they own. Our focus is on the private sector, thus excluding agriculture, forestry, and fishing industries.

2.2. Enlistment Data

The information on individuals' abilities comes from peace-time mandatory conscription in Sweden when all Swedish men had to serve in the armed forces. For two consecutive days, each draftee had to undergo a series of written and physical fitness tests focused on the mental and physical abilities to serve. The conscripts were also interviewed by a licensed psychologist to evaluate their noncognitive skills, ability to work with others, and overall capacity to serve in the Swedish military. Most men were tested when they were

18 or 19, and most men actually served in the military.[1] The data of the enlistment test scores are provided by the Swedish Defense Recruitment Agency (*Rekryteringsmyndigheten*) and Swedish military archives (*Krigsarkivet*). The scores from the various tests can be matched with the individual labor market records by the unique individual identifier. We use Swedish-born cohorts who were tested between the years 1986 to 1996, which implies that the included cohorts were born in the years between 1967 to 1978.[2]

The cognitive skills scores are based on a written test that covers four main components of cognition: logical, verbal, spatial, and technical. Each component includes a total of 40 questions, which are graded based on the Statine (Standard Nine) method (or distribution): 5 corresponds to the middle 20 percentiles; 4 to the next 17 percentiles; 3 to the next 12; 2 to the next 7; and 1 to the bottom 4. The scores 6 to 9 follow a symmetric

[1] Only 0.2 percent of the conscripts refused to do any form of military or civil service, whereas only 0.1 percent requested weapon-free military service (Pliktverket 1994). Given this, we do not focus on the effect of serving in the military on entrepreneurial decisions. The length of military service varied based on placement within the military. It was usually between 7 to 18 months.

[2] Around 3 percent of the male conscripts in the full sample are foreign born and excluded from the analysis.

pattern. We normalize this score to have 0 mean and 1 standard deviation for each yearly cohort.

Cognitive skills are a mixture of pure intelligence and cognitive skills obtained through schooling. This is likely particularly worrisome when skills are measured at different ages.[3] In our case, this is less problematic since all individuals in our sample were the same age at the time of testing (18 or 19 years old), and only around 7 percent did not finish any high school. The nature of the testing and the controls for years of schooling that we include in the empirical estimations imply that cognitive scores are unlikely to be largely biased because of education. Cognitive test scores have been shown to be a good proxy for general intelligence (Carlstedt 2000).

The noncognitive skills score is based on a 20- to 30-minute interview with a certified psychologist. The interview's stated purpose is to evaluate the conscript's aptitude to serve in the Swedish Army and, potentially, in armed combat. Therefore, the focus is on coping with stress and contributing to group cohesion. By the time the interview takes place, the interviewer has access to information on the conscript's test results (both cognitive skills and physical tests) as well as the conscript's school grades and answers to a large set of

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[3] This is the case, for example, of the widely used cognitive scores linked to the NLSY questionnaire, as cognitive ability also affects schooling choices (Cawley et al., 2001, Hansen et al., 2004, Heckman et al., 2006).

questions, such as information about friends, family, hobbies, and so forth.[4] A high score is given if the conscript is emotionally stable, persistent, socially outgoing, willing to assume responsibility, and able to take the initiative.[5] Similar to cognitive abilities, noncognitive skills are expressed on Stanine distribution and normalized by us to have 0 mean and 1 standard deviation for each cohort.

We also have information about health status. Each conscript is examined by a physician and undergoes several physical tests, the scores of which translate into Stanine scores, which we normalize in the same manner as the cognitive and noncognitive abilities scores. One group of scores is focused particularly on endurance and cardiovascular stamina, such as the one measuring endurance that comes from riding a stationary bike for approximately five minutes. We also have a score for strength, which is from grip and other similar strength tests. Lastly, we have information on the height of the individual measured in centimeters. The three different measures capture different aspects of the physical fitness of the individual.

The same conscript data has been used to study individual outcomes such as income (Lindqvist & Vestman 2011), the likelihood of being a CEO or a politician (Adams et al., 2018, Dal Bó et al., 2017), and criminal behavior (Hjalmarsson & Lindquist 2019). The

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[4] See Lindqvist and Vestman (2011) for a more detailed discussion.

[5] See Edin et al. (2022) and Mood et al. (2012) for a detailed discussion.

advantage of using such military data is that it covers nearly the entire population of men, all tested at the same age. One disadvantage is that women are not tested population-wide similarly. Consequently, we include only men in our sample.

To complement the military test scores, we estimate an individual-specific and time-invariant ability measure. Specifically, we estimate a wage regression following the methodology proposed by Abowd et al. (1999) and Card et al. (2013).[6] The resulting individual fixed effect (AKM henceforth) corresponds to the wage premium the labor market assigns to an individual beyond observable traits such as gender, educational attainment, or experience. Cognitive and noncognitive abilities are also valuable as a wage employee, and so are other time-invariant factors, such as motivation. To the extent that these unobservable to the econometrician are observed and rewarded by employers, they should be reflected in the AKM coefficient. By including AKM in the regressions for entrepreneurs, we want to capture the effect of cognitive and noncognitive abilities that goes above and beyond the effect that these variables have upon wages in the labor market.

[6] We use a period from 1993 to 2004 to estimate the time-invariant individual wage determinant across the whole population of Swedish male employees. This is done so that there is no overlap between the period used to estimate our purged AKMs and the one in which we perform our main estimations.

