The wrong entrepreneurs? Family wealth, talent, and aggregate outcomes

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Abstract

We investigate how the joint distribution of skills and parental wealth affects the number and performance of firms founded, and the effect on aggregate outcomes. Using Swedish administrative data we find that higher parental wealth is associated with an increased rate of entry into entrepreneurship, but a weakened selection into entrepreneurship on both cognitive and non-cognitive skills. These abilities in turn matter for different firm outcomes. Cognitive ability is associated with higher probabilities of patenting, becoming a top 5% firm in terms of revenue, and surviving, while non-cognitive ability predicts all measures of firm size, by revenue and workers, but not patenting or firm exit. In our two-period model, we show that a liquidity channel of parental wealth cannot rationalize the observed weakening of skill-based selection along the parental wealth distribution, whereas an insurance channel can generate this pattern. To quantify the effect of the weakened selection on skill, we build a quantitative GE model featuring both a liquidity and an insurance channel of parental wealth, as well as a link between founder skills and firm outcomes. We conclude that our findings point to a potential misallocation introduced by parental wealth through its role in the entry decision.

Keywords: Entrepreneurship; talent allocation; occupational choice; IQ; non-cognitive abilities; parental wealth; liquidity; consumption insurance; firm performance

I. Introduction

Firms are a key driver of productivity and growth in economies, and it is therefore important to understand who is selecting into entrepreneurship, and how that affects the quality of firms founded. While a better chance of firm success should incentivize individuals with the right skills to select into entrepreneurship, barriers to entry could

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affect the selection in ways that generate an equilibrium with an inefficient pool of entrepreneurial talent. For example, parental wealth alleviates entry barriers by providing liquidity and allowing talented individuals to start firms. However, parental wealth can also insure personal consumption against poor business outcomes, encouraging entry among individuals whose skills predict weaker firm performance. While parental wealth and talent are correlated, highly skilled individuals are born to parents anywhere in the wealth distribution. We want to investigate how the joint distribution of parental wealth and skill affects who becomes an entrepreneur, how many firms are founded, and how the resulting performance of companies affects aggregate outcomes. To answer this question, we analyze Swedish data on individuals, their parental background, and their firms, introduce a theory of the channels connecting parental wealth and the entry margin, and finally build and calibrate a GE model intended to quantify the effects on aggregate outcomes.

Others have investigated how individuals select into occupations (Hsieh et al. (2019)) and find that barriers to entry can affect the talent allocation, with consequences for aggregate outcomes. It has also been documented that entry into entrepreneurship depends on wealth (Chodorow-Reich et al. (2024), E. Hurst and Lusardi (2004)) and family background (Vladasel et al. (2021), Sørensen (2007)) and that individuals' cognitive and non-cognitive traits affect firm outcomes (Kardaslar et al. (2026), Lappi et al. (2023)). The finding that wealth increases entry could reflect an increased entry across skill levels, but wealth might also change how strongly entry depends on skill. We find that while parental wealth increases the probability of becoming an entrepreneur, it weakens the relationship between skill and selecting into entrepreneurship.

We use rich micro data from Sweden containing information on male individuals born from 1972-1979, their cognitive and non-cognitive test scores from the mandatory military conscription exam, parental background and wealth, and all firms founded by these individuals between 2004 and 2018, including financial statements, matched worker data, and patents. The military conscription test was usually taken between the ages of 18 and 20, and it was mandatory and near-universal, while wealth data is measured in 1999 and comes from tax filings, which means both skills and parental wealth are measured before the start of the firm founding activities in 2004. Entrepreneurs are defined as individuals who were owner-operators of a closely held company in the first year after it was registered, and who hired at least one other person at some point. We match information on firm size by revenue and workers, patents, and firm exit. Utilizing this dataset, we can investigate how cognitive and non-cognitive skills predict entry into entrepreneurship jointly with parental wealth, and how entrepreneur skills predict firm size, patenting activity, and survival.

We find that while parental wealth increases the probability of becoming an entrepreneur

between 2004 and 2018 on average, it weakens the relationship between skill and selecting into entrepreneurship. This means that individuals at the top of the skill distribution are not as strongly affected by parental wealth as those with lower skill. Looking at cognitive skills and fixing non-cognitive skill at the median, an individual at the 10th percentile of both the parental wealth and the cognitive skill distribution has a predicted 6.25% probability of entering entrepreneurship, moving up the skill distribution to the 90th percentile increases the probability to 7.04%, a skill gap in entry of 0.79 percentage points. At the 90th percentile of the parental wealth distribution, we would instead move from an entry probability of 6.81% to 6.96%, a gap of 0.14 percentage points.[1]

While the entry patterns are similar across skill types, we find that their relationship with firm outcomes differs. Higher cognitive abilities are associated with more patenting and lower firm exit, as well as a higher probability of becoming a top 5% firm by revenue. Importantly, while cognitive ability predicts becoming very large by revenue, it is not associated with expected average firm size, whether measured by revenue or employment, which is predicted by non-cognitive skills. At the same time, these non-cognitive skills are not associated with patenting activity or firm exit. Summarizing, cognitive and non-cognitive skills are associated with different measures of firm success.

Next, we introduce a back-of-the-envelope calculation to get a sense of the magnitude of these patterns by equalizing the parental wealth level at the mean, keeping total wealth constant, and using the estimated coefficients to compare predictions based on the actual parental wealth levels with the counterfactually assigned level. Overall, the number of entrepreneurs increases by 1.6% as some individuals get more access to family wealth, but the cognitive and non-cognitive skill level of the average entrepreneur decreases: the stronger skill-based selection is offset by the reduction of entry among the otherwise 'family wealthy' individuals, who are on average more skilled. Hence, the average firm is smaller in terms of workers (-.1%) and patents less (-1.2%), but not in terms of predicted average revenue which increases (+.4%), as more equal access to wealth increases firm size and outweighs the lower average measured skills. In the aggregate, revenue increases by 2%, workers by 1.5%, and patenting by 0.3% due to an increase in the number of entrepreneurs by 1.6%. These results illustrate the observed relationships, not accounting for general equilibrium effects.

Existing literature clearly establishes a liquidity channel of wealth in entrepreneurship entry, see for example Chodorow-Reich et al. (2024) or Colmsjö (2026). Beyond liquidity, other channels are found to be at work when selecting into careers, for example in E. Hurst and Lusardi (2004), who show that future inheritances predict entrepreneurship, which

[1]To set a level in this quantification, we normalize the entry probability of the median skill-median wealth individual to the overall entry rate and add that constant to every estimate instead of predicting based on controls, which preserves percentage-point differences.

should not primarily be due to liquidity. Our two-period model features both a liquidity channel, through which parents can help finance the entry cost, and an insurance channel, by which parents can insure the individual against low personal consumption if the project fails. We find that both channels lead to a positive association between parental wealth and the entry rate. With regards to the skill-selection pattern, we show that the liquidity channel makes selection on skill stronger among wealthy parents, which goes against our empirical findings. Intuitively, the startup help makes entry easier, and even more so for highly skilled individuals, such that the already existing gap in entry between high and low skill individuals increases. The insurance provided reduces the downside risk which is more relevant for low skill individuals, who are therefore more strongly affected in their entry decision as parental wealth, and the insured share of their income, increases. The change in the insurance share along the parental wealth distribution must be large enough relative to the change of the startup help in order to generate the overall weakening sorting on skill in parental wealth we see in the data.

The quantitative questions remain unanswered by the two-period model. In particular, this model does not feature a firm side that allows us to map skills into firm outcomes such as firm size or exit. Moreover, general equilibrium effects need to be taken into account when examining aggregate outcomes. Our quantitative model incorporates these elements and distinguishes eight groups, consisting of two levels each of cognitive skills, non-cognitive skills, and parental wealth. We calibrate the model to annual entry rates and the distribution of individuals across these groups. The model also matches observed relative wages across groups reasonably well, an untargeted moment that we use to benchmark its predictions. In the current calibration, however, the insurance channel fails to dominate, such that the model is unable to generate weaker skill-based selection at higher wealth levels. Reproducing this selection pattern remains an important task for the quantitative analysis. Once the model can account for this pattern, we aim to use it to examine the aggregate consequences of wealth-dependent selection, assess potential misallocation of entrepreneurial talent, and evaluate policies such as inheritance taxation, entrepreneur insurance, and startup funding.

We will discuss and relate to the relevant literature in Section 2, and introduce the data we use in Section 3 before presenting our empirical results in Section 4. Theoretical results from a two-period model follow in Section 5, and our quantitative model is described in Section 6, before we conclude.

II. Background and Literature

This paper is motivated by a broader literature on the allocation of talent. Hsieh et al. (2019) show how barriers to entry for women and Black individuals leads to a misallocation in the allocation of talent across occupations. We will argue that the lack of parental

wealth can constitute a entry barrier in relative terms, when compared to individuals with more parental wealth. A conceptually related paper is Dal Bó et al. (2017), who investigate who becomes a politician, and find that Sweden manages to attract skilled politicians who are at the same time representative of the society as a whole. They find stronger skill-based selection into politics among individually from lower socioeconomic backgrounds. Similarly, we find stronger selection on skills into entrepreneurship among people with lower parental wealth. The idea that the relative returns to different skills across occupations is relevant for self-selection into a career goes back to Roy (1951). In our context, Hartog et al. (2010) makes progress towards understanding the trade-off an individual might face when deciding to enter entrepreneurship or an alternative career path. They find that some skills have higher returns in employment earnings, while others seem more predictive of earnings as an entrepreneur. At the same time, a more balanced skill bundle is associated with higher earnings for entrepreneurs. In our model, we will carefully calibrate the returns to two dimensions of skills in entrepreneurship and on the labor market to take these findings into account.

Previous work finds a connection between wealth and entry. E. Hurst and Lusardi (2004) find that wealth is positively associated entrepreneurship only after the 95th percentile of the wealth distribution, and no evidence that wealth matters more in industries that require higher initial investments. More recently, Chodorow-Reich et al. (2024) use shocks to stock market wealth to establish a causal relationship, finding that stock market wealth increases firm founding at moderate wealth levels, and interpret this finding as stock market wealth relaxing financial constraints. We look at parental wealth instead, measured prior to observed entrepreneurship, and focus on the interaction with skills, finding that higher parental wealth increases the rate of entry on average, but decreases the selectiveness of skill.

