Enterprising up the ladder: Are some entrepreneurs more upwardly mobile than others?

Himal Gautam*

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Abstract

Does entrepreneurship generate upward wealth mobility, and for whom does it matter the most? Using Norwegian administrative data on 26,970 entrepreneurs, I find that entrepreneurs advance 6.4 percentile points beyond their parents within 5 years of entry. Roughly half of this gap is already present at entry, and the rest is accumulated afterward. These gains, however, vary sharply by background. Post-entry gains are the largest in the middle of the parental wealth distribution. Poorer entrepreneurs show larger pre-entry advantages than post-entry gains, and the wealthiest gain little in relative terms but are the most likely to remain at the top. Education matters in two ways: entrepreneurs with less formal schooling see the largest relative gains, while those with technical degrees are the most likely to reach the top decile. Business graduates see the weakest outcomes. Wealth mobility is notably lower than suggested by income-based measures.

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*Department of Finance, BI Norwegian Business School, Oslo, Norway. Email: himal.gautam@bi.no.

1 Introduction

Entrepreneurship is often portrayed as a pathway for individuals to rise beyond their economic circumstances. But does entrepreneurship actually deliver upward wealth mobility, and if so, for whom?

Despite the prominence of this question in public discourse, direct evidence is quite scarce. Entrepreneurs hold a disproportionate share of aggregate wealth (Cagetti and De Nardi, 2006). At the same time, a longstanding literature questions whether starting and owning a business actually pays. Hamilton (2000) finds that most self-employed workers earn less than they would in wage employment, interpreting the gap as a preference for non-pecuniary benefits. Moskowitz and Vissing-Jørgensen (2002) show that private entrepreneurial investments do not yield higher risk-adjusted returns than public equity. If entrepreneurship generates low financial returns, the concentration of wealth among entrepreneurs is puzzling, and the popular narrative of entrepreneurship as a pathway to upward mobility may be driven by selection more than the entrepreneurial spell itself.

In this paper, I use Norwegian administrative data on 26,970 entrepreneurs and matched non-entrepreneurs over 2005-2017 to measure the wealth mobility of entrepreneurs directly. Norway provides a particularly rich setting to study this question as the state levies a tax on net wealth. This means that tax records contain detailed information on various components of individual wealth, in addition to various sources of income. Since tax liabilities depend on the reported wealth, there are strong incentives for accurate reporting. The administrative records cover the full population eliminating issues such as sample attrition and non-response that limit survey-based studies. My analysis draws on a 20% random sample of the population providing a large and representative panel. Individuals can be linked to their parents making it possible to directly measure intergenerational wealth positions. And detailed data on education, income, and firm ownership allow me to identify entrepreneurs precisely, and match them to comparable non-entrepreneurs on a rich set of pre-entry characteristics.

I define entrepreneurs as founders of incorporated limited liability (AS) firms who serve as CEO or Chair and hold more than 5% of the firm's shares. This definition focuses on ventures with growth potential, and excludes the self employed whose outcomes may resemble the

outcomes of salaried workers more closely (Levine and Rubinstein, 2017). The restriction to incorporated firms also aligns with Schoar's (2010) distinction between subsistence and transformational entrepreneurship. I then construct a comparison group using entropy balancing (Hainmueller, 2012), reweighting non-entrepreneurs to match entrepreneurs exactly on parental wealth, own wealth, detailed educational attainment, age, gender, and municipality at the time of entry. This does not establish causality on its own, but ensures that any difference in wealth outcomes between the two groups cannot be attributed to observable differences in background.

I study mobility along three complementary dimensions. **Intergenerational mobility** compares the entrepreneur's wealth rank at 5 and 10 years after entry to the parent's rank in the year before the entrepreneur's entry. This is the broadest measure of whether entrepreneurs end up higher in the distribution than their parents. **Pre-entry mobility** measures the gap in rank between the entrepreneurs and their parents at the year of entry. Any gap here precedes the entrepreneurial spell, so it reflects selection. **Post-entry mobility** compares the entrepreneur's own wealth rank at 5 and 10 years after entry to their own rank at the year of entry, isolating the change during the entrepreneurial spell. Within each dimension, I use two relative measures: the *rank gap* (difference in wealth percentile rank) and *upward movement* (probability of moving up at least one quintile). In addition to that, I also use *top 10% achievement* which measures the probability of reaching the top decile of the wealth distribution where the largest entrepreneurial wealth gains are concentrated.

Five years after entry, entrepreneurs advance 6.4 percentile points beyond their parents' wealth position relative to matched non-entrepreneurs, are 6.2 percentage points more likely to move to a higher wealth quintile, and are 14.5 percentage points more likely to be in the top decile. These effects grow stronger at the ten-year horizon. Without entropy balancing, the rank gap at the five-year horizon is 16.4 percentile points, more than double the balanced estimate, indicating that selection on observables accounts for more than half of the raw rank gap.

Jointly, the three dimensions help separate wealth gains entrepreneurs have prior to entry from wealth gains they have during their entrepreneurial spell. At the time of entry, future entrepreneurs already sit 3.9 percentile points above their parents and are 6.6 percentile points more likely to be in the top decile. These correspond to roughly half of the correspond-

ing five-year intergenerational effects, though robustness checks measuring both positions one year before entry suggest the pre-entry advantage is smaller (1.5 percentile points), with the difference reflecting wealth changes that coincide with entry. The post-entry results also show substantial gains after entry. Entrepreneurs advance 3.3 percentile points relative to their own position at entry and are 8.6 percentage points more likely to move to a higher wealth quintile within five years. These effects persist and grow at the ten-year horizon. While selection accounts for a larger share of the intergenerational rank gap than post-entry accumulation, the post-entry gains are still significant and economically meaningful. This decomposition also serves as a check on the role of observables. If selection alone drove the intergenerational gap, post-entry gains should be negligible. They are not.

These average effects mask substantial heterogeneity by parental wealth. Entrepreneurs whose parents are in the middle of the wealth distribution (Q2-Q3) see the strongest intergenerational rank gains, at approximately 7 to 7.5 percentile points, while those from the richest families (Q5) gain 5.5. Yet, when it comes to reaching the top of the distribution, the pattern flips. Entrepreneurs from the wealthiest families are the most likely to make it to, or remain in the top decile. Entrepreneurship serves different functions depending on where in the distribution one starts. It generates upward rank mobility for those with parents in the middle of the distribution, and preserves wealth at the top of the distribution.