Our focus is on the success of the entrepreneurial firm. Previous research on entrepreneurship (e.g., Levine & Rubinstein 2016, Hamilton 2000) has largely focused on entrepreneur earnings. This choice is likely driven by ease of data access and measurability. However, entrepreneurs can shift between capital and labor income; and they can pay themselves high wages or instead re-invest firm profits. Entrepreneurs have also been shown to underreport their incomes by up to 30% (Hurst et al., 2014). This evidence suggests that an entrepreneur's income is an imperfect measure of firm performance. Accordingly, in addition to personal income, we measure an entrepreneur's success by the performance of the firm he creates. We are able to do so because we are able to match each Swedish individual to the firm they created (or work for).

Our basic measure of firm performance is total factor productivity (TFP). We measure TFP by estimating a value-added production function with capital and labor inputs. We follow the commonly used semiparametric method proposed by Ackerberg et al. (2015).[7] Each firm's TFP is estimated as the residual of the production function corresponding to the firm's 1-digit industry code level.

So as to "bridge" the previous literature on entrepreneur performance, we also measure entrepreneur earnings from the newly-created business. Specifically, we include all income

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[7] Alternative semiparametric methods such as Levinsohn and Petrin (2003) produce similar estimates.

that is taxed as labor income. We note that this variable is bunched around the minimum income threshold required by Swedish tax authorities to be eligible for social security benefits, which is consistent with the earlier observation that entrepreneurs have the ability (and incentive) to shift income across different channels, thus rendering income a more problematic performance measure.[8]

The correlation between earnings and total factor productivity is around 0.22. Earnings and productivity vary in the same direction, but the correlation is very far from perfect.

The estimation sample is comprised of the years from 2005 to 2019. We include only entrepreneurs that started the firm during that time period. We allow the firms to be started at any point during our estimation time frame. However, many newly established firms exit after a few years, which means we have an unbalanced panel. In addition, the firm can be started with a team instead of only one person, a possibility we control.[9]

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[8] In order to be eligible for sick-leave insurance, an individual must earn at least 384,400 SEK in 2022 prices on a yearly level. To receive parental and childcare insurance, the minimum level is 483,000 SEK per year.

[9] The results are also robust to clustering the standard errors at the firm instead of individual-level.

2.3. Descriptive Statistics

Table 1 presents descriptive statistics at the entrepreneur level. All the financial data is deflated to constant 2016 price levels and denoted in Swedish Krona (SEK). The average entrepreneur earns around 420,000 SEK annually, which is equivalent to around 50,200 dollars (in 2016 prices). The relatively large standard deviation, around 189,000 SEK, is consistent with evidence regarding variation in entrepreneurial earnings (Hamilton 2000). On average, entrepreneurs in our sample are 42 years old, have some post-high school education, and 15 years of employment experience. Most entrepreneurs are married with young children living at home, and around 43 percent have a father who also is or has been an entrepreneur.

[TABLE 1 HERE]

Given that the cognitive and noncognitive scores were normalized for the whole population, positive mean values for these variables indicate that there is positive self-selection into entrepreneurship. This is consistent with Adams et al. (2018) result, which shows that Swedish companies are led by individuals with higher cognitive and noncognitive skills. Cognitive skills, noncognitive skills and AKM are positively but imperfectly correlated. The highest correlation is between cognitive and noncognitive skills (0.318), which is somewhat smaller than the approximately 0.40 found by (Butschek & Sauermann 2019). The correlations of the AKM residual with cognitive and noncognitive skills are 0.273 and 0.219, respectively. This suggests that the military test scores and the estimated AKM factor convey different information about individuals. Cognitive and noncognitive skills are not perfectly observed (or perfectly rewarded) by employers, and the individual wage premia may also be affected by other time-invariant characteristics such as grit, confidence, or perseverance. In sum, our descriptive results provide evidence suggesting that the AKM factor should not be considered equivalent to cognitive skills, as it encompasses other invariant traits relevant to an individual's performance.

Table 2 presents descriptive statistics at the firm level.

[TABLE 2 HERE]

3. RESULTS

3.1. Main Results

The basic empirical model we estimate for the productivity equations is the following:

$$ln\,(Y_{it}) = \partial_1 A_i^c + \partial_2 A_i^{nc} + \beta X + \gamma_{st} + \gamma_k + \gamma_l + \gamma_c + \gamma_t + \varepsilon_{it} \quad (1)$$

where Y_{it} is firm *i's* TFP in year *t*; A_i^c are A_i^{nc} are measures of an entrepreneur's cognitive and noncognitive abilities, respectively; and X includes a large set of individual- and firm-level covariates. At the level of the entrepreneur, we include age, age square, schooling, employment experience, prior entrepreneur experience (dummy), marital status (dummy), children living at home (dummy), father's schooling years, father's entrepreneur experience (dummy), and the natural logarithm of the father's average yearly earnings. At the firm level, we include the natural logarithm of the number of employees, and an indicator of whether there are multiple owners in the firm. We also control for firm age *st*, industry k, labor market l, enlistment cohort c, and year t fixed effect and ε_{it} is the error term. Estimation is performed for the years from 2005 to 2019. Clustered standard errors at the individual level are displayed in parenthesis.

Table 3 presents our first regressions. The results show that, when included alone, each one of the skill measures has a positive relationship with firm productivity. However, the coefficient associated with cognitive skills drops to zero when we control for noncognitive abilities. The coefficient associated with noncognitive ability, on the other hand, remains quantitatively very similar and with very similar precision. Including the AKM residual in (4) leaves the results qualitatively unchanged, even if the quantitative estimate of the effect of noncognitive ability is reduced by a third. This suggests that the AKM residual includes information relative to abilities, but also that noncognitive ability is relevant for the productivity of entrepreneurial firms beyond the effect that it has upon wages in the job market. In terms of effect size, our estimates suggest that a one-standard-deviation increase in noncognitive ability increases firm productivity by 1.9 percent. [10] [11]

[TABLE 3 HERE]

Our results align with the idea that an entrepreneur's human capital plays a role in their performance (Gennaioli et al., 2013, Lucas 1978, Murphy et al., 1991). It further contributes to our understanding of *how* human capital affects performance by showing that soft skills, rather than pure intelligence, are the primary performance drivers. This is consistent with evidence that entrepreneurs work longer hours and endure higher stress levels (Ajayi-Obe & Parker 2005), two features that are more closely related to noncognitive abilities.