Turning to mechanisms linking wealth to entrepreneurial activity, a liquidity channel is proposed in Chodorow-Reich et al. (2024), and earlier evidence using US data comes from Evans and Jovanovic (1989) who estimate a structural model and find evidence for liquidity constraints in firm founding. Patterns described in Evans and Leighton (1989), whereby the rate of entry into self-employment is constant across the first 20 years of working life, are also in line with a story of liquidity constraints and the need to build up savings to enter. Colmsjö (2026) delivers evidence on a liquidity channel from parental wealth specifically, finding that the rate of firm founding reacts positively to inter-vivos transfers. We believe that the evidence for a liquidity channel is strong, and therefore feature liquidity constraints and the possibility of parents to help with business start-up costs in our model.

Other work has found evidence for channels through which the family background affects entrepreneurship activity beyond liquidity. Using sibling correlations, Vladasel et al. (2021)

build a hierarchy of family background factors affecting entrepreneurial entry beyond wealth, such as genetics, parental entrepreneurship, parental immigration, and family structure. Lindquist et al. (2015) distinguishes pre and post birth factors using Swedish adoption data, and find that the post birth factors accounts for 2 times as much of the decomposition of intergenerational transmission of entrepreneurship as pre birth factors. They posit role modeling as important channel, which is also found by Sørensen (2007) to be an important determinant in the inter-generational transmission of self-employment using Danish data. Evidence that parental resources can affect career choices also comes from Haeck and Laliberté (2025), who find that children of higher income parents are more likely to go into 'desirable' jobs and E. G. Hurst and Pugsley (2015) who show that non-pecuniary benefits of entrepreneurship can play a role in connecting background and entrepreneur entry. Related, Färnstrand Damsgaard et al. (2017) show that the type of financial support matters for entrepreneurial decisions beyond entry, as entry support encourages safer projects, while R&D support increases entry without affecting the type of project. Finally, E. Hurst and Lusardi (2004) find that not just past, but also future inheritances matter for entrepreneurial entry, pointing to channel linking family wealth to entrepreneurship in addition to current liquidity. In this work, we add to this literature by showing in a simple two-period model that a liquidity channel of parental wealth alone cannot generate the entry patterns that we observe in the data. More specifically, the startup help only increases the selectiveness on skill along the parental wealth distribution. Instead, we introduce an insurance channel, which allows parents to protect their child's personal consumption in the case of poor firm performance and can generate a decrease in selectiveness based on skill at higher wealth levels, as individuals with lower skills are less exposed to bad outcomes in entrepreneurship at high levels of wealth, prompting them to enter entrepreneurship.

Another determinant of the self selection into different career paths are an individual's abilities. Åstbro and Bernhardt (2005) contributes to the theoretical understanding of the mechanisms at play. In a model of selection into entrepreneurship, they show that skill can increase both the resources available to start a firm due to higher labor market earnings, as well as the desired investment level. Additionally, the outside option increases in skill as well such that the overall direction of the entry probability in skill is ambiguous. Levine and Rubinstein (2017) uses US CPS data to investigate who becomes an incorporated and unincorporated entrepreneur. They find that illicit behavior as a teenager, as well as skills and non-cognitive traits increase the probability of becoming an incorporated entrepreneur. In this work, we use a cognitive and non-cognitive skill measure from the military conscription exam to see how these skills affect entry into entrepreneurship. Note that we define an entrepreneur as an initial owner-operator of a closely held company that eventually employs at least one other person. Our results are in line with their finding

that personal traits affect who becomes an entrepreneur. In addition, we also find that the selection on skill is weakened by parental wealth.

There is a broad literature on the determinants of firm outcomes. First, the entrepreneur's own wealth is found to increase firm performance, as concluded by Ring (2023) and Chodorow-Reich et al. (2024) using data on Norwegian stock-market holdings of entrepreneurs, pointing to financing constraints. Hvide and Møen (2010) finds that the positive relationship between owner wealth and profitability reverses in the top wealth quartile for entrepreneurs running startups. Finally, the structure of firm finances seems to matter. Andersen et al. (2026) show that higher concentration of the owners personal wealth in the firm induces more conservative risk-taking, leading to lower measured performance, and Svensson (2007) demonstrate that government-financed R&D in start ups lowers the probability of patent commercialization. We document that parental wealth increases firm size measured by revenue and decreases the exit probability among Swedish entrepreneurs in the cohort we study, conditional on entrepreneur skill.

Entrepreneur skill is linked to firm outcomes as well. Kardaslar et al. (2026) use data from Germany linking the Big 5 personality traits and risk tolerance of owner-managers to firm size in terms of employment and find that while some traits, such as extraversion and risk tolerance, are associated with a larger firm size, others are not. We also find that the relationship between entrepreneur skill and firm outcomes differs across skill types. Importantly, cognitive ability is not associated with expected average firm size, whether measured by revenue or employment, which is predicted by non-cognitive skills. This is a central finding in Lappi et al. (2023), who use similar data. We look at additional firm outcomes and find that higher cognitive abilities are instead associated with more patenting and lower firm exit, as well as a higher probability of becoming a top 5% firm by revenue. Non-cognitive skills are not associated with patenting activity or firm exit. Summarizing, cognitive and non-cognitive skills are associated with different measures of firm success.

Related literature looks at the relationship between parental background, talent, and inventions. Bell et al. (2019) find that an individual's socioeconomic background plays a role in whether they become an inventor and identify exposure to inventors when growing up as one mediating factor. Aghion et al. (2023) instead focuses on parental education and causally links it to a higher probability of inventing. While we look at patenting outcomes as well, we link them to firms instead of individuals. We investigate which types of firm founders lead to firms that produce inventions, rather than who becomes an inventor. Cognitive skills of the entrepreneur play a role in firm patenting, while parental wealth and non-cognitive skills are not associated with firm patenting. Akcigit et al. (2025) show how family resources affect access to education, subsequent selection into becoming an inventor, and aggregate innovation. This is closely related to Akcigit et al. (2023), who

find that transformative entrepreneurs, defined as those who hire an R&D worker, have higher cognitive skill in Danish data. They focus on the role of barriers to education in the allocation of talent across careers and subsequent entrepreneurial types, while we are investigating the role of parental wealth which changes the skill-based selection pattern into entrepreneurship directly.

The fact that parental wealth affects both the rate of entrepreneurship, and the composition of entrepreneurs, naturally connects the joint distribution of parental wealth and skill to firm outcomes, which in turn affect aggregates. Quadrini (2000) also analyzes the reverse relationship as well, that is how entrepreneurship affects household savings, also across generations. They find that entrepreneurs have higher upward wealth mobility than workers. Gentry and Hubbard (2001) also document differences in savings behavior and portfolios between entrepreneurs and employees. Finally, Cagetti and De Nardi (2006) build and calibrate a model of occupational choice featuring entrepreneurial entry, exit, and investment under borrowing constraints. In their model, voluntary bequests allow some high-ability individuals to start or expand businesses, linking intergenerational transfers to firm size, aggregate capital, and wealth concentration. We complement this literature by studying how parental wealth interacts with cognitive and non-cognitive skills in entrepreneurial entry, what that implies for firm outcomes, and aggregates. Our theory distinguishes a liquidity channel and an insurance channel for parental wealth effects in the selectiveness on skills into entrepreneurship, while our quantitative model is designed to examine the aggregate consequences of the joint distribution of parental wealth and skill through these selection mechanisms.

III. Data

A. Data

We use Swedish registry data to link individuals to their parents and to the firms they found.[2] We define an entrepreneur as the owner of a company that employs at least one worker, and a founder is an entrepreneur observed in the first year a company is registered.

We restrict our analysis to entrepreneurship in closely held companies (a so called 'fåmansföretag'[3]) founded from 2004, which is the first year from which we can identify firm owners. Most newly founded companies in Sweden are closely held companies.[4] We consider entrepreneurial entry until 2018. The truncation follows from our definition of entrepreneurship, which requires sufficient follow-up time to identify companies that eventually hire at least one worker.

[2]See Appendix A for further details.

[3]A closely held company is a firm where four or fewer ownership groups control more than half of the voting rights.

[4]56.2% of all firms founded in Sweden during 2004-2018, that hired at least one worker and ever became active, are closely held companies. This number is consistent with the 60% reported by the Swedish government (Kommittén om förenklad beskattning av ägare till fåmansföretag (2024)).

To study how an individual's financial family background and their own personal ability interact in the process of making career choices, we use a sample of men born between 1972 and 1979 that we observe in the military records and for which we can measure family wealth at a sufficiently early point in time to serve as a proxy for the family's wealth during the individual's upbringing. We use wealth data on individuals and their parents observed in 1999 drawn from the Swedish wealth registry which covers the years 1999-2006 when Sweden levied a wealth tax. We define family wealth as the sum of individual and parental assets.

To examine the role of individual ability in entrepreneurship, we use a measure of cognitive ability, which we call IQ, and a measure of non-cognitive ability. Both measures come from the Swedish military conscription exam which was mandatory and almost universally taken by men aged around 18-20 in our observed years. The IQ measure is constructed from raw data on four test scores designed to assess different dimensions cognitive ability, such as language, logic, spatial, and technical understanding. For non-cognitive ability, we utilize a measure of individual psychological capacity ('PF') derived from the military enlistment database. The metric ranges from 0 to 9, with higher values indicating greater ability. Each individual score is determined by a psychologist and is derived from both written tests and one-on-one interviews, with the goal of determining the ability of the person to persevere in stressful, uncertain, and complex situations. A detailed discussion of both the testing procedure and the test scores, see J. P. Nilsson (2017) and P. Nilsson and Linnros (2026). More detailed measures of non-cognitive ability are available, as psychologists assess test-takers across a number of sub-scores, which we use to check the robustness of our empirical results.

We utilize several variables from the business register for the period 2004–2021 to measure the success of the companies founded by these entrepreneurs. We examine firm size—in terms of revenue, number of employees, and share capital, as well as the likelihood that the company becomes part of a larger conglomerate during its lifespan. We also look at the probability of firm exit, that a firm reaches the 95th percentile of all firms in terms of revenue, and the likelihood of growing into a company with at least 250 employees. Furthermore, we link patent data from the European Patent Office (EPO) to the companies in our sample to investigate how entrepreneurial ability interacts with patenting activity.