Less educated entrepreneurs gain the most in relative rank, but highly educated entrepreneurs are the most likely to reach the very top. Entrepreneurs with only secondary education see the largest intergenerational rank gains (9.9 percentile points), while those with a master's or PhD see the smallest (5.3). The probability of reaching the top decile moves in the opposite direction, from 12.5 percentage points for secondary-education entrepreneurs to 20.1 for those with a master's or PhD at the five-year horizon. The pre-entry results suggest that these entrepreneurs have different paths. Entrepreneurs with a secondary education already sit 8.5 percentile points above their parents before entry, but gain only 3.4 percentile points after entry. For those with a master's or PhD, the pre-entry gap is 2.8 and the post-entry gap is 2.4. Selection effects seem stronger for the least educated, while post-entry gains are more modest, but evenly sized across all education levels.

The highly educated entrepreneurs dominate when looking at the probability of reaching the top decile of the wealth distribution. Entrepreneurs with a bachelor's degree or higher

are roughly 19 to 20 percentage points more likely to reach the top decile than matched non-entrepreneurs, compared with about 12.5 for those without university education. This advantage is not just because of selection. While highly educated entrepreneurs are already more likely to be in the top decile before entry, the gap over less educated entrepreneurs grows substantially in the years after.

The field of education also matters in this context. Business graduates enter entrepreneurship at roughly twice their population share, consistent with Lazear's (2004; 2005) prediction that individuals with generalist skill sets are more likely to start firms. Yet, their wealth outcomes are the weakest of any group. They gain only 2.7 percentile points above their parents, and are 5.3 percentage points less likely to move to a higher quintile relative to entrepreneurs without the three specialized fields I look at here (business, engineering and science). Engineering and science graduates see the strongest effects, particularly for reaching the top decile. Comparing the results across the three dimensions provides more insights. Entrepreneurs with science degrees show almost negligible pre-entry wealth gains, yet see large intergenerational gains, suggesting that their mobility is primarily driven by post-entry wealth accumulation. Entrepreneurs with engineering degrees have strong gains both before and after entry. The returns to entrepreneurship thus appear higher for technical specialists over generalists, at least when measured in terms of upward wealth mobility. Consolidating all the evidence, entrepreneurship is associated with meaningful upward wealth mobility. It does not merely reflect pre-existing advantages, and it also does not operate as a great equalizer. The returns systematically vary based on where in the distribution one starts, and what human capital one brings to the venture. These findings complement the income-based evidence in the existing literature. I find substantially higher income mobility than wealth mobility among entrepreneurs in the same data, suggesting that looking at income may overstate the degree to which entrepreneurship reshapes individuals' long-run economic positions.

This paper contributes to three strands of literature. First, I examine entrepreneurial returns from a perspective of wealth accumulation rather than income or returns to investment. Second, I provide new evidence on the role of entrepreneurship in intergenerational wealth mobility. Third, I document rich heterogeneity in who benefits from entrepreneurship, and through what channels.

Hamilton (2000) finds that most self-employed workers earn less than they would in wage employment, and Moskowitz and Vissing-Jørgensen (2002) show that private entrepreneurial investments do not yield higher risk-adjusted returns than public equity. Berglann et al. (2011), using Norwegian data, find that entrepreneurs earn more than comparable employees once selection on observables is accounted for. These papers focus on earnings or investment returns, and do not speak about wealth accumulation directly. Earning a lower salary does not necessarily imply failing to accumulate wealth if entrepreneurs build equity in their firms (Cagetti and De Nardi, 2006; Quadrini, 2000). Conversely, higher income does not necessarily translate to higher wealth if income gains are transitory, or consumed rather than saved. By shifting the focus to wealth, I show that entrepreneurship is associated with substantial upward mobility in the wealth distribution, and the probability of reaching the top decile is stronger for entrepreneurs with technical education even after accounting for selection on observables.

Chetty et al. (2014) document large geographic variation in income mobility in the United States, and Chetty et al. (2017) report a decline in absolute mobility over time. Fagereng et al. (2020) show substantial persistence in wealth at the top, driven in large part by private investments, and also find that entrepreneurs exhibit greater mobility in Norway. Charles and Hurst (2003) document intergenerational wealth persistence in the United States. These studies raise an obvious question of whether entrepreneurship can drive mobility lower in the distribution or whether they primarily preserve wealth at the top. I show that the answer depends on where in the distribution one chooses to focus, and that the rank-based measures and the top 10% measures tell different, yet important stories about the same population.

The paper is most directly related to the link between entrepreneurship and economic mobility. An extensive literature establishes that family background shapes entry into entrepreneurship through liquidity constraints (Evans and Jovanovic, 1989; Holtz-Eakin et al., 1994a,b), human capital investments (Black and Devereux, 2011; Fairlie and Robb, 2007), and the presence of entrepreneurial role models in the family (Lindquist et al., 2015). Hurst and Lusardi (2004) show that liquidity constraints may not matter to the same extent for all entrepreneurs by showing that the wealth-entry relationship is flat except at the very top of the distribution. Most closely related to my study, Lindquist and Vladasel (2025)

study intergenerational income mobility among Swedish entrepreneurs and suggest that the apparent upward mobility of incorporated entrepreneurs is largely driven by selection on observable and unobservable traits. My analysis with a focus on wealth complements their findings on income mobility. I find meaningful post-entry wealth gains in addition to selection, suggesting that while the type of person who becomes an entrepreneur matters, the entrepreneurial spell itself also generates wealth.

Finally, the heterogeneity results add what is perhaps the most novel dimension. Existing work typically estimates average returns to entrepreneurship. I show that these averages mask systematic variation by parental wealth, level of education, and field of study that changes the interpretation of the role of entrepreneurship. The rank-based and top-decile measures tell different stories about the same population. Looking at mobility across different time horizons and with different benchmarks (intergenerational, pre-entry, and post-entry), I find that the relative importance of selection and treatment also varies across groups. The finding that business education leads to the weakest wealth outcomes while technical education leads to the strongest, despite business graduates being the most likely to become entrepreneurs, has important implications for how we think about the interaction between human capital and venture creation.

I describe the Norwegian administrative data and construction of key variables in Section 2, explain the details of the entropy balancing procedure and the three dimensions of mobility in my analysis in Section 3, and present the results in Section 4.