[10] Full results with the control variables are found in Appendix Table A1. The results are robust to using pre-entrepreneurship earnings as a proxy for opportunity cos instead of the AKMs. Using last pre-entrepreneurship earnings instead of the AKM renders an estimate of the effect of noncognitive ability to be 2.66%, thus much closer to that estimated in Column (3) than when using the AKM's.

[11] We also have an inherent survivorship problem as we have an unbalanced panel of entreprenuers. The entrepreneurs that survive for longer in the market potentially bias the baseline estimations as they have more repeated observations of their abilities in the sample. We adjust for this problem by using the inverse of the total number of years we observe the entrepreneur as weights in the regression. Results are presented in Appendix Table A2 are in line with our baseline results.

Our results are also consistent with previous findings that noncognitive skills are more important in the labor market (Acemoglu & Autor 2011, Heckman & Rubinstein 2001). In this sense, we extend previous findings about employed work to entrepreneurship. However, differently from previous research, we find no positive effect on cognitive abilities.

3.2. Extension: Types of Cognitive Skills

In our baseline estimations, we include the standardized scores from an overall measure of individuals' cognitive abilities. These scores are based on a written test, which has four different components of cognitive ability. The first two components are meant to measure logical and verbal aptitude. The third component includes questions pertaining to spatial perception. Finally, the fourth component measures technical and science-related skills. This division has been used in prior research on earnings (Dougherty 2003, Hartog et al., 2010, Levine & Rubinstein 2016)

Private communication with the psychologists in the Swedish army indicates that the first two subcomponents both measure logical and verbal abilities and that it is not easy to assign a score to each one of these components. Accordingly, we aggregate them into one single component by adding the test scores together. As before, we normalize the resulting three different cognitive test scores for each yearly cohort. Results remain qualitatively the same when the four scores are included separately.

Table 4 displays the results of a series of regressions where we split cognitive skills into its subcomponents. We first consider each component separately (regressions 1 to 3) and then combine the three in the same regressions (regressions 4 and 5). Strikingly, we find that the overall scores hide some significant variation in how cognitive ability translates into entrepreneurial productivity. The logical and verbal components are positively related to productivity: a one-standard-deviation increase in logical and verbal ability is associated with a 2.5 percent increase in productivity. Dougherty (2003) shows that these skills matter for employee wages. Our results suggest that such a relation also holds for entrepreneurs.

[TABLE 4 HERE]

Spatial skills, in contrast, are negatively related to productivity: a one-standard-deviation increase in spatial skills is associated with a 2.7 percent decrease in productivity. Finally, we find no evidence of technical skills being related to productivity. This contrasts with Hartog et al. (2010), who find that science-oriented ability generates higher returns. We find no such evidence based on our data and for the actual entrepreneurial firm productivity.

Overall, our results provide further evidence that not all types of cognitive abilities translate into higher entrepreneurial success. It is interesting to note that our measure of noncognitive ability is a mixture of the ability to cope with stress and leadership attributes such as being socially outgoing, willing to assume responsibility, and able to take the initiative. Verbal and logical abilities, on the other hand, are the dimensions of intelligence that are indicative of the ability to formulate and express a reasoning and thus of the ability to persuade others, which is exactly the type of intelligence that psychologists deem to be more relevant for leadership (Simonton 1985).

3.3. Extension: Type of Firm

In principle, different firms require different types of entrepreneurial skills. So far, we have pooled all firms together. One natural extension is to estimate separate coefficients for different types of firms. We distinguish between services and manufacturing; high-technology and other industries (following the Eurostat definition);[12] small (less than 10 employees) and large firms; and between firms owned by the entrepreneur alone as opposed to firms with multiple owners. For each division group, we run a separate regression and register the point estimate of cognitive and noncognitive abilities as well as a 95 percent confidence interval.

[FIGURE 1 HERE]

Figure 1 shows the result of this exercise. The most significant result is that the null effect of cognitive abilities in our main regressions is driven by opposite effects in high-technology and non-high-technology industries: higher cognitive abilities make for better

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[12] 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.

entrepreneurs in the high-tech industries, whereas the opposite is true in all other industries. In addition, it is worth noting that the effect of both cognitive and noncognitive abilities is larger (significantly positive) for small firms, those firms in which the direct influence of the entrepreneurs is definitely more predominant.

3.4. Extension: Physical Abilities

As mentioned earlier, our regressions show a general positive effect of cognitive skills on productivity when this measure is taken in isolation. However, when noncognitive skills are added, such an effect disappears. This is a common problem in econometrics: omitting a regressor may create a spurious effect. Prior research (Gurley-Calvez et al., 2009, Hamilton 2000) found that entrepreneurs need abilities and skills to cope with high levels of stress and long work hours. This suggests that we add physical scores from the enlistment tests to our set of entrepreneur characteristics. In fact, similar to the cognitive and noncognitive regression issue, it might be that the estimated effect of noncognitive abilities is weakened or disappears once we include physical characteristics.