B. Descriptives

We have data on 200.723 individuals in our cohort, for which we observe the main variables of interest, namely parental wealth and cognitive and non-cognitive scores. Between 2004 and 2018, we can link 13.735 of these individuals to 13.770 firms as founders, which means the rate of entry into entrepreneurship is approx. 6.8%. On average, they found 1.09 firms, with the median being 1 firm, and about 90 individuals in the cohort found more

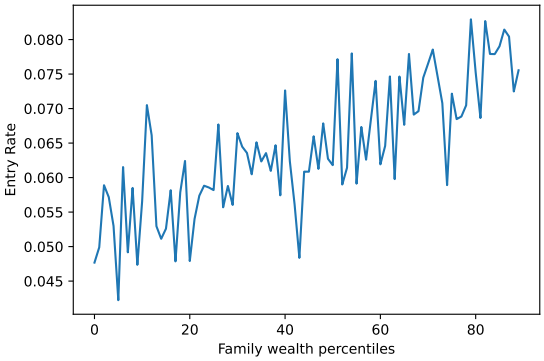


Figure 1: Probability of becoming an entrepreneur across family wealth percentiles.

than two firms. Finally, 1.086 entrepreneurs found more than 1 firm, while 1.036 firms have more than one founder.

Looking at the entry rate for different levels of parental wealth in Figure 1, we find that it seems to increase pretty consistently across percentiles. This contrasts E. Hurst and Lusardi (2004), who find that the relationship between own wealth and entrepreneurship turns positive only after the 95th percentile of the wealth distribution.

To get a sense of how representative the firms in our sample are for the overall firm distribution, we report descriptives for both samples in Table 1. Moreover, Figure 2 plots the distribution of firm size in terms of log revenue in 2021 of all firms founded since 2004, and the ones in our sample, i.e. where an individual in the cohort of interest could be matched as a founder. The distribution looks similar, with our sample firms being slightly larger in the mid range. This does not come as a surprise, as our cohort is restricted to individuals who are in their 20s at the start of the observed period, male, and Swedish at the time they had to take the military conscription exam. At the same time, the average firm in the founder sample is smaller than the average firm in the full sample. This is due to some very large firms. Note that we compare closely held companies to all firms, i.e. also those that are newly founded by large conglomerates, for example to restructure business.

Table 1: Firm Characteristics: Sample versus All Swedish Firms

	All firms	Our sample
Maximum total revenues	15213	11404
Maximum number of employees	15	14
Founding year	2011	2010
Exit rate	4%	3%
Number of firms	246117	14375

Notes: This table illustrates the mean outcomes for firms founded by entrepreneurs in our sample compared to all Swedish firms founded since 2004.

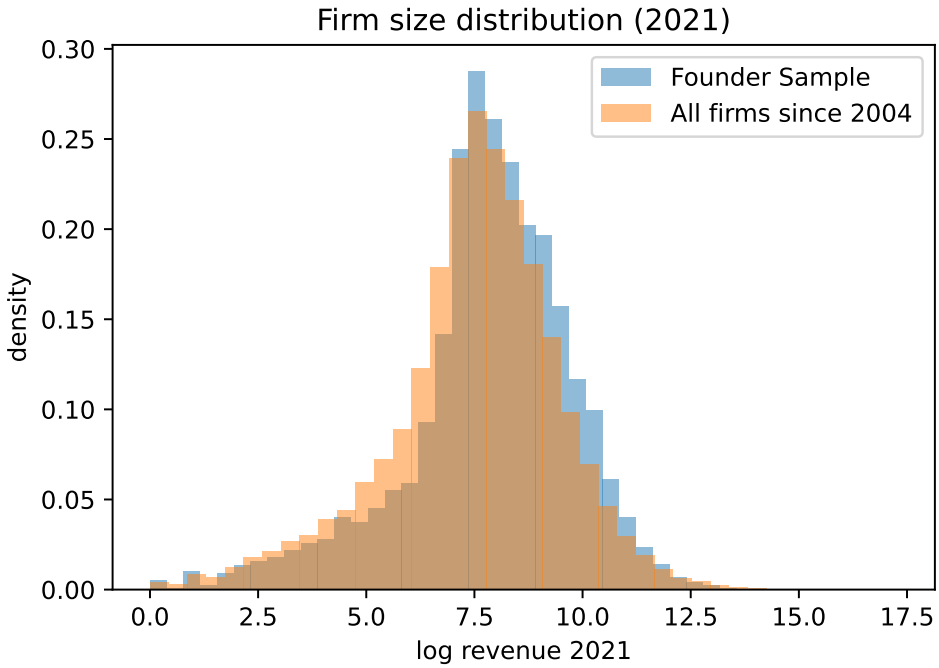


Figure 2: Firm size distribution in 2021, all firms founded since 2004 vs. those in the sample who have a matched founder in the cohort of interest.

IV. Empirical results

A. *Entry into entrepreneurship*

We estimate a linear probability model of entrepreneurial entry on IQ, non-cognitive ability and family wealth. To study if the selection on ability changes across the family wealth distribution we include the interaction of family wealth with both ability measures. The specification is:

$$\begin{aligned} 100 \times \mathbb{1}\{Entrepreneur_i = 1\} = \beta_0 IQ_i + \beta_1 PF_i + \beta_2 \log(assets_{i,p}) + \\ \beta_3 IQ_i \times \log(assets_{i,p}) + \beta_4 PF_i \times \log(assets_{i,p}) + X_i'\gamma + \varepsilon_i \end{aligned} \tag{1}$$

where $\log(assets_{i,p})$ is the logarithm of the combined assets of individual i's and his parents p, and X_i is a vector of controls, including education and county fixed effects, parental income and a binary variable indicating parental entrepreneurship status. We standardize IQ and non-cognitive ability to mean of zero and unit standard deviation.

Table 2 reports our results. Column (1) reports the OLS estimates from a regression on IQ, non-cognitive ability and family wealth, without the interaction of wealth with ability. Column (2) presents the coefficient estimates from a regression including the interaction terms but excluding additional controls, and column (3) reports the estimates for the full model.

We find that IQ, non-cognitive skills and family wealth are all predictive for the probability

Table 2: Entrepreneurial Entry

	(1)	(2)	(3)
IQ	0.149**	0.848***	1.552***
	(0.059)	(0.210)	(0.260)
Non-cognitive ability	0.970***	1.447***	1.755***
	(0.061)	(0.237)	(0.289)
Log family assets	0.116***	0.070***	0.074***
	(0.017)	(0.021)	(0.025)
IQ × log family assets		-0.054***	-0.059***
		(0.016)	(0.020)
Non-cognitive ability × log family assets		-0.037**	-0.044**
		(0.018)	(0.022)
Additional controls	No	No	Yes
Observations	200,723	200,723	182,800
Entry rate (%)	6.578	6.578	6.754
R^2	0.002	0.002	0.006
Adjusted R^2	0.002	0.002	0.006

Notes: The dependent variable is $100 \times \mathbb{1}\{Entrepreneur_i = 1\}$. IQ and non-cognitive ability are standardized to mean zero and unit standard deviation; log family assets is unscaled. All specifications include industry and founding-year fixed effects. Additional controls in column (3) include education and county fixed effects, parental entrepreneurship, and parental income. HC1 heteroskedasticity-robust standard errors are reported in parentheses. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

of becoming an entrepreneur, but that the interaction of ability with family wealth is negative. That is, both IQ and non-cognitive ability are less predictive for entrepreneurial entry the greater an individual's family wealth. This suggests that there is a weaker selection into entrepreneurship on ability for higher family wealth levels. Note that the estimates are robust to including other controls, such as eduction, parental entrepreneurship, and others variables. For details, refer to Appendix E.

The effect is sizable, which can be illustrated with the following numerical example.[5] For an individual with median non-cognitive skill level, the estimated gap in the entry rate between the 90th and the 10th IQ percentile is about 0.79 percentage points in the lowest family wealth decile, compared to 0.14 percentage points in the highest wealth decile. The implied fall in selection into entrepreneurship on IQ from the lowest to the highest family wealth decile is about 82%. Analogously, for an individual with median IQ level, the gap in the entry rate between the highest and lowest non-cognitive skill deciles is 2.41 percentage points in the lowest family wealth decile compared to 2.11 in the highest wealth decile, a fall of about 12%.

[5]See Appendix A for details.

Whether the effect is economically meaningful in the sense that it could indicate a misallocation of entrepreneurial talent with consequences for overall productivity depends on whether such abilities are relevant for business growth and innovation. In the section that follows, we examine how cognitive and non-cognitive abilities are associated with firm performance.

B. Founder characteristics and firm outcomes

We estimate a linear regression of different measures of firm success on IQ, non-cognitive ability and family wealth:

$$Y_{ifp} = \beta_0\ IQ_i + \beta_1 PF_i + \beta_2 \log(assets_{i,p}) + \alpha_{j(f)} + \delta_{t(f)} + \varepsilon_{if} \tag{2}$$

where $\alpha_{j(f)}$ and $\delta_{t(f)}$ denote industry and starting-year fixed effects. Y_{ifp} is the outcome of firm f founded by individual i with parents p. We consider six firm outcomes: firm size by revenue, the probability of exit, the probability of ever applying for a patent, the patent intensity, the probability of reaching the top 5% of the total firm size distribution and the probability that the firm employs at least 250 workers.

The results are presented in Table 3. Each column represents the regression of a distinct firm outcome on its founder's ability and family wealth. We define firm size by revenue as the logarithm of the company's highest achieved revenue, and patent intensity as the total number of inventions a firm applies for patents for, normalized by industry and the company's founding year. IQ and non-cognitive abilities are standardized to mean zero and unit standard deviation.

Table 3: Entrepreneurial Success

	Ever patents (pp)	Patent intensity (norm.)	Firm size (revenue) (%)	Top 5% by revenue (pp)	>250 workers (pp)	Exit (pp)
IQ	0.468***	0.380***	-1.89	0.622***	0.022	-0.425**
	(0.081)	(0.111)	(2.07)	(0.217)	(0.051)	(0.173)
Non-cognitive skill	-0.060	0.073	12.1***	1.12***	0.137**	0.149
	(0.078)	(0.104)	(2.16)	(0.212)	(0.057)	(0.156)
Log family assets	0.003	0.011	1.68**	0.142**	0.022	-0.253***
	(0.017)	(0.015)	(0.660)	(0.063)	(0.015)	(0.068)
Founding-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean dep. variable	0.684	0.428	7.65	6.25	0.403	3.03
R-squared	0.054	0.005	0.201	0.032	0.036	0.015
Adjusted R-squared	0.048	-0.002	0.196	0.026	0.030	0.008
Observations	14,905	14,905	14,905	14,618	14,905	14,905

Notes: HC1 heteroskedasticity-robust standard errors are reported in parentheses. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively. All regressions include two-digit industry and founding-year fixed effects. Binary dependent variables are multiplied by 100; effects on log outcomes are reported as percentage changes. IQ and non-cognitive skill are standardized to mean zero and unit standard deviation. Log family assets is unscaled.