2 Data

I use Norwegian administrative data maintained by Statistics Norway and the Norwegian Tax Authority. The data link individual tax records to registers covering educational attainment, employment, municipality of residence, and family relationships. Tax records contain detailed information on income, wealth holdings, and firm ownership. Education records include field of study at the 3-digit NUS level. Family links allow me to connect children directly to their parents, which is essential for measuring intergenerational mobility.

The analysis is based on a 20% random sample of all individuals in the Norwegian Population Register. Within this sample, I construct a panel of new entrepreneurs from administrative

records on the population of Norwegian limited liability companies and their owners over 2005–2017. I then match these individuals with data on employment, wealth, income, gender, age, education, and family relationships. This produces a comprehensive record of the owners of new firms, their employment histories, their family backgrounds, and a range of demographic attributes.

2.1 Identifying new entrepreneurs

I restrict the sample to entrepreneurs who conduct business through limited liability (AS) firms. I exclude self-employed individuals for two reasons. First, previous work suggests that self-employed individuals have outcomes that are more similar to salaried workers than incorporated business owners, and that incorporated entrepreneurs are positively selected on both cognitive and noncognitive skills (Levine and Rubinstein, 2017). Secondly, this approach also aligns with the distinction between subsistence and transformational entrepreneurship (Schoar, 2010). Incorporated (AS) firms are more likely to represent ventures with formal legal structure and growth potential than necessity driven self-employment.

I define an individual as an entrepreneur if they are the CEO or Chair of an AS firm and own more than 5% of the firm's shares. I label the first year in which an individual satisfies both criteria simultaneously as their year of entry into entrepreneurship. Since all individuals who founded firms in 2005 or earlier appear as entrepreneurs from the start of the data, I remove all entries for individuals identified as entrepreneurs in 2005 to ensure that the sample captures new entrants. I retain only individuals for whom at least one parent is identified in the population. While the initial sample is drawn from a 20% random subsample of the Population Register, I link individuals to their parents regardless of whether the parents appear in the subsample, avoiding unnecessary attrition.

This produces a panel of 26,970 entrepreneurs entering between 2006 and 2017. Table B.1 reports the number of new entrepreneurs entering in each year. The comparison group consists of individuals who are never identified as entrepreneurs during the sample period (2005–2017), yielding 318,600 individual-year observations for entrepreneurs and 4,971,802 individual-year observations for non-entrepreneurs (Table B.2).

2.2 Measurement of key variables

I measure wealth as gross wealth: the sum of financial wealth, housing wealth, and private business wealth as reported in the tax records. This measure excludes debt. The choice of gross rather than net wealth reflects three considerations. First, gross wealth captures the scale of economic resources under an individual's control, which is the relevant object for studying accumulation. Second, business equity and real estate, the primary channels through which entrepreneurship might generate mobility, enter gross wealth directly. Third, net wealth is frequently negative for young or leveraged entrepreneurs, which would make rank-based comparisons with the general population difficult to interpret. Similar measurement choices are standard in the Norwegian wealth data literature (Fagereng et al., 2020). I verify this choice in Section 4.6 by replicating the main results using net wealth (gross wealth minus total debt). The net wealth results are not meaningfully different, but attenuated at the five-year horizon, consistent with entrepreneurs being leveraged at entry. The effects are positive and significant by year $t+10$ suggesting that wealth accumulation eventually outpaces the debt entrepreneurs take to fund entry.

All wealth and income variables are converted to percentile ranks within each calendar year. Following Chetty et al. (2014), I use rank-based measures throughout the analysis. Ranks have three advantages in this setting: they are invariant to the skewness of the wealth distribution, they are directly comparable across cohorts and time periods, and they produce linear intergenerational relationships that simplify interpretation. I compute ranks based on the full distribution of observations in the 20% sample for each year.

I use three income variables. Wage income includes total taxable salary for the calendar year. Capital income includes interest, dividends, rents, and net gains on asset sales. Total income includes both wage and capital income as well as transfers, and is the most comprehensive measure. I examine ranks based on all three. In addition, I observe bank deposits at year-end, which are relevant given the longstanding interest in the relationship between saving behavior and entrepreneurship (Quadrini, 2000).

Education is recorded using the 6-digit Norwegian Standard Classification of Education (NUS), which encodes both the level and field of study. For the heterogeneity analysis, I classify individuals into four broad levels: secondary education (less than high school), high

school, bachelor's degree, and master's or PhD. I classify fields of study into business, science, engineering, and a residual category (Other/None). Programs affiliated with more than one field are labeled Multiple fields. For the entropy balancing procedure, I use the 3-digit NUS code, which captures the common level and broad field of education without the extreme granularity of the 6-digit classification.

2.3 Who becomes an entrepreneur?

Entrepreneurs and non-entrepreneurs differ along several dimensions that are correlated with wealth accumulation. Table B.2 provides a broad summary of the full sample pooled across individual-year observations. Entrepreneurs tend to be wealthier, earn more, have wealthier parents, and are slightly older and more educated than non-entrepreneurs. Business graduates constitute a much larger share of entrepreneurs than of the general population. The gender imbalance is stark: women represent only about a quarter of the entrepreneurs in the sample.

Own wealth is strongly associated with entry. Figure A.2 shows that the rate of entry into entrepreneurship climbs monotonically with wealth decile, with a pronounced jump at the top. The relationship between parental wealth and entry (Figure A.1) is flatter across the middle of the distribution but rises sharply at the 9th and 10th deciles. This pattern is consistent with Hurst and Lusardi (2004), who find that the wealth-entry relationship in the United States is flat except at the very top, and suggests that liquidity constraints bind primarily for the wealthiest potential entrants.

Despite the relatively flat entry rates across the middle when measured by parental wealth, children of wealthy parents are substantially overrepresented among entrepreneurs. Entrepreneurs with parents in the bottom 40% of the wealth distribution account for only about 10% of the sample, while those with parents in the top decile account for over 30% (Tables B.7 and B.8). This concentration reflects the compounding effects of parental wealth on both own wealth accumulation and the resources available to start a firm.

Wealth also influences the timing of entry. The peak entry ages are 30-49 (Figure A.4), but entrepreneurs with parents in the top quintile enter earlier and with less dispersion in age at entry, while those from the bottom quintile show a wider spread (Table B.12). Education delays entry monotonically: higher educational attainment is associated with later entry

(Table B.10), and the delay is longest for entrepreneurs from lower-wealth backgrounds (Table B.16). Parental wealth appears to offset the delay imposed by education, consistent with wealthier families providing the financial cushion needed to enter entrepreneurship sooner after completing a degree.