[TABLE 5 HERE]

We include three specific physical variables as alternative measures of overall health and stress-coping skills related to physical ability. First, the physical standardized score, which essentially measures endurance and cardiovascular stamina (normalized to zero mean and unit variance). Second, a measure of muscular strength (normalized to zero mean and unit variance). Third, height (measured in centimeters). The three different health measures capture different aspects of the physical fitness of the individual.

As can be seen in Table 5, when included alone, all the individual health measures are positively correlated with higher productivity. However, when the three are included at the same time (Column 4), the effect of strength disappears. When cognitive and noncognitive abilities are also included, the only one that retains relevance is the height of the entrepreneur.[13] A one-centimeter increase in height is associated with a 0.2 percent increase in firm productivity. Alternatively, a one-standard-deviation increase in entrepreneur height is associated with a 1.2 percent increase in firm productivity.

Previous research (Hamermesh & Biddle 1994, Mobius & Rosenblat 2006) argues that the link between height and income stems from childhood investments in health human capital or factors such as self-esteem and social dominance. Overall, the results suggest that merely physical ability is not a primary driver of entrepreneurial success, and that height is a proxy for unobserved factors that are positively associated with productivity. Prior

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[13] An individual's strength and fitness can change over time and results should be interpreted with this caveat. However, we note that physical attributes at young ages can have persistent consequences in the labor market. Even in the case of height, that is less likely to change much over time, Persico et al. (2004) observed that height in adolescence (age 16) matters more for wages than age at adult age (33).

research (Case & Paxson 2008) also suggests that height and cognitive skills are positively correlated and that a large portion of the height premium in earnings is due to cognitive ability. We find little evidence of it in our setting. The correlation in our sample is 0.109, and the estimated effect of height remains unchanged with the inclusion of cognitive and noncognitive abilities. We also note that the inclusion of physical measures does not change our baseline results regarding the effect of cognitive and noncognitive abilities. This suggests that the relevant abilities encapsulated in the noncognitive score are less related to physical ability and more related to qualities such as being a leader or keeping a balanced social life.

3.5. Extension: Earnings

As mentioned earlier, so as to "bridge" the previous literature on entrepreneur performance, we also measure entrepreneur earnings from the newly-created business as a performance measure. The first two columns of Table 6 present, side by side, the results of similar regressions with TFP and entrepreneur earnings as the dependent variables. The first regression basically replicates the third regression in Table 3 and is presented here for comparison purposes. The results for earnings as a dependent variable (second regression column) are remarkably similar to those of TFP. Given the noise of the earnings variable (for the reasons mentioned before), we find it remarkable that a one-standard-deviation increase in noncognitive skills has essentially the same proportional effect on TFP and earnings, namely 1.99 percent. We also confirm that, like TFP, the effect of cognitive skills on earnings is zero once we account for noncognitive skills.

[TABLE 6 HERE]

Column (3) presents a regression similar to column (2) but estimated without AKM. Column (3) provides a direct comparison with column (4), where an identical regression is estimated for a sample of wage earners. The results show that the effects of both cognitive and noncognitive abilities are positive for wage earners and larger in magnitude than the corresponding estimates for entrepreneurs.

Columns (5) and (6) present the results for the sample of individuals who switched at least once between entrepreneurship and wage work. This subsample allows us to estimate the within effect of cognitive and noncognitive abilities. Column (5) shows that the effects of both cognitive and noncognitive abilities on wage earnings are positive (0.8% and 4.9%, respectively). However, each of these effects is reduced by about 3.6% when individuals become entrepreneurs. This results in a negative effect of 2.8% for cognitive ability and a positive effect of 1.3% for non-cognitive ability. The independent effect of switching to entrepreneurship is positive and estimated to be 2.5%, but this effect is reduced for individuals with high cognitive ability and for those with low noncognitive ability.

In column (6) we add fixed effects to the estimation. The independent effect of switching into entrepreneurship is now estimated to be negative (1.2%), but the penalty suffered by those with high cognitive and noncognitive abilities is now estimated to be 2.6% and 2.2%, respectively.

3.6. Robustness

Instead of focusing on TFP as a performance indicator, we consider four alternative firm performance measures: value-added per employee, net sales, net sales per employee, and firm profits. The results, included in Table 7, are in line with our main findings. In particular, noncognitive ability shows a positive relationship with all performance measures, further validating that softer skills are important in all aspects of entrepreneurial success. Differently from TFP, we have evidence that cognitive abilities have a negative effect on firm sales.

[TABLE 7 HERE]

An individual can start a new firm based on various motives, and one might conjecture that entrepreneur characteristics differ depending on the nature of the entry. With that in mind, we slice and extend our sample in different ways so as to test the robustness of our basic results. First, in columns (1) and (2), we distinguish entrepreneurs who entered from an unemployment situation and those who entered from an employment situation. In column (3), we look at a sample of individuals who start a sole proprietorship (as opposed to an incorporated firm). In column (4), we extend our definition of entrepreneurship to include firms that already exist and in which a new entrepreneur is identified. (Up until now, we focused on individuals who switch to entrepreneurship and create a new incorporated firm at the same time.)

The results, shown in Table 8, are largely in line with the basic results. First, the estimate of the effect of noncognitive skills is essentially identical for entrepreneurs who enter from unemployment and for those who come from employment, but it is less precisely estimated for the former than for the latter. Second, for new sole proprietorships and for all incorporated firms, the effect on non-cognitive ability is of a comparable magnitude to the one for new incorporated firms (compare columns 3 and 4 of Table 8 with column 4 of Table 3 and column 2 of Table 6). Third, the effect of cognitive skills is negative for firms emerging from unemployment and for sole proprietorships (and statistically significant for the latter). According to Levine & Rubinstein (2016), sole proprietors have firms that require more manual skills than incorporated firms do. Our evidence suggests that for these firms (and also for firms emerging from unemployment), high cognitive abilities can even be counterproductive. [14]

[TABLE 8 HERE]

[14] Finally, we consider several subsamples based on the type of firm (location, level of competition). We also evaluate the impact of individual background such as education or being married and paternal background such as father's entrepreneurial experience. in Appendix Figures A1 and A2. We find no differences across such dimensions.