We find that entrepreneurial IQ, non-cognitive abilities, and family wealth are all related

to measures of firm success, but are predictive for different outcomes. The founder's IQ is predictive for the firm's patenting activity as well as the probability of the company reaching the top 5% of the overall firm size distribution by revenues. Also, firms founded by entrepreneurs with higher IQ are, on average, less likely to exit. However, we find no evidence that IQ is associated with average firm size. For example, IQ does not significantly predict a higher maximum achieved firm revenue on average, or the probability of growing into a large company in terms of the number of employees. IQ is not significantly related to other measures of firm size we considered in an extended analysis, such as the highest achieved share capital (see Appendix C). It is also not related to the labor share, or the likelihood of becoming part of a group of companies. This contrasts non-cognitive ability, which is strongly associated with all measures related to firm size that we have considered, but not with the probability of exit or with patenting. Note that the estimates are robust to including other controls, such as education, parental entrepreneurship, and others variables. For details, refer to Appendix E.

The finding that non-cognitive ability predict firm size, while cognitive ability does not, is in line with previous findings that has used similar data to estimate the relationship between entrepreneurial ability and firm success. Lappi et al. (2023) find that only non-cognitive abilities are predictive of firm performance, measured by a firm's estimated total factor productivity (TPF).

Together with our novel finding that IQ of the founder is related to patenting and the likelihood of reaching the 95th percentile of company revenue, this may suggest that entrepreneurs with higher IQ are more likely to start enterprises with higher risk and greater expected returns in case of success, while non-cognitive ability may be important for growing the business.

Finally, we find that a founder's family wealth also is predictive for firm size and is additionally associated with a lower exit probability.

C. Stylized facts and back of the envelope quantification

Our empirical analysis leaves us with a number of 'stylized facts':

1. Cognitive and non-cognitive ability and family wealth all predict entrepreneurship.
2. Family wealth weakens the selection into entrepreneurship on skills, both cognitive and non-cognitive.
3. Higher IQ founders are associated with firms that patent and reach the top 5% of the firm size distribution by revenue more, and are less likely to exit.
4. Higher non-cognitive skill founders are associated with firms that are larger on average, across size measures.

5. Entrepreneurs with higher family wealth found firms that are larger on average and less likely to exit.

To get a sense of the magnitude of these findings and understand how the parental wealth distribution features, run a back of the envelope calculation. The wealth level is equalized at the mean to hold total wealth constant. We then use the regression coefficients of a linear projection of firm entry on parental wealth, cognitive, and non-cognitive skill, an interaction between wealth and both skill measures, as well as demographic controls, to predict entrepreneurship entry. Similarly, we predict firm outcomes using a regression of revenue, workers, and patenting, regressed on cognitive and non-cognitive skills as well as parental wealth. As wealth increases entry, individuals previously below the mean in terms of parental wealth are now more likely to enter, whereas individuals above it are now less likely to enter. Further, the selection on skill is now stronger, such that the correlation between entry and skill increases. However, the quality of the average entrepreneur decreases: the stronger selection is offset by the reduction of entry among the otherwise 'family wealthy' individuals who are on average more skilled. Hence, the average firm is smaller in terms of workers (-.1%) and patents less (-1.2%). Notably, better access to wealth increases the average firms size in terms of revenue (+.4%) even though the entrepreneur is less skilled. In the aggregate, revenue increases by 2%, workers by 1.5%, and patenting by .3% due to an increase in the number of entrepreneurs by 1.6%. Note that this is calculated as a difference in predicted outcomes between the observed wealth distribution and equalized parental wealth.[6]

To study the implications of wealth inequality for aggregate productivity, we build a theoretical framework where firm success is linked to entrepreneurial ability and where family wealth affects both entrepreneurial entry and the talent composition among entrepreneurs. We construct a model where: i) higher individual ability predicts a larger entry probability through higher expected entrepreneurial success for high-ability entrepreneurs, ii) more family wealth predicts a higher average entry rate *and* interferes with the ability-dependent entry incentives, weakening the entry probability on ability for higher level of family wealth.

The question remains as to how family wealth increases entry but weakens the selection into entrepreneurship on ability. We consider two channels through which family wealth can increase the entry rate and weaken the dependence of individual ability for the entry decision. First, we posit that family wealth facilitates entry into entrepreneurship by providing access to liquidity. Starting a firm entails costs, both in the form of initial costs of establishment and a loss in consumption resulting from shifting time and effort away from wage-paying employment toward the new venture. Individuals with more family

[6]Full results are included in Appendix D.

wealth thus face lower barriers to entry through a higher access to liquidity, which may increase their entry probability regardless of ability. Support for this liquidity mechanism of parental wealth comes from Colmsjö (2026).

Second, family wealth may affect the selection into entrepreneurship by providing an insurance against the downside risk of entrepreneurship. Individuals from wealthier families may expect future inter-vivos transfers or inheritances to secure consumption throughout the life-cycle regardless of their career choices. By contrast, the lack of the prospect of future consumption support may deter individuals from less affluent families from choosing entrepreneurship, unless their ability is sufficiently high to significantly improve the expected returns to becoming an entrepreneur. In what follows, we analyze the interaction between family wealth and ability in the entry decision in a simple two-period model and we will find that the insurance channel can rationalize the weakened selectiveness in entry, while the liquidity channel works in the opposite direction.

V. Parental wealth and entrepreneurial entry in a two-period model

According to the stylized facts above, family wealth impacts both the rate of starting a firm, and the skill composition of entrepreneurs. Arguably, this happens through two channels: a liquidity channel which helps individuals start and maintain a company, and an insurance channel through which an entrepreneur can be protected against low personal consumption in case their firm is hit with large negative shocks, or fails. We capture these channels in a simple two-period model here, and derive analytical predictions from these two channels. We will demonstrate that the insurance channel is necessary to match the stylized fact that entrepreneurs with high-wealth parents are less selected on their abilities.

A. Set-up

There is a continuum of individuals that live for two time periods $t = 0, 1$. An individual is characterized by her ability and family wealth. Let s denote the non-cognitive skills of an individual, and a her family wealth.

At the beginning of time 0, every individual is a worker, and earns a skill contingent wage $w(s) > 0, w'(s) > 0$. An individual (s, a) can choose to forgo an amount $fw(s)$, $f \sim G(f)$, of consumption to start a firm and become an entrepreneur. An entrant individual obtains consumption support $\chi(a) \in [0, 1]$, from her family, where $\chi'(a) > 0$. Hence, the entry cost of individual (s, a) is $f(1 - \chi(a))w(s)$.

If an individual enters, the project succeeds with probability p, in which case the founding individual gets payoff $\pi(s)$, $\pi'(s) > 0$ in the next period. With probability $1 - p$, the project fails, in which case the individual earns zero profits the following period, and obtains a family wealth dependent consumption support $b(a)w(s)$, $b'(a) > 0$.

B. Solution

An individual with skill and family wealth (s, a), chooses to enter if the expected lifetime utility of becoming an entrepreneur exceeds the lifetime utility of staying a worker, that is iff:

$$u(w(s) - f(1-\chi(a))w(s)) + \beta\Big(pu(\pi(s)) + (1-p)u(b(a)w(s))\Big) \geq u(w(s)) + \beta u(w(s))$$

Assume that $u(c) = \ln(c)$, $\beta > 0$, and $p \in (0,1)$. Let $w(s) > 0$, $\pi(s) > 0$, $\chi(a) \in [0,1)$, and $b(a) > 0$ be continuously differentiable. In the following, we will derive conditions for how the entry cutoff responds to skill and wealth.

Lemma 5.1 (Entry cutoff and selection on skill)**.** *An individual with skill and family wealth (s, a) enters entrepreneurship if and only if $f \leq f^*(a, s)$, where*

$$f^*(a,s) = \frac{1 - \left(\frac{w(s)}{\pi(s)}\right)^{\beta p} b(a)^{-\beta(1-p)}}{1-\chi(a)}. \tag{3}$$

The entry cutoff is increasing in skill if and only if

$$\frac{\pi'(s)}{\pi(s)} > \frac{w'(s)}{w(s)}. \tag{4}$$

Proof. Under logarithmic utility, the entry condition can be written as

$$\ln\Big(1 - f(1-\chi(a))\Big) + \beta p \ln\left(\frac{\pi(s)}{w(s)}\right) + \beta(1-p)\ln b(a) \geq 0. \tag{5}$$

Solving for f gives the stated cutoff. Differentiating yields

$$\frac{\partial f^*}{\partial s} = \frac{\beta p}{1-\chi(a)} \left(\frac{w(s)}{\pi(s)}\right)^{\beta p} b(a)^{-\beta(1-p)} \left[\frac{\pi'(s)}{\pi(s)} - \frac{w'(s)}{w(s)}\right]. \tag{6}$$

All factors outside the square brackets are strictly positive, which establishes the result. □

Lemma 5.2 (Family wealth and skill-based selection)**.** *Suppose that $\pi'(s)/\pi(s) > w'(s)/w(s)$, $\chi'(a) > 0$, and $b'(a) > 0$. Parental startup support increases the sensitivity of the entry cutoff to skill, while parental consumption insurance decreases it. The*

overall sensitivity of the entry cutoff to skill decreases with family wealth if and only if

$$\frac{\chi'(a)}{1-\chi(a)} < \beta(1-p)\frac{b'(a)}{b(a)}. \tag{7}$$

Proof. Differentiating the skill derivative with respect to the two forms of parental support gives

$$\frac{\partial}{\partial \chi}\left(\frac{\partial f^*}{\partial s}\right) = \frac{1}{1-\chi(a)}\frac{\partial f^*}{\partial s} > 0, \tag{8}$$

$$\frac{\partial}{\partial b}\left(\frac{\partial f^*}{\partial s}\right) = -\frac{\beta(1-p)}{b(a)}\frac{\partial f^*}{\partial s} < 0. \tag{9}$$

Applying the chain rule therefore yields

$$\frac{\partial^2 f^*}{\partial s\,\partial a} = \frac{\partial f^*}{\partial s}\left[\frac{\chi'(a)}{1-\chi(a)} - \beta(1-p)\frac{b'(a)}{b(a)}\right]. \tag{10}$$

Since $\partial f^*/\partial s > 0$, the cross derivative is negative if and only if the stated condition holds. □

Assuming a uniform distribution of entry costs $G(f)$ means that the the entry probability $P(s,a)$ follows directly from the entry cut-off. Under this assumption, the liquidity channel alone cannot generate weaker selection on skill as parental wealth increases. The insurance effect must dominate the funding effect for skill-based selection into entrepreneurship to be decreasing in family wealth. The important margin is the proportional reduction in the self-financed share, $\chi'(a)/(1-\chi(a))$, against the proportional increase in consumption insurance, $b'(a)/b(a)$, discounted at by $\beta(1-p)$

VI. Quantitative Model

A. Setup

Environment. The economy is populated by a continuum of infinitely lived individuals, indexed by i, with heterogeneous family wealth a_i and talent composition. Individual talent is a bundle (q_i, s_i) where q_i denotes the IQ level of individual i and s_i is a non-cognitive skill measure. An individual is thus characterized by the three-tuple (q, s, a).