The rate of entry is highest among individuals with a master's degree or PhD and lowest for those with only secondary education (Figure A.3). Among entrepreneurs in the sample, about 47% have completed only high school, and just over 12% hold a master's degree (Table B.9). Science and engineering graduates enter later than others (Table B.11), likely reflecting longer educational programs and the availability of well-paid salaried alternatives.

2.4 How upward mobile are entrepreneurs?

Before turning to the formal analysis, it is useful to examine raw transition matrices for entrepreneurs and non-entrepreneurs. I report the share of individuals in each parental quintile who reach each child quintile within 5 years of entry in Table B.17 (Table B.18 for ten years).

Two patterns stand out. First, entrepreneurs from the bottom quintile are substantially more likely to move up than non-entrepreneurs from the same quintile. While 38.1% of non-entrepreneurs with bottom-quintile parents remain in the bottom quintile themselves, only 13% of entrepreneurs do. This raw gap is striking, though it combines selection and treatment effects that the formal analysis will separate. Second, persistence at the top is stronger among entrepreneurs than non-entrepreneurs: over half of entrepreneurs with top-quintile parents remain in the top quintile, compared with 37.2% of non-entrepreneurs. Entrepreneurship thus appears to be associated with both upward mobility from the bottom and persistence at the top.

Comparing wealth and income transitions reveals an important asymmetry. When the same exercise is conducted using total income (Table B.19) and salary (Table B.20), the disparity between children from different parental wealth backgrounds is smaller than for wealth. Income quintile transitions are more compressed, reflecting Norway's relatively even income distribution and the role of labor market institutions in compressing earnings. A larger share of entrepreneurs appear in higher income quintiles than non-entrepreneurs, but the gaps are more modest than for wealth. This difference between income and wealth mobility

motivates the focus of this paper: income-based measures may substantially understate the extent to which entrepreneurship affects long-run wealth accumulation and economic position.

3 Empirical Strategy

The main identification challenge in studying entrepreneurship and upward mobility is that entrepreneurship is not randomly assigned. Individuals who become entrepreneurs differ from those who do not in ways that predict wealth accumulation: they tend to come from wealthier families, have different educational profiles, and may differ on unobservable traits such as risk tolerance and ambition (Evans and Jovanovic, 1989; Hurst and Lusardi, 2004; Levine and Rubinstein, 2017). A naive comparison of wealth outcomes between entrepreneurs and non-entrepreneurs would conflate the effect of the entrepreneurial experience with the characteristics that led certain individuals to start firms in the first place. I address this challenge in two ways. First, I use entropy balancing (Hainmueller, 2012) to construct a comparison group of non-entrepreneurs that is identical to the entrepreneur sample on observable pre-entry characteristics, including parental wealth, own wealth, educational attainment, demographics, and municipality. This reweighting absorbs the portion of the entrepreneur-control gap that is attributable to observable selection, which turns out to be substantial: the raw rank gap falls by 61% after balancing.

What entropy balancing cannot address is selection on unobservables. Entrepreneurs may differ from non-entrepreneurs in ambition, risk tolerance, or ability in ways that are not captured by the administrative data. I therefore complement the balancing approach with a second strategy: evaluating wealth mobility along three dimensions that help distinguish selection from post-entry accumulation.

Pre-entry mobility, measured at the moment of entry, captures the extent to which future entrepreneurs are already on upward trajectories before starting a firm. Post-entry mobility isolates the change in an entrepreneur's own wealth position after entry. If unobservable selection alone drove the intergenerational gap, post-entry gains should be negligible. They are not, but pre-entry advantages are also large, suggesting that both channels contribute meaningfully to the observed intergenerational gap.

Together, the two strategies do not fully establish causality, but they narrow the range of plausible explanations in a way that neither approach alone can.

3.1 Establishing counterfactuals

Entropy balancing is a preprocessing method that reweights comparison-group observations so that the weighted distribution matches the treated group on specified moments of the covariate distribution (Hainmueller, 2012). Unlike propensity score matching, which achieves approximate balance, entropy balancing achieves exact balance by construction. It also retains all observations in the comparison group rather than discarding unmatched individuals, which means the estimates reflect the effects for the full population of entrepreneurs rather than only those with convenient matches.

I balance on the following covariates, each chosen to address a specific dimension of selection into entrepreneurship. Parental wealth rank controls for the intergenerational transmission of wealth and the resources available to fund a venture (Holtz-Eakin et al., 1994a,b). Own wealth rank captures the individual's pre-entry financial position, which reflects both accumulated savings and any prior asset returns (Hurst and Lusardi, 2004). Educational attainment (3-digit NUS code) controls for human capital, which affects both the probability of entry and the quality of the venture. Age and gender capture life-cycle effects and the well-documented gender gap in entrepreneurship.

All covariates are measured in the year prior to entry. I compute weights separately for each entry year and age group, which implicitly matches individuals within the same cohort facing the same broad macroeconomic conditions. The procedure balances on the first moment (mean) of each covariate. While entropy balancing can also match on higher moments, the combination of a large covariate set, the granularity of the 3-digit education codes, and the within-cell matching makes balancing on means sufficient to achieve close distributional overlap.

For the estimates to have a causal interpretation, the key identifying assumption is that the covariates fully explain selection into entrepreneurship conditional on the cell structure. This assumption is strong. The covariates capture the common drivers of entrepreneurial entry: financial resources, human capital, demographics, and opportunity. They do not capture unobservable traits such as risk tolerance, ambition, social connections, or entrepreneurial

talent.

The estimates therefore measure the mobility effects of entrepreneurship for individuals with identical observable pre-entry characteristics, but they cannot fully separate the treatment effect of the entrepreneurial experience from selection on unobservables. The three-dimension framework described below helps assess how much of the remaining gap is likely attributable to each channel.

3.2 Dimensions and measures of mobility

I evaluate mobility along three dimensions, each designed to capture a different aspect of the relationship between entrepreneurship and wealth accumulation. The dimensions differ in what they compare (children to parents, or children to themselves) and when they measure outcomes (at entry, or at post-entry horizons). Used in isolation, each dimension has limitations. Used together, they provide a more complete picture than any single measure and help disentangle selection from post-entry wealth accumulation.