4. CONCLUSION

What makes a good entrepreneur? Specifically, what entrepreneur characteristics lead to highly productive firms? Our paper contributes to answering these questions. Using a rich dataset of Swedish (male) entrepreneurs, we show that entrepreneur noncognitive skills contribute significantly to the new firm's performance. By contrast, cognitive skills do not. If anything, we find that, except for high-tech industries, cognitive skills have a negative effect on post-entry performance.

At the macro level, our paper contributes to the understanding of aggregate productivity. Measures of total factor productivity (the residual of the production function estimation) show significant differences across firms and across countries. As Prescott (1998) put it in the title of his Nobel Laureate Lecture, "Needed: A Theory of Total Factor Productivity." While we don't offer such a theory, we provide a set of empirical findings that hopefully help in that quest.

Bloom & van Reenen (2007) work provides a series of clues as to the determinants of TFP, namely in the form of management practices. Our approach complements theirs. Presumably, the two approaches are complementary. In fact, one promising line of future research is whether the variation in management practices documented by Bloom & van Reenen (2007) is in any way related to the entrepreneur's (or the CEO's) characteristics, namely their cognitive and noncognitive skills.

Finally, Kaplan et al. (2009) seminal paper focuses on one of the central issues in venture capital, namely whether "investors in start-ups should place more weight on the business ("the horse") than on the management team ("the jockey")." While we do not address that question specifically, our research contributes to the discussion of what makes a start-up successful.

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TABLES

Table 1. Entrepreneur Descriptive Statistics

VARIABLES	Mean	Median	std	Min	Max
Cognitive	0.221	0.0256	0.915	-2.183	2.089
Noncognitive	0.295	0.515	0.925	-2.701	2.421
AKM	-0.848	-0.889	0.401	-3.088	1.760
Earnings (in SEK)	418,731	406,335	189,294	1,414	5.529e+06
Age	41.64	42	4.730	28	52
Schooling	12.66	12	2.122	7	21
Employment Experience (in years)	15.10	15	4.263	2	26
Married	0.554	1	0.497	0	1
Children	0.764	1	0.425	0	1
Father Education (in Years)	11.19	11	3.052	6	21
Father Entrepreneur	0.430	0	0.495	0	1
Ln(Father Income)	11.19	12.01	2.769	0	15.42
Endurance	0.159	-0.105	0.989	-3.562	2.178
Strength	0.164	0.0344	0.977	-2.639	2.042
Height (in cm)	179.9	180.0	6.30	153.0	206.0
Number of Observations	89,551				
Number of Individuals	17,910				

Table 2. Firm Descriptive Statistics

VARIABLES	Mean	Median	Std. dev.	Min	Max
Ln(TFP)	12.48	12.48	0.967	-4.136	16.83
Ln(Sales)	15.05	14.97	1.506	0	21.17
Ln(Sales Per Employee)	13.93	13.96	1.040	0	20.21
Ln(Profit)	12.65	12.79	1.646	0	19.39
Ln(Labor)	1.123	0.693	1.098	0	7.561
Firm Age	2.878	2	3.027	0	14
High Tech (1=high-tech sector)	0.394	0	0.489	0	1
Multiple Owner (1=multiple owner)	0.388	0	0.487	0	1
Number of Observations	89,551				
Number of Individuals	17,910				

Table 3. Entrepreneur Characteristics and Firm TFP

Dependent Variable: ln(TFP)	(1)	(2)	(3)	(4)
Cognitive IQ	0.0134**		0.0081	-0.0006
	(0.006)		(0.006)	(0.006)
Noncognitive IQ		0.0286***	0.0273***	0.0190***
		(0.005)	(0.006)	(0.005)
AKM	NO	NO	NO	YES
Observations	89,551	89,551	89,551	89,551
Individuals	17,910	17,910	17,910	17,910
R squared	0.390	0.390	0.390	0.394

Notes: All estimations include the control variables: age, age square, schooling, and employment experience of the individual, and whether the individual has been an entrepreneur in the past, is married, has children living at home, the maximum years of schooling of the father, an indicator whether father has been or is an entrepreneur and the natural logarithm of the average yearly earnings of the father. At the firm level, we include the natural logarithm of the number of employees, and an indicator of whether there are multiple owners in the firm. Estimations also include firm age, industry, labor market, cohort, and year fixed effects. The estimation sample comprises years from 2005 to 2019. Clustered standard errors at the individual level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table 4. Components of Cognitive Ability

Dependent Variable: ln(TFP)	(1)	(2)	(3)	(4)	(5)
Logical and Verbal	0.0220***			0.0329***	0.0249***
	(0.006)			(0.007)	(0.007)
Spatial		-0.0112**		-0.0286***	-0.0271***
		(0.005)		(0.006)	(0.006)
Technical			0.0109*	0.0114	0.0067
			(0.006)	(0.007)	(0.008)
Noncognitive IQ	0.0241***	0.0292***	0.0258***	0.0243***	0.0151**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
AKM	NO	NO	NO	NO	YES
Observations	77,959	77,959	77,959	77,959	77,959
Individuals	15,429	15,429	15,429	15,429	15,429
R-squared	0.391	0.390	0.390	0.392	0.396

Notes: The same as in Table 3 *** p<0.01, ** p<0.05, * p<0.1.