Entry into entrepreneurship. At any given time, an individual can be either a worker or an owner of a firm. A worker earns a wage $w(q,s)$ depending on its talent, where $w_q > 0$ and $w_s > 0$. Since there are no savings, per-period consumption of a worker is given by:

$$c(q,s) = w(q,s)$$

At the beginning of each period, workers draw an idiosyncratic entry cost $F \sim G(F)$. After observing the realization of F, the worker chooses whether to enter entrepreneurship. Family wealth reduces the share of the entry cost that must be financed by the worker. Specifically, the entrant pays:

$$\chi(a)F$$

Since $\chi_a(a) < 0$, individuals from wealthier families finance a smaller share of the entry cost themselves.

The value of a worker with talent and family-wealth composition (q, s, a) is thus:

$$V^W(q, s, a) = \mathbb{E}_F[\max\{u(w(q, s)) + \beta V^W(q, s, a), V^E(q, s, a, F)\}]$$

where V^E is the value of entry into entrepreneurship.

Upon entry, the individual draws a permanent firm-specific parameter θ from the distribution

$$\theta \sim \Psi(\theta \mid s)$$

with mean $\mathbb{E}[\theta|s]$ and variance σ^2. The parameter θ scales the firm's revenues. We assume $\frac{d\mathbb{E}[\theta|s]}{ds} > 0$, so that individuals with higher non-cognitive skills establish firms with higher expected revenue potential.

The value of entry is thus:

$$V^E(q, s, a, F) = u(w(q, s) - \chi(a)F) + \beta \int_\Theta \sum_{z \in Z} p_0(z) V(q, s, a, \theta, z) d\Psi(\theta|s)$$

where V is the continuation value of operating a firm. z is a firm-specific productivity shock governed by a finite-state Markov process. $p_0(z)$ denotes the probability of drawing productivity state z in the first operating period of the firm.

The profits of a firm founded by entrant (q, s, a), with productivity state z, are given by:

$$\pi(q, \theta, z) = \max_l \{z\theta l^\alpha - Wl - \kappa(q)\}$$

where l denotes labor input, and W is the aggregate wage per efficiency unit of labor. $\kappa(q)$ is an additional operating cost with $\kappa_q < 0$.

Firm exit. The per-period consumption of an entrepreneur is:

$$c(q, \theta, z, a) = \pi(q, \theta, z) + b(a)$$

$b(a)$ denotes the consumption support available to an entrepreneur with family wealth a.[7]

In any given time period, the entrepreneur can choose to exit or to continue operating the firm. If the firm exit, the entrepreneur consumes b and becomes a worker next period. The value of an entrepreneur is then given by:

$$V(q, s, a, \theta, z) = \max\{u(\pi(q, \theta, z) + b(a)) + \beta \mathbb{E}_{z'|z}[V(q, s, a, \theta, z')], u(b(a)) + \beta V^W(q, s, a)\}$$

An entrepreneur will choose to exit iff:

$$u(b(a)) + \beta V^W(q, a, s) \geq u(\pi(q, \theta, z) + b(a)) + \beta \mathbb{E}_{z'|z}[V(q, s, a, \theta, z')]$$

Within-period firm problem. At the beginning of each period, the entrepreneur observes the current productivity state z. Then, if the entrepreneur chooses to continue production, they take the wage index W as given and optimally chooses labor to maximize profits:

$$\max_l z\theta l^\alpha - Wl - \kappa(q) \tag{11}$$

The first order condition yields the labor demand function given the firm type θ, and the time-varying shock z, and wages W:

$$z\theta\alpha l^{\alpha-1} = W \Rightarrow l(\theta, z; W) = \left(\frac{z\theta\alpha}{W}\right)^{\frac{1}{1-\alpha}} \tag{12}$$

Plugging the labor demand equation back into the profit function yields:

$$\pi(q, \theta, z) = (z\theta)^{\frac{1}{1-\alpha}} \left(\frac{\alpha}{W}\right)^{\frac{\alpha}{1-\alpha}} - W\left(\frac{z\theta\alpha}{W}\right)^{\frac{1}{1-\alpha}} - \kappa(q) \tag{13}$$

$$= (1-\alpha)(\theta z)^{\frac{1}{1-\alpha}} \left(\frac{\alpha}{W}\right)^{\frac{\alpha}{1-\alpha}} - \kappa(q). \tag{14}$$

We further define the operating costs as

$$\kappa(q) = \gamma q^{-\delta} \tag{15}$$

[7] b captures that family wealth can serve as an insurance by mitigating the consumption loss resulting from uncertain entrepreneurial income. This channel is different from the liquidity mechanism introduced through family-wealth dependent initial financial support to enter entrepreneurship.

Labor markets. Firms employ workers from a staffing agency, which is a representative, competitive producer of the labor composite L. Labor is bundled according to:

$$L = \int_{Q\times S\times A} qsd\Gamma^w(q,s,a;W), \tag{16}$$

where $\Gamma^w(q,s,a;W)$ is the density of individuals with skill bundle (q,s), and family wealth a, that is a worker given wage level W. Wages are set to fulfill a zero profit condition:

$$WL - \int_{Q\times S\times A} w(q,s)d\Gamma^w(q,s,a;W) = 0, \tag{17}$$

which is in line with

$$w(q,s) = Wqs. \tag{18}$$

The aggregate wage clears labor markets:

$$W : \int_{Q\times S\times A\times\Theta\times Z} l(\theta,z;W)d\Phi(q,s,a,\theta,z) = \int_{Q\times S\times A} qsd\Gamma^w(q,s,a;W) \tag{19}$$

B. Solution

Functional Forms.

$$\begin{aligned} \chi(a) &= \frac{1}{1+\eta a}, & \eta \geq 0 \\ u(c) &= \log c \\ \kappa(q) &= \gamma q^{-\delta} \\ b(a) &= \kappa_b a \end{aligned}$$

Distributions. Household types are distributed over

$$\mathcal{Q}\times\mathcal{S}\times\mathcal{A} = \{q_L, q_H\}\times\{s_L, s_H\}\times\{a_L, a_H\},$$

according to the joint population distribution $\mu(q,s,a)$.

Entry costs are distributed according to

$$F \sim U(0,\bar{F}).$$

Conditional on non-cognitive skill s, permanent firm productivity satisfies

$$\log \theta \mid s \sim \mathcal{N}\left(\log s - \frac{\sigma_\theta^2}{2}, \sigma_\theta^2\right),$$

so that $\mathbb{E}[\theta \mid s] = s$.

Firm productivity evolves on

$$\mathcal{Z} = \{0, z_1, z_2, z_3\},$$

where $z = 0$ is an absorbing closure state. From each positive productivity state, the firm closes exogenously with probability d. Conditional on survival, productivity evolves according to the transition matrix Q. Hence,

$$P = \begin{pmatrix} 1 & 0 & 0 & 0 \\ d & (1-d)Q_{11} & (1-d)Q_{12} & (1-d)Q_{13} \\ d & (1-d)Q_{21} & (1-d)Q_{22} & (1-d)Q_{23} \\ d & (1-d)Q_{31} & (1-d)Q_{32} & (1-d)Q_{33} \end{pmatrix}.$$

New firms draw their initial productivity state from p_0 over the positive productivity states.

Algorithm. To solve the model numerically, we use an algorithm that guesses the wage level W, solves the value functions for entrepreneurs and workers, entry probabilities, and firm exit cut-off values. Given these decisions, we compute the stationary distribution of workers and entrepreneurs, accounting for entry, exit, and firm productivity shocks. We then aggregate firms' labor demand and workers' effective labor supply and check if demand and supply coincide. If not, a new guess for the wage level is picked and the process is repeated until labor markets clear.

C. Calibration

We calibrate the model in two steps. First, we set a number of parameters externally, summarized in Table 4. Then, the remaining parameters are calibrated internally by targeting entrepreneurship rates, i.e. the rate of being an entrepreneur) and annual entry into entrepreneurship. These parameters are summarized in Table 5. We define eight groups in our cohort, split at the median of parental wealth, cognitive skill, and non-cognitive skills. We then normalize the average parental wealth in the low wealth group to 1, $\underline{a} \equiv 1$, which implies that the normalized average wealth level among the high wealth individuals is $\bar{a} = 8.1$. Similarly, we normalize the average IQ to 1, which leaves us with average high IQ $\bar{q} = 1.097$ and average low IQ $\underline{q} = 0.903$. For skill levels we get $\bar{s} = 1.191$ and $\underline{s} = 0.854$. We also get the mass of population for each group from the data. In the following, we will go through the remaining internally an externally

calibrated parameters. In Table 4 we list the externally set parameters. The exponent on

Parameter	Description	Value	Source
α	Labor exponent	0.300	Data
β	Discount factor	0.950	External
$\mathcal{Z}$	Productivity states	$\{0, .15, .90, 1.50\}$	External
p_0	Initial productivity distribution	$(0, .15, .70, .15)$	External
Productivity transitions conditional on survival			
$Q_{1,\cdot}$	From $z = 0.150$	(0.650, 0.300, 0.050)	External
$Q_{2,\cdot}$	From $z = 0.900$	(0.080, 0.840, 0.080)	External
$Q_{3,\cdot}$	From $z = 1.500$	(0.040, 0.160, 0.800)	External

Table 4: Calibration: externally and directly assigned parameters.

the production function α matches the observed aggregate labor share among our firms. The annual discount factor β is set to a standard value of 0.95. The remaining moments describe the idiosyncratic productivity process. As mentioned before, we then target

Parameter	Description	Value	Source
$\bar{F}$	Maximum entry cost	9.497	Internal
η	Wealth sensitivity of entry costs	0.023	Internal
γ	Operating cost scale	0.791	Internal
δ	IQ elasticity of operating costs	0.001	Internal
κ_b	Family consumption support rate	0.044	Internal
σ_θ	Dispersion of idea quality	0.137	Internal
d	Exit probability	0.018	Internal

Table 5: Calibration: internally calibrated via method of moments.

entrepreneurship rates, i.e. the probability of being an entrepreneur, and annual entry rates, for each of the 8 types of people defined by their bundle of IQ, skill, and parental wealth, (q_i, s_i, a_i). By targeting these moments, we jointly estimate the maximum entry cost $\bar{F}$, the sensitivity of entry costs with respect to parental wealth η, the operating cost function parameters γ and δ, the consumption insurance rate level κ_b, the dispersion of idea quality σ_θ, and the exogenous exit probability d.