Dimensions

Intergenerational mobility measures whether entrepreneurs end up higher in the wealth distribution than their parents. For instance, I compare the entrepreneur's wealth percentile rank at horizon h years after entry to the parent's wealth percentile rank in the year before entry. This is the broadest of the three dimensions: it captures the full extent of upward movement relative to the previous generation, incorporating both any pre-existing advantages and any gains from the entrepreneurial experience. This dimension connects the paper to the large literature on intergenerational mobility that uses parent-child rank comparisons as the primary outcome (Chetty et al., 2014; Fagereng et al., 2020).

Pre-entry mobility captures the extent to which future entrepreneurs are already on upward trajectories before starting a firm. I compare the entrepreneur's wealth position at the time of entry to the parent's position at the same date. Because this comparison is made before the entrepreneurial spell can have had any direct effect on wealth, any gap between entrepreneurs and matched non-entrepreneurs along this dimension reflects selection: the types of individuals who choose to become entrepreneurs are already different. Large pre-entry effects would indicate that observed intergenerational mobility is driven

substantially by who becomes an entrepreneur, rather than by what happens after they start.

Post-entry mobility isolates the change in wealth position that accumulates during the entrepreneurial spell. I compare the entrepreneur's wealth position at horizon h to their own position at the time of entry. Because entropy balancing matches on own pre-entry wealth, any post-entry divergence from the comparison group reflects differential wealth accumulation during the entrepreneurial experience itself.

The three dimensions provide a partial check on the selection problem. If unobservable traits such as risk tolerance, talent, or access to networks fully accounted for the intergenerational mobility gap, this should be visible in the pre-entry dimension: future entrepreneurs would be ahead of their parents before starting a firm, not after. In this scenario, post-entry gains should be negligible. If, on the other hand, the entrepreneurial experience itself generates wealth, post-entry gains should be substantial even after conditioning on observable characteristics. The finding that post-entry gains account for a meaningful share of intergenerational effects, documented in Section 4, is more consistent with entrepreneurship contributing to wealth accumulation than with selection alone.

I note, however, that this framework cannot fully rule out selection on time-varying unobservables that coincide with entry. I evaluate outcomes at the point of first entry and do not require the individual to remain an entrepreneur. This means the estimates capture the effect of starting a firm, regardless of whether the venture survives, rather than the effect of being an active entrepreneur at a given horizon (Dillon and Stanton, 2017).

One concern regarding the pre-entry dimension could be intergenerational transfers around the time of entry. If a parent transfers wealth to the child in the year of entry, the child's rank rises and the parent's rank falls simultaneously, mechanically widening the rank gap. This means that the pre-entry estimates at the year of entry (t) may overestimate the selection effect. In section 4.6, I address this by measuring both the child's and the parent's wealth one year before entry (at $t-1$). The pre-entry differences between entrepreneurs and non-entrepreneurs a year before entry are smaller in the year before entry, but is positive and significant.

Measuring mobility

Within each dimension, I report three complementary measures of mobility.

Rank Gap is a continuous measure of mobility expressed in percentile points, with different comparison baselines depending on the dimension of mobility I am looking at. Percentile ranks range from 0 to 100, representing an individual's position in the national wealth distribution. For **intergenerational** mobility, I calculate the rank gap by comparing the child's percentile rank at horizon h with the parent's rank at $t-1$:

$$RG^{IG}_{i,t,h} = y_{i,t+h} - p_{i,t-1}$$

For **pre-entry** mobility, I compare the child's and parent's percentile ranks both measured at the entry year:

$$RG^{PRE}_{i,t} = y_{i,t} - p_{i,t}$$

For **post-entry** mobility, I compare the child's rank at horizon h with their own rank at t:

$$RG^{POST}_{i,t,h} = y_{i,t+h} - y_{i,t}$$

where $y_{i,t}$ represents individual i's wealth percentile rank at time t, and $p_{i,t}$ represents the parental wealth percentile rank. When both parents are present, I use the higher-wealth parent's rank. The notation $t-1$ denotes the year immediately prior to entrepreneurship entry, t represents the entry year, and $h \in \{5, 10\}$ indicates outcomes measured 5 and 10 years post-entry. Rank-based measures have three advantages: they are invariant to the skewness of the wealth distribution, directly comparable across cohorts and time periods, and produce approximately linear intergenerational relationships (Chetty et al., 2014).

Upward Movement is a binary indicator that equals 1 if an individual moves to a higher wealth quintile than their comparison baseline. Wealth quintiles are constructed by dividing the percentile distribution into five equal groups: Q1 (0-20th percentile), Q2 (20-40th percentile), Q3 (40-60th percentile), Q4 (60-80th percentile), and Q5 (80-100th percentile). For **intergenerational** mobility, upward movement occurs when the child's wealth quintile

at horizon h exceeds the parent's quintile at $t-1$:

$$UM_{i,t,h}^{IG} = \mathbf{1}[Q_{i,t+h}^{child} > Q_{i,t-1}^{parent}]$$

For **pre-entry** mobility, upward movement is measured when the child's quintile at entry exceeds the parent's quintile at entry:

$$UM_{i,t}^{PRE} = \mathbf{1}[Q_{i,t}^{child} > Q_{i,t}^{parent}]$$

For **post-entry** mobility, upward movement occurs when the individual's quintile at horizon h exceeds their own quintile at t:

$$UM_{i,t,h}^{POST} = \mathbf{1}[Q_{i,t+h}^{child} > Q_{i,t}^{child}]$$

This measure captures discrete upward transitions across major wealth categories, complementing the continuous rank gap by focusing on whether individuals cross salient thresholds rather than how far they move within a given quintile.

Top 10% Achievement is a binary variable that equals 1 if an individual reaches the top decile of the wealth distribution (≥90th percentile). This measure represents an absolute wealth threshold but varies in timing depending on the dimension of mobility I am looking at. For **intergenerational** and **post-entry** mobility, top 10% achievement is measured at horizon h:

$$T10_{i,t,h} = \mathbf{1}[y_{i,t+h} \geq 90]$$

For **pre-entry** mobility, top 10% achievement is measured at the entry year:

$$T10_{i,t} = \mathbf{1}[y_{i,t} \geq 90]$$

While the threshold (90th percentile) remains constant across dimensions, the timing differs: pre-entry analysis examines top wealth tier entry at business formation, while the other dimensions assess top wealth tier entry at post-entry horizons. A positive entrepreneurship

effect indicates that starting a firm increases the probability of reaching the top decile, whether measured at entry or at subsequent horizons. The top 10% threshold is motivated by the descriptive evidence that entrepreneurs are heavily concentrated in the upper tail of the wealth distribution (Section 2) and by the finding that wealth persistence is strongest at the top (Fagereng et al., 2020). Table B.23 summarizes the three dimensions and three measures and how they interact.