Table 5. Physical characteristics

Dependent Variable: ln(TFP)	(1)	(2)	(3)	(4)	(5)	(6)
Endurance	0.0190***			0.0184***	0.0102*	0.0107*
	(0.005)			(0.005)	(0.006)	(0.006)
Strength		0.0124***		0.0055	0.0013	0.0010
		(0.005)		(0.005)	(0.005)	(0.005)
Height			0.0026***	0.0025***	0.0023***	0.0021***
			(0.001)	(0.001)	(0.001)	(0.001)
Cognitive IQ					0.0073	-0.0013
					(0.006)	(0.006)
Noncognitive IQ					0.0253***	0.0172***
					(0.006)	(0.006)
AKM	NO	NO	NO	NO	NO	YES
Observations	89,387	89,387	89,387	89,387	89,387	89,387
Individuals	17,872	17,872	17,872	17,872	17,872	17,872
R-squared	0.390	0.390	0.390	0.390	0.391	0.395

Notes: The same as in Table 3 *** p<0.01, ** p<0.05, * p<0.1.

Table 6. Earnings

Dependent Variable:	Ln(TFP) Entrepreneurs	Ln(Earnings) Entrepreneurs	Ln(Earnings) Entrepreneurs	Ln(Earnings) Employees	Ln(Earnings) Within entrepreneur variation	Ln(Earnings) Within entrepreneur variation
	(1)	(2)	(3)	(4)	(5)	(6)
Cognitive IQ	-0.0006	-0.0020	0.0058	0.0268***	0.0076**	
	(0.006)	(0.004)	(0.004)	(0.001)	(0.004)	
Noncognitive IQ	0.0190***	0.0199***	0.0274***	0.0659***	0.0490***	
	(0.005)	(0.003)	(0.004)	(0.001)	(0.003)	
Entrepreneurship					0.0247***	-0.0123**
					(0.005)	(0.005)
Entrepreneurship * Cognitive IQ					-0.0355***	-0.0264***
					(0.004)	(0.004)
Entrepreneurship * Noncognitive IQ					-0.0357***	-0.0218***
					(0.004)	(0.004)
Individual FE	NO	NO	NO	NO	NO	YES
AKM	YES	YES	NO	NO	NO	NO
Observations	89,551	89,551	89,551	3,764,722	255,534	255,534
Individuals	17,910	17,910	17,910	319,585	17,882	17,882
R-squared	0.394	0.265	0.251	0.309	0.264	0.094

Notes: The same as in Table 3. Column 4 includes a sample of employees. Columns 5 and 6 include the same entrepreneurs as in our main estimations but now also their employment experiences. *** p<0.01, ** p<0.05, * p<0.1.

Table 7. Alternative Performance Measures

Dependent Variable:	Ln(Value Added per Employee)	Ln(Sales per Employee)	Ln(Sales)	Ln(Profit)
	(1)	(2)	(3)	(4)
Cognitive IQ	-0.0051	-0.0234***	-0.0239***	-0.0091
	(0.006)	(0.009)	(0.009)	(0.013)
Noncognitive IQ	0.0219***	0.0512***	0.0513***	0.0339***
	(0.005)	(0.008)	(0.008)	(0.011)
Observations	89,551	89,551	89,551	75,061
Individuals	17,910	17,910	17,910	16,746
R-squared	0.179	0.105	0.550	0.252

Notes: The same as in Table 3 *** p<0.01, ** p<0.05, * p<0.1.