This calibration succeeds in matching the targeted moments quite well, as presented in Figure 3. The model does undershoot the entrepreneurship rates for low IQ groups while it overstates the high IQ entry rates. A similar pattern persists for the annual entry probabilities.

To get a sense of the performance of the model, we benchmark it against two types of untargeted moments. Figure 4 shows that the relative average firm revenue and the

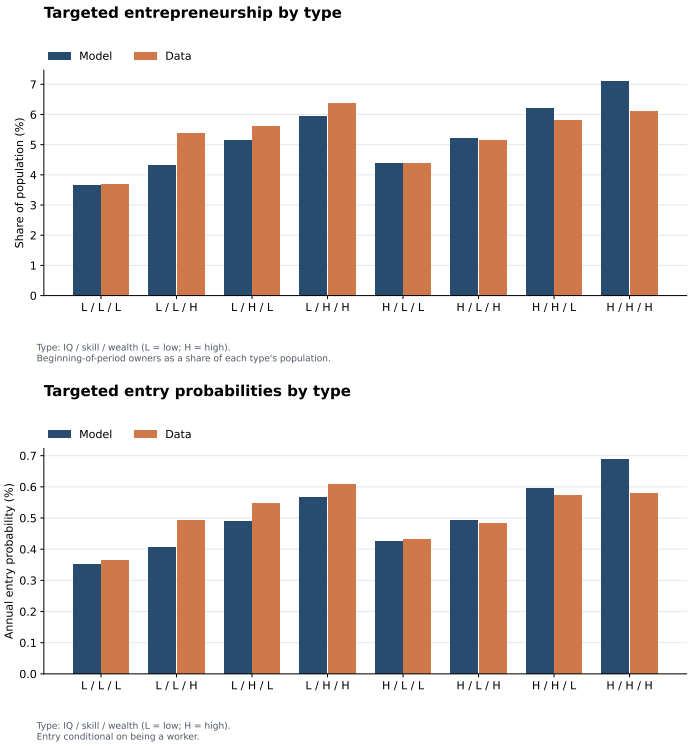


Figure 3: Targeted moments

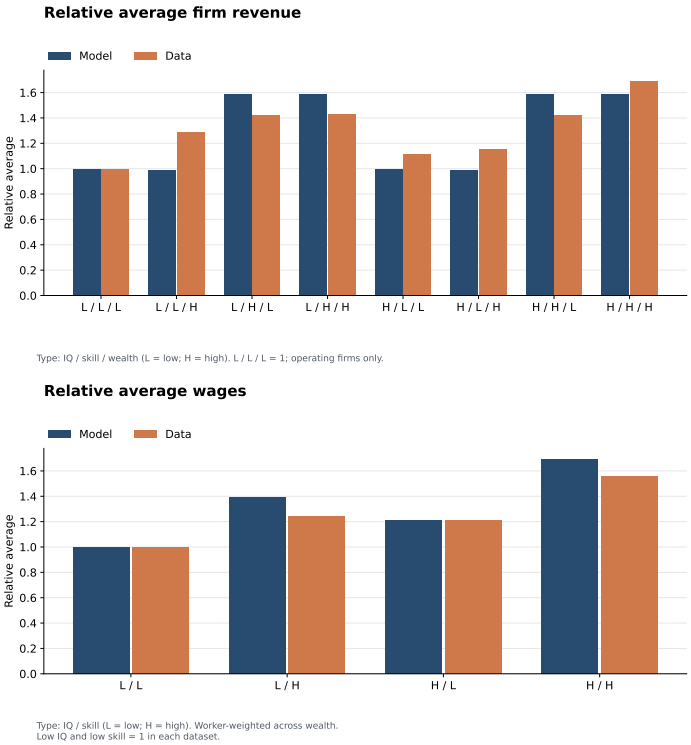


Figure 4: Untargeted moments

relative wages are partly matched well. The model generates the relative patterns well, although it seems to not get the quantitative pattern right.

A pattern that is not generated yet is that selectivity on skill is weakened as parental wealth increases. At the moment, the effect coming from parental startup help dominates such that the total effect goes in the wrong direction. Future versions of this model and its calibration will address this shortcoming. This will then allow us to run quantitative counterfactuals taking GE effects into account, and to do policy analysis, such as an inheritance tax, entrepreneur insurance, and various subsidies.

VII. Conclusion

In this project, we ask how the joint distribution of parental wealth and skill affects who becomes an entrepreneur, how many firms are founded, and how the resulting performance of companies affects aggregate outcomes. We find that parental wealth increases the rate of entry into entrepreneurship on average, but decreases the selectiveness on ability, whether looking at cognitive or non-cognitive skills. Moreover, these skills matter for different firm outcomes. While higher cognitive skills are associated with a higher probability of patenting, becoming a firm in the top 5% of the firm size distribution by revenue, and a lower exit rate, non-cognitive skills predict firm size, whether measured in terms of revenue or workers. In a two-period model of firm entry, we show that a liquidity channel of parental wealth, through receiving financial support from parents when founding a firm, cannot rationalize the decreasing skill-selectiveness in wealth. Instead, an insurance mechanism which protects entrepreneurs personal consumption from bad firm outcomes generates this pattern. The insurance effect dominates if the size of the insurance increases strongly enough in parental wealth relative to the increase in the startup help. Overall, our findings imply that parental wealth, by being linked to who selects into entrepreneurship, affects the firm distribution and aggregate outcomes.

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I. Appendix

A. Data

Individuals. **Data sources** The empirical analysis is based on data from different sources. We use individual-level data from several registers from Statistics Sweden (SCB). Data on age, sex, municipality and region is retrieved from the Longitudinal Integration Database (LISA). Information on educational level and labor and business income is obtained from the labor market statistics register (RAMS).

We use wealth data from the Swedish Wealth register ('Förmögenhetsregistret'). The register contains records on each individual's yearly wealth and spans the period 1999-2006, when Sweden had wealth taxation. We use the Population register (RTB), that links individual to their parents, to identify individuals' own and parental wealth.

Data on individuals' cognitive and non-cognitive abilities is retrieved from the Military Enrollment Archive Register ('Inskrivningsregistret').[8] This register contains a comprehensive list of measures of mental abilities for all Swedish males who were conscripted for mandatory military service between 1969 and 1997.

Because the conscription and wealth registers do not overlap in time, we restrict the analysis to the last cohort for which conscription data are available (men aged 18–25 in 1997/i.e. born between 1972 and 1979) and link these individuals to parental wealth measured in 1999. A limitation of this approach is that we capture parental wealth when the individuals are aged 20–27, by which point some may already have made their career choices. However, we argue that these records provide a reasonable proxy for parental wealth at the beginning of adult life for all individuals in the cohort, since wealth levels are relatively stable over time and unlikely to have changed substantially. To account for the possibility that some individuals may already have received transfers or inheritances by 1999, we also control for their own wealth in that year.

Data cleaning and construction

The Longitudinal Integration Database (LISA) contains yearly data on age, sex, municipality, and region for the whole Swedish population (all individuals aged 15 and above). We use the 1997 records and limit the sample to males aged 18 to 25 years. We identify and remove four exact duplicate rows from the sample. Additionally, there are 8 pairs of rows with differing entries for the same individuals. Only two of those individuals appear in our conscription data and for those we decide to drop one record from each pair at random.

The Labor Market Statistics Register (RAMS) contains yearly data on educational

[8]This register is provided by the Swedish National War Archives ('Krigsarkivet') at the Swedish national Archives ('Riksarkivet').

attainment and income for the entire Swedish population. To capture each individual's highest attained level of education, we use the 2009 records. At this point, our cohort of interest is between 30 and 37 years old. Although there is formally no upper limit to the age at which individuals may complete higher education, most individuals have finished their studies and established their careers by this stage.[9] We identify and drop all exact duplicate rows from the sample. This leaves us with 32 individuals with duplicate entries. Of those, we remove all rows with missing education data. This leaves us with 6 individuals with double entries. Since none of those individual appear in our 1997 LISA data, we choose to remove them altogether.

The conscription data include information on 1,525,842 individuals, many of whom have multiple records. We remove all exact duplicates and exclude observations with missing information on psychological traits (i.e., cases where both SAFH and SIPE entries are missing). This leaves approximately 600,000 individuals with multiple remaining rows, for whom we keep the rows with the lowest number of missing values. The final dataset comprises about 1,270,000 observations.

The Population Register (RTB) contains yearly data on individuals and their relatives. We extract parental identifiers for each individual in 1999, our chosen reference year to match the wealth data. We remove exact duplicates and are left with ten individuals recorded with more than one pair of parents. This may reflect reporting errors or adoptions. In the absence of further information, we exclude these individuals from the dataset. Given the negligible number of cases, this is unlikely to introduce bias.

From the Wealth Register ('Förmögenhetsregistret'), we use the 1999 data. We drop all exact duplicates and additionally exclude about 300 observations with missing information on wealth and debt. The remaining 32 individuals with duplicate entries are also removed, following the same logic as before. We replace missing values in parental wealth with 0, and windsorize values smaller than one at zero when taking logs.

To construct a dataset linking individuals' own and parental wealth, we merge the wealth data with the population data using the mother, father, and individual identifiers. After merging, we drop the identifier columns and obtain a dataset containing information on mothers', fathers', and individuals' own wealth and debt for all matched cases in the Population Register.