4 Results

I organize the results into five parts. I first establish the baseline effects of entrepreneurship on wealth mobility across all three dimensions. I then examine heterogeneity by parental wealth background, showing that entrepreneurs whose parents are in the middle of the wealth distribution see the strongest intergenerational rank gains. Third, I extend the analysis to education level, where entrepreneurs with the least formal education exhibit the largest relative gains but the lowest probability of reaching the top decile. Fourth, I explore variation by field of study, revealing that engineering and science graduates see the strongest outcomes for reaching the top of the distribution while business graduates see the weakest mobility effects across nearly every metric. Finally, I present evolution plots showing how wealth and income trajectories diverge for entrepreneurs and matched non-entrepreneurs over time.

4.1 Baseline effects across mobility dimensions

The baseline specification compares mobility outcomes between entrepreneurs and a reweighted sample of non-entrepreneurs who are identical on observable pre-entry characteristics including parental wealth, own wealth, educational attainment, demographics, and life-cycle stage. The entropy balancing procedure generates weights such that the comparison group has the same mean characteristics as entrepreneurs on all covariates, constructing a counterfactual for what entrepreneurs would have experienced had they remained in wage employment.

$$y_{i,t+h} = \alpha + \beta \cdot \text{New Entrepreneur}_{i,t} + \lambda_{\text{entry_year}} + \lambda_{\text{municipality}} + \lambda_{\text{education}} + \lambda_{\text{par_q}} + \varepsilon_{i,t,h} \quad (1)$$

where $y_{i,t+h}$ represents the mobility outcome for individual i who entered entrepreneurship at time t, measured at horizon $h \in \{5, 10\}$ years post-entry. The dependent variable takes different forms depending on the mobility metric: rank gap (percentile point change), upward movement (binary quintile improvement indicator), or top 10% achievement (binary top 10% indicator). The coefficient β captures the effect of entrepreneurship entry on mobility outcomes. The model includes fixed effects for entry year ($\lambda_{\text{entry_year}}$), municipality of residence ($\lambda_{\text{municipality}}$), detailed education classification ($\lambda_{\text{education}}$), and parental wealth quintile ($\lambda_{\text{par_q}}$). For pre-entry specifications, outcomes are measured at t rather than $t+h$ to capture mobility at the time of entry into entrepreneurship. For post-entry specifications, the dependent variable measures change relative to the individual's own pre-entry position rather than parental benchmarks.

I report the baseline results for intergenerational mobility using entropy-balanced weights in Table B.24. Entrepreneurs advance 6.4 percentile points beyond their parents' wealth position within five years of entry, rising to 7.8 percentile points at the ten-year horizon. The probability of moving to a higher wealth quintile is 6.2 percentage points higher for entrepreneurs than matched non-entrepreneurs at five years. Entrepreneurship increases the probability of reaching the top decile by 14.5 percentage points at the five-year horizon, growing to 18.8 percentage points by year ten.

Comparing these estimates with those from the same specification without entropy balancing (Table B.36) illustrates the importance of addressing selection on observables. The unweighted entrepreneur coefficient for the rank gap is 16.4 percentile points. More than double the balanced estimate of 6.4, a 61% reduction attributable to observable selection. The top decile coefficient falls from 24.2 to 14.5 percentage points, a 40% reduction. Observable selection thus accounts for a large share of the raw mobility gap, though the share varies across metrics: selection explains more of the average rank displacement than it does of the probability of reaching the upper tail.

These effects on intergenerational mobility are substantial, but a central question is whether entrepreneurs accumulate wealth after entry or whether individuals who are already on upward trajectories select disproportionately into entrepreneurship. To distinguish between these channels, I compare the intergenerational results with outcomes measured at the moment of entry and with changes relative to entrepreneurs' own positions at entry.

I report the results for pre-entry mobility in Table B.28. Compared to matched non-entrepreneurs, future entrepreneurs already sit 3.9 percentile points above their parents before starting a firm. They are 3.6 percentage points more likely to have moved to a higher wealth quintile than their parents, and 6.6 percentage points more likely to be in the top decile. These pre-entry effects are roughly half the magnitude of the intergenerational effects observed five years post-entry, indicating that a meaningful share of the observed mobility reflects selection.

However, notable pre-entry advantages do not account for the full effect. The post-entry mobility results in Table B.32 show that entrepreneurs advance 3.3 percentile points relative to their own position at entry within five years, and are 8.6 percentage points more likely to move to a higher wealth quintile. These effects persist and grow at the ten-year horizon, reaching 5.0 percentile points and 9.0 percentage points, respectively. All estimates are significant at the 1% level.

Taken together, the three dimensions tell a consistent story. Selection accounts for a somewhat larger share of the intergenerational rank gap than post-entry accumulation (3.9 versus 3.3 percentile points), but the post-entry gains are highly significant and economically meaningful. The fact that the pre-entry and post-entry effects roughly sum to the total gap provides a useful consistency check. However, the pre-entry estimate of 3.9 percentile points has a caveat. Since I measure the ranks for both the parent and the child at the entry year, any intergenerational transfers around entry would widen the rank gap mechanically. Robustness checks measuring both parental and child ranks at $t-1$ show a pre-entry rank gap of 1.5 percentile points (Table B.48), suggesting that the entry-year estimate captures not only pre-existing mobility, but also wealth changes that coincide with entry itself such as firm capitalization or intergenerational transfers. The post-entry gains benchmarked against the entrepreneur's own pre-entry wealth remains sizeable under all specifications. If inheritance or unobserved selection alone drove the intergenerational gap, post-entry gains should be negligible. They are not.

The baseline estimates capture the average effect of entrepreneurship across the full sample of entrants. However, the descriptive evidence in Section 2 showed that entrepreneurs are disproportionately drawn from wealthy families: the top parental wealth decile alone accounts for 31% of entrepreneurs (Table B.7). A natural question is whether the mobility

gains are concentrated among those who start with advantages, or whether entrepreneurship generates upward movement across the distribution. I now turn to heterogeneity along three dimensions: parental wealth background, level of education, and field of study. For each analysis, the attribute of interest is excluded from the entropy balancing covariates to preserve variation along that dimension, while matching on all other observable characteristics. I match within entry year and age group cells throughout all specifications.