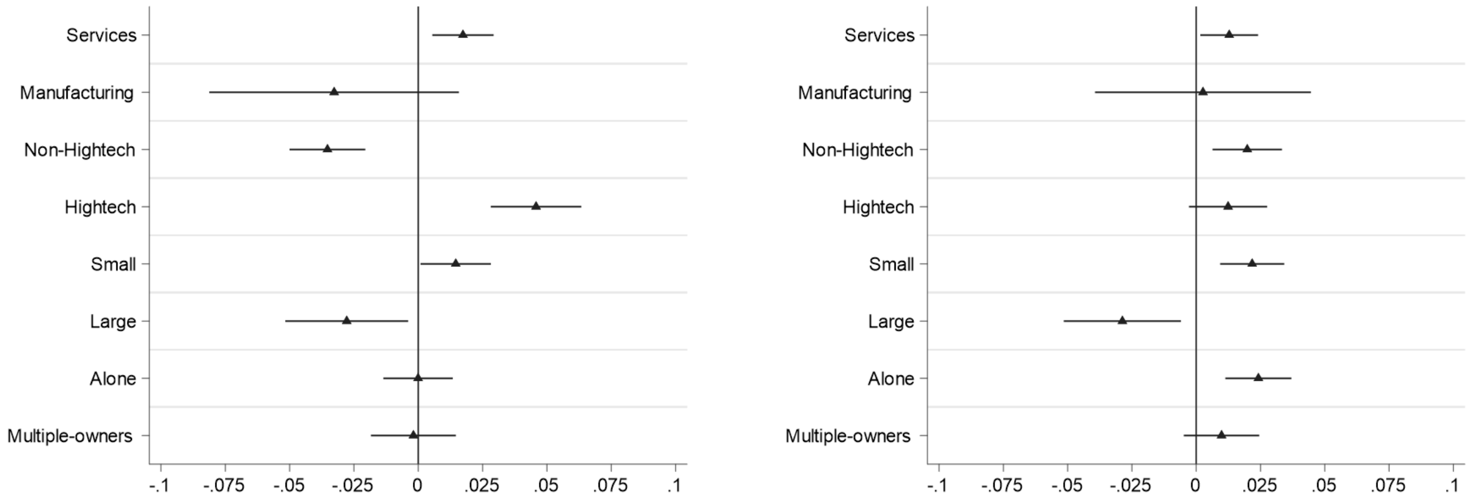
Table 8. Different types of new firms

	New Incorporated Firms From Unemployme nt	New Incorporated Firms From Employment	New Sole Proprietor Firms	All Incorporated Firms
	(1)	(2)	(3)	(4)
Panel A. Dependent Variable: ln(TFP)				
Cognitive IQ	-0.0510**	0.0008	-0.0264***	-0.0048
	(0.021)	(0.006)	(0.009)	(0.003)
Noncognitive IQ	0.0241	0.0211***	0.0126	0.0120***
	(0.017)	(0.006)	(0.008)	(0.003)
Observations	7,241	80,510	92,003	321,874
Individuals	1,864	16,153	22,290	50,777
R-squared	0.297	0.408	0.086	0.446
Panel B. Dependent Variable: Ln(Earnings)				
Cognitive IQ	-0.0209	-0.0020	-0.0214***	-0.0073***
	(0.015)	(0.004)	(0.007)	(0.002)
Noncognitive IQ	0.0327***	0.0217***	0.0168***	0.0167***
	(0.012)	(0.004)	(0.006)	(0.002)
Observations	7,241	80,510	89,462	322,209
Individuals	1,864	16,153	21,809	50,772
R-squared	0.259	0.268	0.096	0.286

Notes: The same as in Table 3 *** p<0.01, ** p<0.05, * p<0.1.

FIGURES

Figure 1. The marginal effects of cognitive skills (left panel) and noncognitive skills (right panel)



Notes: All estimations include the control variables: age, age square, schooling, and employment experience of the individual, and whether the individual has been an entrepreneur in the past, is married, has children living at home, the maximum years of schooling of the father, an indicator whether father has been or is an entrepreneur and the natural logarithm of the average yearly earnings of the father. At the firm level, we include the natural logarithm of the number of employees, and an indicator of whether there are multiple owners in the firm. Estimations also include firm age, industry, labor market, cohort, and year fixed effects. The estimation sample comprises years from 2005 to 2019. Clustered standard errors at the individual level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

APPENDIX

Table A1. Full Results - Entrepreneur Characteristics and Firm TFP

Dependent Variable: ln(TFP)	(1)	(2)	(3)	(4)
Cognitive IQ	0.0134**		0.0081	-0.0006
	(0.006)		(0.006)	(0.006)
Noncognitive IQ		0.0286***	0.0273***	0.0190***
		(0.005)	(0.006)	(0.005)
Endurance	0.0183***	0.0090	0.0092	0.0097
	(0.005)	(0.006)	(0.006)	(0.006)
Age	0.0063	0.0071	0.0066	-0.0013
	(0.016)	(0.016)	(0.016)	(0.016)
Age^2	-0.0002	-0.0002	-0.0002	-0.0003**
	(0.000)	(0.000)	(0.000)	(0.000)
Schooling	0.0224***	0.0228***	0.0215***	0.0214***
	(0.003)	(0.003)	(0.003)	(0.003)
Employment Experience	0.0060***	0.0058***	0.0058***	0.0052***
	(0.001)	(0.001)	(0.001)	(0.001)
Serial Entrepreneur	-0.1161***	-0.1166***	-0.1169***	-0.1191***
	(0.011)	(0.011)	(0.011)	(0.011)
Married	0.0073	0.0055	0.0051	0.0040
	(0.010)	(0.010)	(0.010)	(0.010)
Children	0.0414***	0.0389***	0.0394***	0.0362***
	(0.013)	(0.013)	(0.014)	(0.014)
Father Education	0.0011	0.0012	0.0009	0.0004
	(0.002)	(0.002)	(0.002)	(0.002)
Father Entrepreneur	-0.0144	-0.0143	-0.0147	-0.0152*
	(0.009)	(0.009)	(0.009)	(0.009)
Father Earnings	0.0051***	0.0047***	0.0047***	0.0041***
	(0.001)	(0.001)	(0.001)	(0.001)
Size	-0.4221***	-0.4230***	-0.4229***	-0.4289***
	(0.005)	(0.005)	(0.005)	(0.005)
Multiple owner	0.0687***	0.0701***	0.0701***	0.0769***
	(0.010)	(0.010)	(0.010)	(0.010)
AKM				0.2029***
				(0.015)
Observations	89,551	89,551	89,551	89,551
Individuals	17,910	17,910	17,910	17,910
R squared	0.390	0.390	0.390	0.394