Finally, we merge all datasets together. The resulting dataset contains information on age, location, education, income, psychological traits, and own and parental wealth for

[9]While it has become more accepted in recent years to attain higher education or change career path at a higher age, the share of individuals doing so is probably small? In any case, such cases are not relevant for our study: at the time of writing, our cohort (aged 46 to 53) would not have had sufficient time to complete a new education, establish a new business, and engage in innovation activities following a career transition made after age 30–37.

Swedish males born between 1972 and 1979 (a total of about 284,000 observations).

Firms. Most of the firm data is taken from the firm registry of Statistic Sweden (SCB), called *SCB's Företagsregister*, at the level of a legal entity. From here, we get data on when the company was registered (and potentially de-registered), the legal form, revenue and share capital for each year, the company status (e.g. in bankruptcy, liquidation, fusion etc.), and industry. We include all firms that are either registered as a partnership (general or limited), called *handelsbolag/kommanditbolag* or as a limited liability company, i.e. *aktiebolag*, excluding banks and insurances. We focus on firms founded between 2004 and 2021 in our main analysis, and firms founded between 2004 and 2018 where we need information on firm performance after it was founded. We also drop all firms where the the de-registration year is earlier than the year of registration. We then define firm exit as either a bankruptcy or a liquidation. Moreover, we add a variable that captures whether the firm was ever economically active.

For each firm, we merge data from the labor market statistics register (RAMS), which contains the variable "StatusF". This variable is a categorical variable that marks whether a given individual working at a company is also owns (part of) that company, i.e. whether they are an entrepreneur. The data distinguishes active and passive entrepreneurs, depending on whether they work more or less than a third of a regular full-time job for that company. Note that this variable is only available in our data from 2004, and only for so-called *fåmansföretag*, which are closely held companies.

The definition of a closely held company according to Swedish regulation is a company where four or fewer co-owning parties have more than half of the voting rights. Note that "co-owning parties" could be groups of people rather than individuals, for example if different members in the same family own part of the company, they might be counted as one ownership group, so the definition includes many Swedish firms. We use this data to identify founders, by assuming that owner-entrepreneurs of a company in the first year of its existence are founders of that company. From the same database, we also link information on the number of workers and wages.

II. Entry

A. Numerical example

This exercise is intended to clarify the economic madnitude of the estimated coefficients. We normalize an individual with median wealth, IQ, and PF score to the average entrepreneurship rate of 6.82. This is simply a normalization to take care of potentially varying controls. We then use the coefficients on IQ, PF, and wealth, as well as the skill-wealth interactions to calculate how the entry rate would change if we vary skills or parental wealth. Table 6 holds non-cognitive skill PF at it the median level while varying

IQ, and vice versa for Table 7.

Table 6: Predicted entrepreneurship entry rates at median skill (5)

	Wealth percentile				
IQ percentile (score)	10th	25th	50th	75th	90th
10th (84.5)	6.25	6.50	6.62	6.72	6.81
25th (92.5)	6.45	6.63	6.71	6.78	6.85
50th (101.3)	6.68	6.77	6.82	6.85	6.89
75th (109.2)	6.88	6.90	6.91	6.92	6.93
90th (115.5)	7.04	7.00	6.98	6.97	6.96
Difference in entry rate top IQ vs bottom IQ (pp)	0.79	0.50	0.37	0.25	0.14

Notes: Entry rates are in percent. Top IQ is P90 and bottom IQ is P10. Differences are in percentage points.

Table 6 shows that the gap in the entry rate between percentile 10 IQ and percentile 90 IQ decreases in wealth, from .79 percentage points to 0.14 percentage points. Also note that while wealth increases entry on average, it actually decreases it for very high IQ levels.

Table 7: Predicted entrepreneurship entry rates at median IQ (101.26)

	Wealth percentile				
Skill percentile (score)	10th	25th	50th	75th	90th
10th (3)	5.47	5.63	5.71	5.77	5.83
25th (4)	6.07	6.20	6.26	6.31	6.36
50th (5)	6.68	6.77	6.82	6.85	6.89
75th (6)	7.28	7.34	7.37	7.39	7.42
90th (7)	7.88	7.91	7.92	7.93	7.95
Difference in entry rate top skill vs bottom skill (pp)	2.41	2.28	2.21	2.16	2.11

Notes: Entry rates are in percent. Top PF is P90 and bottom PF is P10. Differences are in percentage points.

Table 7 shows a similar pattern, although reduction in the selectiveness on non-cognitive skill is somewhat smaller, while the gap in entry rates between low and high skilled individuals is significantly larger at 2.11 to 2.41 percentage points.

All in all, these effects are economically meaningful considering the relatively low average entry rate into entrepreneurship.

III. Firm success

In this section, we present additional regression results on firm success.

A. *PF score details*

Figure 5 presents the estimation results on the PF score when introducing it as a categorical variable instead of a numerical one. We conclude that there are no clear patterns in the categorical coefficients that indicate that there are discontinuous or nonlinear relationships at play. We therefore decide to use the raw PF score as a continuous variable in our main specifications.

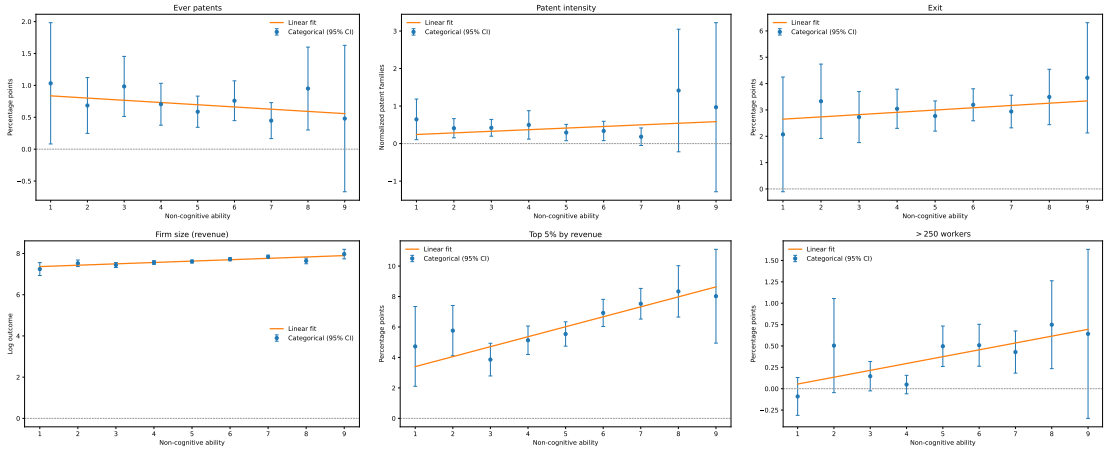


Figure 5: Fitted values; categorical versus linear

B. *Firm size distribution*

In our main regression results, we find that founder IQ predicts the probability of the firm to become a top 5% firm in terms of revenue. At the same time, IQ is not associated with firm size otherwise. This is because the mode of the firm size distribution is shifted down for higher IQ founders, while the right tail is thicker. This pattern is documented in Figure 6.

C. *Additional outcomes*

In addition to the firm success measures reported in the main body of this paper, we have also run regressions for alternative firm outcomes. These are reported in Table 8. We find that the labor share is not related to IQ, non-cognitive skill or family assets. Measuring firmsize in terms of the share capital instead of revenue shows the same patters, with wealth and non-cognitive skill predicting firm size in terms of share capital, and IQ being unrelated to it.

Finally, we look at group structure. Becoming part of a corporate group as well as the size of the group conditional on being acquired are predicted by non-cognitive skill and wealth, but not IQ. There is some concern that becoming part of the group means that some of the revenue is now reported in the financial statements of the mother company, biasing down measures of revenue and generating the result that higher IQ levels are not associated with firm size. However, as IQ does not predict becoming part of a group, this

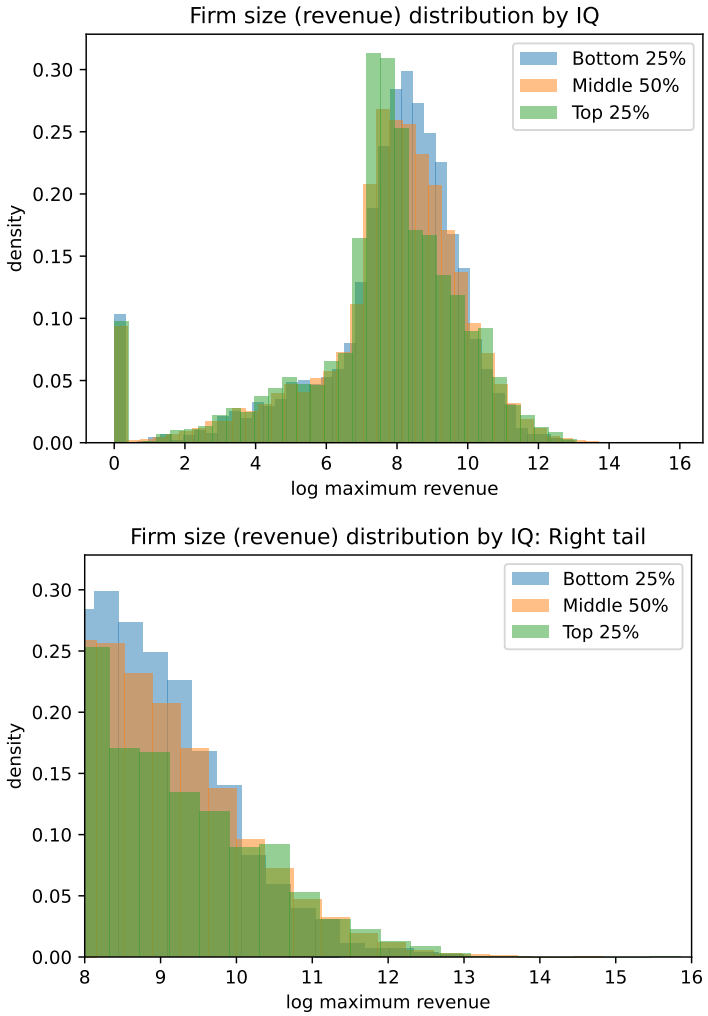


Figure 6: Firm size (revenue) distribution by IQ

does not seem to be the case.

IV. Back of the envelope counterfactual: Full results

To get a sense of the magnitude of these findings and understand how the parental wealth distribution features, run a back of the envelope calculation. The wealth level is equalized at the mean to hold total wealth constant. We then use the regression coefficients of a linear projection of firm entry on parental wealth, cognitive, and non-cognitive skill, an interaction between wealth and both skill measures, as well as demographic controls, to predict entrepreneurship entry. Similarly, we predict firm outcomes using a regression of revenue, workers, and patenting, regressed on cognitive and non-cognitive skills as well as parental wealth. We summarize the key take-aways in the main body of the paper, but provide the full list of outcomes here in Table 9.