4.2 Heterogeneity by parental wealth

To examine whether the returns to entrepreneurship differ by family background, I divide individuals into quintiles based on their parents' position in the wealth distribution in the year prior to entry. Here, I compute separate entropy balancing weights that balance on own wealth rank, educational attainment, and gender, but exclude parental wealth rank from the set of covariates. By removing parental wealth from the balancing procedure, I allow entrepreneurs and non-entrepreneurs to differ along this dimension within each cell, enabling meaningful comparisons across quintiles. I extend the baseline model (1) by interacting entrepreneurship entry with parental quintile indicators with Q5 (the richest quintile) as the omitted category:

$$y_{i,t+h} = \alpha + \sum_{q \in \{Q1,\ldots,Q4\}} \beta_q \left(\text{New Entrepreneur}_{i,t} \times \mathbf{1}\{P_{i,t-1} = q\}\right) + \lambda_{\text{entry_year}} + \lambda_{\text{municipality}} + \lambda_{\text{education}} + \varepsilon_{i,t,h} \tag{2}$$

where P_i denotes individual i's parental wealth quintile and $\mathbf{1}\{P_{i,t-1} = q\}$ is an indicator variable equal to 1 if the parent belongs to quintile q at $t-1$. The coefficients β_q measure the entrepreneurship effect for each parental wealth quintile relative to the omitted category (Q5, the richest quintile). This specification allows me to test whether entrepreneurship's mobility effects vary systematically across the family wealth distribution. Note that parental wealth quintile fixed effects ($\lambda_{\text{par_q}}$) are excluded from this specification to avoid perfect collinearity with the linear terms, as the full set of interactions fully saturate the parental wealth categories.

I present the results for intergenerational mobility by parental wealth in Table B.25. The point estimates for the rank gap at the five-year horizon are largest for entrepreneurs

whose parents are in the middle of the distribution: 7.5 percentile points for Q3 and 7.3 for Q2, compared with 5.5 for Q5. The Q1 estimate is also sizeable at 7.0 percentile points, though the interaction term is imprecisely estimated due to the smaller sample in this group (912 entrepreneurs, Table B.9). The Q4 estimate falls between these groups at 6.7 percentile points. While the differences across Q1 through Q3 are not individually statistically distinguishable from one another, the gap between the middle quintiles and Q5 is both economically meaningful and statistically significant.

The differences are more pronounced for upward quintile mobility. Entrepreneurs from Q4 are 15.0 percentage points more likely to move to a higher wealth quintile than their parents, followed by Q3 at 13.3 percentage points and Q2 at 6.1. The Q1 effect is smaller at 3.9 percentage points. These estimates are relative to Q5, for which the base effect is essentially zero. The near-zero base for Q5 reflects a mechanical ceiling: parents in the top wealth quintile cannot, by construction, have children who move to a higher quintile. The large Q4 effect is therefore particularly informative, as it captures the probability that entrepreneurs from near-top backgrounds break into the top tier.

The pattern reverses for the probability of reaching the top decile. The Q5 base effect is 16.6 percentage points, and all four interaction terms are negative, indicating that entrepreneurs from the richest backgrounds are the most likely to reach or remain in the top decile. The total effects range from 11.8 percentage points for Q4 to 12.8 for Q2, with Q1 at 12.5. These differences are smaller in absolute terms than those for the rank gap or upward movement, but the consistent pattern is clear: access to the top of the distribution is most strongly associated with entrepreneurship among those who already come from wealth.

Entrepreneurship thus serves different functions depending on where in the parental wealth distribution one starts. It generates the largest intergenerational rank gains for those in the middle, the highest probability of reaching the top decile for those already near the top, and positive but imprecisely estimated effects at the bottom. These patterns are consistent with entrepreneurship facilitating upward mobility for middle-wealth families while reinforcing persistence at the very top.

The pre-entry estimates in Table B.29 give additional insights into the heterogeneity observed in intergenerational outcomes. Future entrepreneurs across all parental quintiles exhibit positive pre-entry mobility relative to matched non-entrepreneurs, but the magnitudes differ.

The pre-entry rank gap is largest for Q2 (5.2 percentile points) and Q1 (5.1), and smaller for Q3 (4.7), Q4 (4.4), and Q5 (2.8). Entrepreneurs from less wealthy backgrounds thus show larger pre-entry advantages, suggesting that selection into entrepreneurship from the bottom of the distribution is more strongly associated with already being on an upward trajectory. The pattern for upward quintile mobility differs: Q3 (7.9 pp) and Q4 (7.0 pp) show the largest pre-entry effects, while Q2 is lower (4.9 pp). As with the intergenerational specification, the Q5 base for upward mobility is mechanically zero.

The post-entry results in Table B.33 show the wealth gains that entrepreneurs accumulate after entry. Entrepreneurs with the wealthiest parents (Q5) advance 2.4 percentile points relative to their own position at entry, and entrepreneurs from Q3 show a comparable gain of 2.4 percentile points. The remaining quintiles are lower: 1.7 for Q4, 1.3 for Q2, and 0.9 for Q1, though none of the interaction terms are statistically significant at conventional levels. The post-entry rank gains are thus modest and relatively uniform across the parental wealth distribution. The picture is somewhat different for upward quintile mobility, where the middle quintiles show the largest post-entry effects: 6.4 percentage points for Q3 and 6.0 for Q2, compared with 5.3 for Q4, 5.1 for Q1, and 3.2 for Q5.

Examining all three dimensions together, a clear pattern emerges regarding the relative roles of selection and post-entry wealth accumulation. For Q1 entrepreneurs, the pre-entry rank gap (5.1 percentile points) far exceeds the post-entry gain (0.9), consistent with selection playing the dominant role. The same holds for Q2, where the pre-entry gap of 5.2 dwarfs the post-entry gain of 1.3. For Q3, selection is still the larger contributor (4.7 versus 2.4), but the post-entry gains are more meaningful. For Q5, the two components are roughly equal (2.8 versus 2.4). The gradient is instructive: the further down the parental wealth distribution, the more the intergenerational rank gap is attributable to who selects into entrepreneurship rather than what happens after entry.

These patterns are reinforced by differential survival. Five-year survival rates rise from roughly 60% for Q1 to approximately 80% for Q5 (figure A.6), consistent with differential access to financial resources and fallback options across the parental wealth distribution.

Parental wealth shapes both the magnitude and nature of entrepreneurial mobility gains. But human capital represents a second, potentially independent channel. Highly educated individuals may have access to different types of ventures, different networks, and different

fallback options in the labor market. I now turn to how mobility patterns vary by education level.