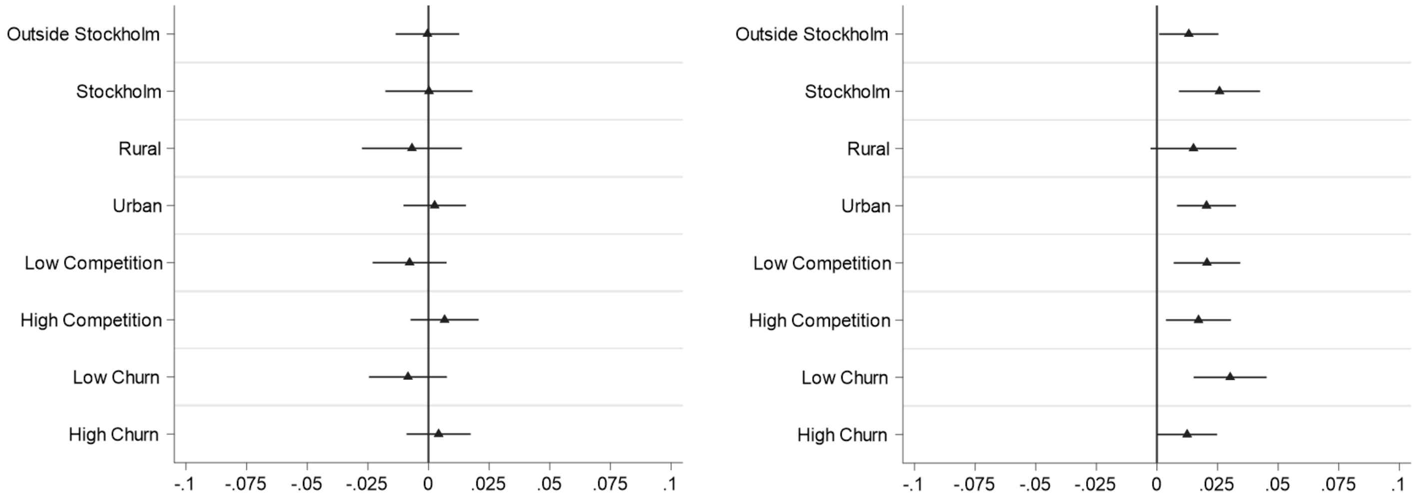
Notes: Estimations also include firm age, industry, labor market, cohort, and year fixed effects. The estimation sample comprises years from 2005 to 2019. Clustered standard errors at the individual level in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A2.
Results – Survival Bias

Dependent Variable: ln(TFP)	(1)	(2)	(3)	(4)
Cognitive IQ	0.0152**		0.0086	-0.0008
	(0.007)		(0.007)	(0.007)
Noncognitive IQ		0.0351***	0.0337***	0.0248***
		(0.007)	(0.007)	(0.007)
AKM	NO	NO	NO	YES
Observations	89,551	89,551	89,551	89,551
Individuals	17,910	17,910	17,910	17,910
R-squared	0.342	0.342	0.342	0.347

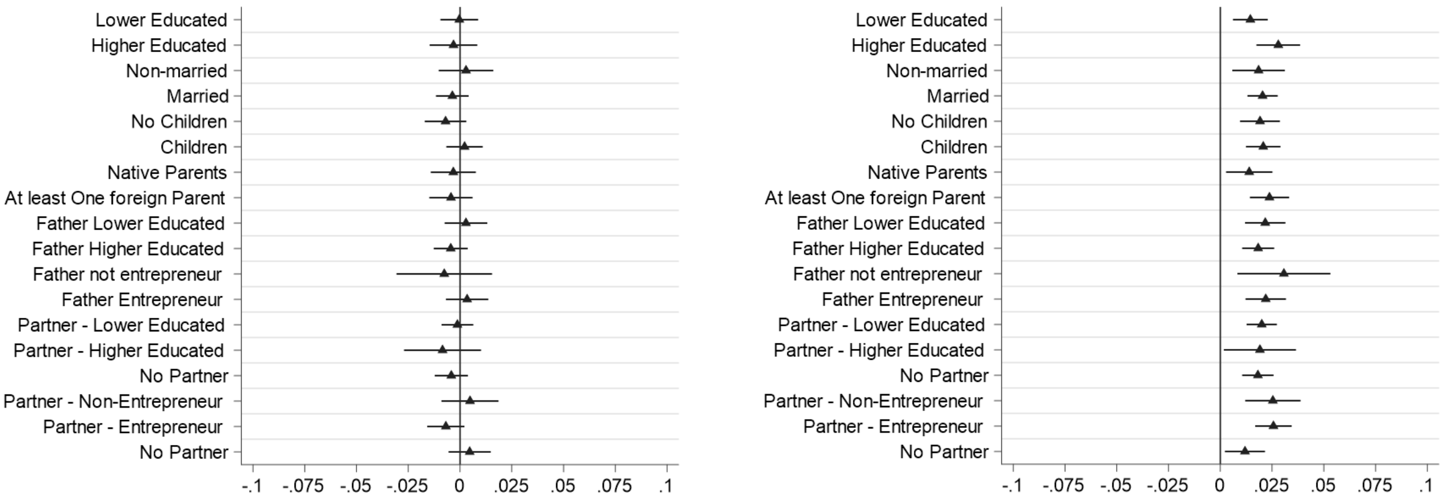
Notes: The same as in Table 3. All estimations are weighted by the inverse of the total number of observations of the firm to control for survival bias. *** p<0.01, ** p<0.05, * p<0.1.

Figure A1. The marginal effects of cognitive skills (left panel) and noncognitive skills (right panel)



Notes: All estimations include the control variables: age, age square, schooling, and employment experience of the individual, and whether the individual has been an entrepreneur in the past, is married, has children living at home, the maximum years of schooling of the father, an indicator whether father has been or is an entrepreneur and the natural logarithm of the average yearly earnings of the father. At the firm level, we include the natural logarithm of the number of employees, and an indicator of whether there are multiple owners in the firm. Estimations also include firm age, industry, labor market, cohort, and year fixed effects. The estimation sample comprises years from 2005 to 2019. Clustered standard errors at the individual level in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure A2. The marginal effects of cognitive skills (left panel) and noncognitive skills (right panel)



Notes: All estimations include the control variables: age, age square, schooling, and employment experience of the individual, and whether the individual has been an entrepreneur in the past, is married, has children living at home, the maximum years of schooling of the father, an indicator whether father has been or is an entrepreneur and the natural logarithm of the average yearly earnings of the father. At the firm level, we include the natural logarithm of the number of employees, and an indicator of whether there are multiple owners in the firm. Estimations also include firm age, industry, labor market, cohort, and year fixed effects. The estimation sample comprises years from 2005 to 2019. Clustered standard errors at the individual level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1