Table 8: Entrepreneurial Success

	Firm size (sharecap) (%)	Labor share (pp)	Ever part of a corporate group (pp)	Size of biggest corporate group (nr)
IQ	-1.30	2.64	0.243	0.569
	(1.57)	(8.34)	(0.371)	(0.497)
Non-cognitive skill	8.90***	1.74	1.68***	1.14**
	(1.59)	(7.54)	(0.348)	(0.446)
Log family assets	3.23***	4.33	0.377***	0.214**
	(0.533)	(2.67)	(0.107)	(0.090)
Founding-year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Mean dep. variable	2.47	111.3	21.1	8.49
R-squared	0.473	0.109	0.079	0.081
Adjusted R-squared	0.469	0.102	0.073	0.056
Observations	14,905	11,894	14,905	3,143

Notes: HC1 heteroskedasticity-robust standard errors are reported in parentheses. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively. All regressions include two-digit industry and founding-year fixed effects. Binary dependent variables are multiplied by 100; effects on log outcomes are reported as percentage changes. IQ and non-cognitive skill are standardized to mean zero and unit standard deviation. Log family assets is unscaled.

Change relative to baseline (%)	Equal wealth	No entry interactions
Entrepreneurs		
Number	+1.59	+162.55
Average IQ	−0.33	+0.49
Average PF	−0.78	−0.70
Average firm outcomes		
Revenue	+0.38	−0.03
Workers	−0.11	−0.30
Patenting probability	−1.22	+4.50
Aggregate outcomes		
Revenue	+1.97	+162.48
Workers	+1.47	+161.77
Number of patenting firms	+0.34	+174.38

Table 9: Full results of numerical back of the envelope counterfactual.

V. Additional controls

When including additional controls in our regressions, such as education, county, parental entrepreneurship, and parental income, the main results remain, as presented in Figure 7 and 8.

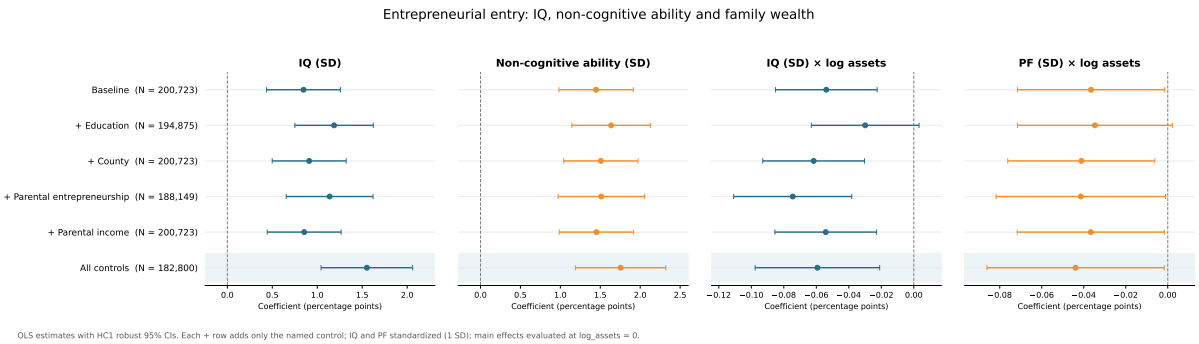
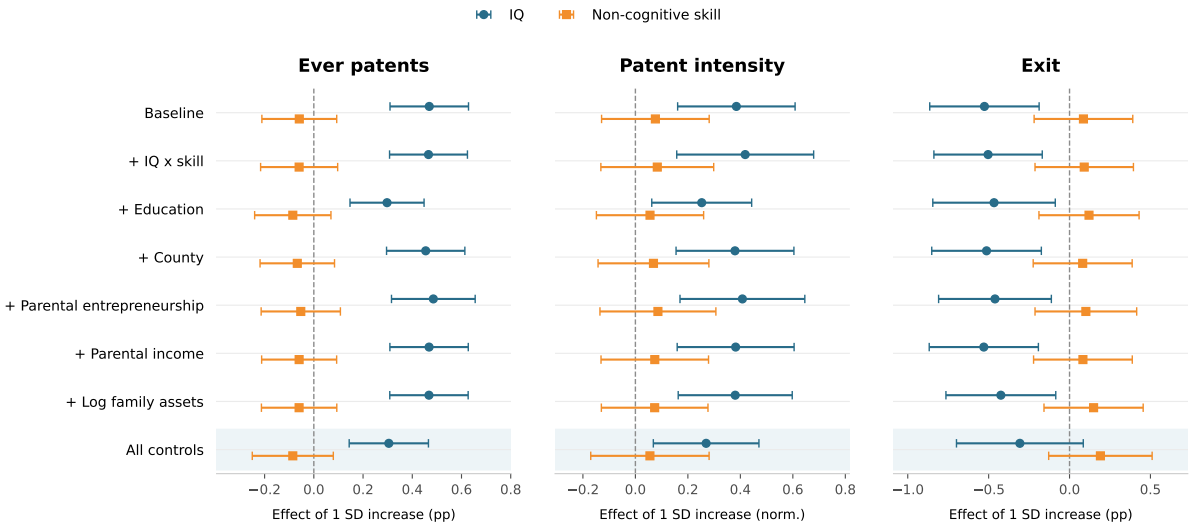
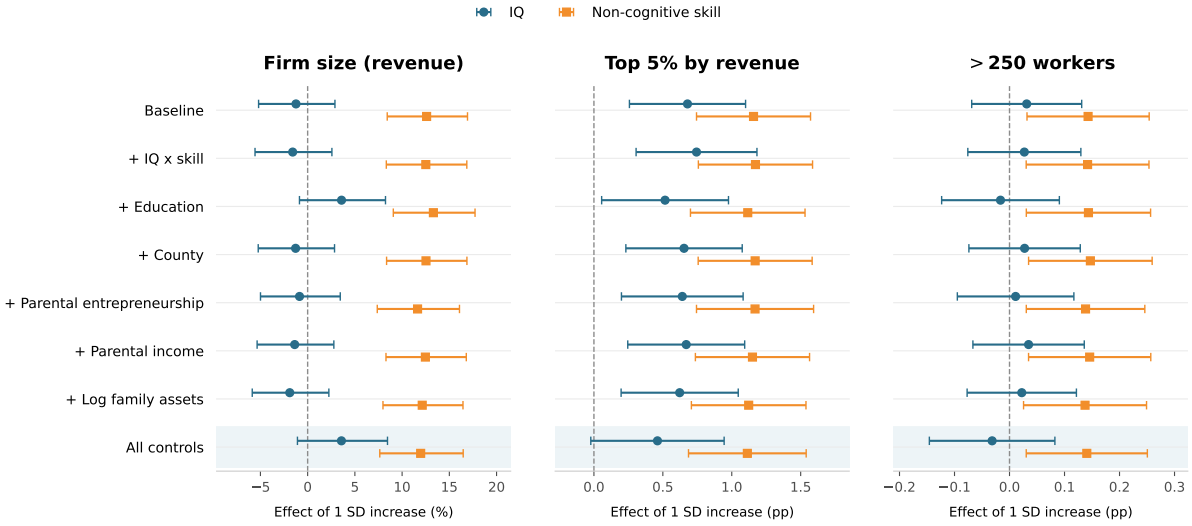


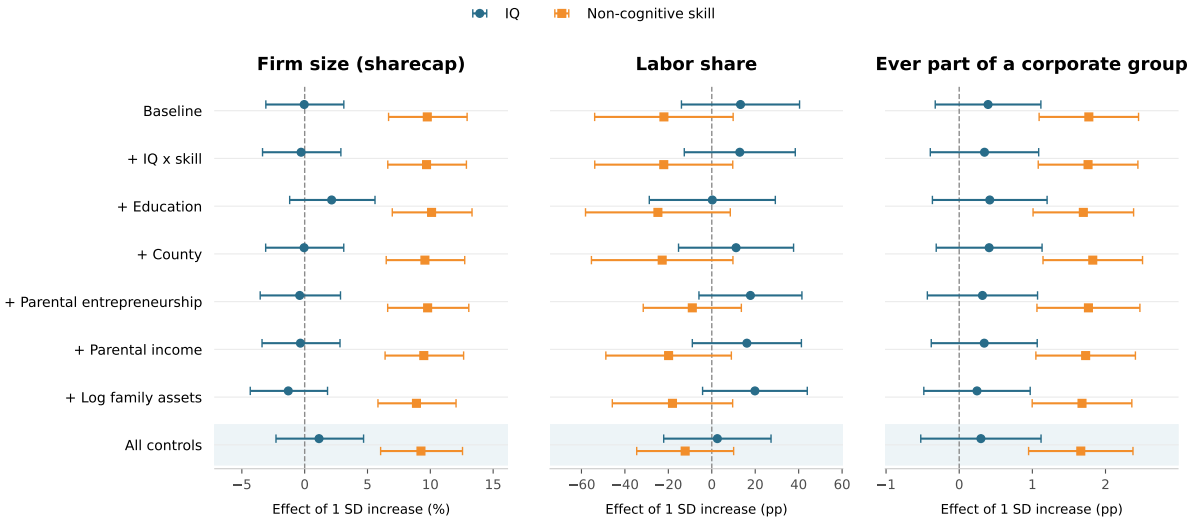
Figure 7: Main coefficients with additional controls in entry regressions.



Dots: effects of a one-standard-deviation increase; bars: HC1-robust 95% confidence intervals. IQ and non-cognitive skill are estimated jointly in every regression.
Baseline: IQ + non-cognitive skill + founding-year fixed effects + industry fixed effects. The interaction row adds IQ x skill; other + rows add only the named control.



Dots: effects of a one-standard-deviation increase; bars: HC1-robust 95% confidence intervals. IQ and non-cognitive skill are estimated jointly in every regression.
Baseline: IQ + non-cognitive skill + founding-year fixed effects + industry fixed effects. The interaction row adds IQ x skill; other + rows add only the named control.



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Baseline: IQ + non-cognitive skill + founding-year fixed effects + industry fixed effects. The interaction row adds IQ x skill; other + rows add only the named control.

Figure 8: Main coefficients with additional controls in firm success regressions.