4.3 Heterogeneity by level of education

I next examine whether the mobility effects of entrepreneurship vary by education level. I group individuals into four categories: those with secondary education (less than high school), high school graduates, bachelor's degree holders, and those with a master's degree or PhD. I compute entropy balancing weights that balance on own wealth rank, parental wealth rank, and gender, but exclude education identifiers from the set of covariates. I extend the baseline model (1) by interacting entrepreneurship entry with education-level indicators, with secondary education as the omitted category:

$$y_{i,t+h} = \alpha + \sum_{e \in \{\text{HS,BA,MA/PhD}\}} \gamma_e \left(\text{New Entrepreneur}_{i,t} \times \mathbf{1}\{\text{Edu}_{i,t} = e\} \right) + \lambda_{\text{entry_year}} + \lambda_{\text{municipality}} + \lambda_{\text{par_q}} + \varepsilon_{i,t,h} \tag{3}$$

where Edu_i denotes individual i's highest educational attainment and $\mathbf{1}\{\text{Edu}_i = e\}$ is an indicator variable equal to 1 if the individual has education level e. The coefficients γ_e measure the entrepreneurship effect for each education level relative to the omitted category (Secondary education). This specification tests whether entrepreneurship's mobility effects vary by human capital endowments. Unlike the parental wealth specification, education fixed effects ($\lambda_{\text{education}}$) are excluded to avoid collinearity with the interaction terms, while parental wealth quintile fixed effects ($\lambda_{\text{par_q}}$) are retained as they remain orthogonal to the education interactions.

Table B.26 shows that entrepreneurs with the least formal education exhibit the strongest intergenerational rank gains. Entrepreneurs who have not completed high school advance 9.9 percentile points beyond their parents within five years of entry. The gains are lower for the other education groups: 5.8 percentile points for high school graduates, 6.9 for those with a bachelor degree, and 5.3 for those with a master degree or PhD. The pattern is not strictly monotonic: bachelor graduates gain more than high school graduates. The interaction terms for high school (-4.1) and master/PhD (-4.7) are of similar magnitude, while the bachelor interaction is smaller (-3.0), suggesting that the bachelor degree, perhaps through its combi-

nation of human capital and relatively lower opportunity cost compared with postgraduate education, is associated with stronger entrepreneurial returns in relative terms.

The pattern reverses sharply for the probability of reaching the top decile. The total effects increase monotonically with education: 12.5 percentage points for secondary, 12.6 for high school, 18.6 for bachelor, and 20.1 for master/PhD. The interaction terms for bachelor (+6.1 pp) and master/PhD (+7.6 pp) are both large and significant at the 1% level, while the high school interaction is essentially zero. Entrepreneurship thus appears to serve different functions across educational levels. For those with limited formal education, it is associated with substantial movement up the wealth distribution in relative terms. For the highly educated, the relative rank gains are more modest, but the probability of reaching the very top is considerably higher. The pre-entry mobility results in Table B.30 show that future entrepreneurs with secondary education have the largest pre-entry rank gap at 8.5 percentile points relative to their parents. The gaps are smaller for the other groups, though the ordering differs from the intergenerational pattern: bachelor graduates show a pre-entry gap of 3.9 percentile points, master/PhD of 2.8, and high school graduates of 2.7, with high school and master/PhD reversing their relative positions compared to the intergenerational results. The top-decile results show a different pattern. Here, master/PhD holders show the strongest pre-entry advantage, being 11.4 percentage points more likely to be in the top decile at entry, compared with 5.9 for secondary education. In other words, secondary-educated entrepreneurs stand out for how far they had already moved up the distribution before starting a firm, while highly educated entrepreneurs stand out for how high they already were.

The post-entry results in Table B.34 reveal a relatively flat pattern for rank gains across education levels. Secondary-education entrepreneurs advance 3.4 percentile points relative to their own position at entry, compared with 3.8 for high school, 3.1 for bachelor, and 2.4 for master/PhD. None of the interaction terms are statistically significant at the five-year horizon, though the master/PhD interaction reaches significance at the ten-year horizon (-3.0 pp, significant at 1%), suggesting that the divergence between education groups grows over time.

The pattern is more differentiated for upward quintile mobility after entry. Entrepreneurs with secondary education are 11.1 percentage points more likely to move to a higher wealth

quintile, declining monotonically to 10.1 for high school, 7.1 for bachelor, and 4.4 for master/PhD. The substantially lower figure for master/PhD holders likely reflects a ceiling effect: these entrepreneurs tend to start at higher wealth quintiles, leaving less room for quintile transitions. Their gains are more likely to show up as movement within the top of the distribution, consistent with the strong top decile effects observed in the intergenerational specification.

Taken together, the three dimensions suggest that entrepreneurship serves as a vehicle for wealth mobility across all education levels, but through different mechanisms and with different implications. For entrepreneurs with only secondary education, the pre-entry rank gap (8.5 percentile points) is large relative to the post-entry gain (3.4), consistent with selection playing a more prominent role: these individuals were already moving up the distribution before starting a firm. For the more educated groups, the pre-entry gaps are smaller relative to the post-entry gains, pointing to a larger role for entrepreneurship itself. The sharpest heterogeneity, however, emerges in who reaches the top of the distribution. Highly educated entrepreneurs, particularly those with a master degree or PhD, are far more likely to enter the top decile, both because they start closer to it and because entrepreneurship pushes them further in. Less-educated entrepreneurs, by contrast, achieve larger rank gains in relative terms but rarely break into the top decile. The comparison with unbalanced estimates (Table B.37) reinforces the importance of selection for the least-educated group: entropy balancing reduces the secondary-education entrepreneur coefficient from 25.8 to 9.9 percentile points, indicating that a large share of the raw gap is attributable to observable differences.

The preceding analysis captures the quantity of human capital but not its content. An entrepreneur with a business degree and one with an engineering degree may have equivalent years of schooling but bring fundamentally different skills to a venture. I now disaggregate by field of study. Since field of education is only identified for individuals with higher education, the sample composition should be borne in mind when interpreting the results.

4.4 Heterogeneity by field of study

Finally, I examine whether the type of education matters for entrepreneurial success by grouping individuals according to their field of study. I focus on individuals with higher education and categorize them into four categories: business, science, engineering, and those

with degrees that span multiple (i.e. among business, science, and engineering) fields. I use the same entropy balancing weights as in the education heterogeneity analysis, since field of study and level of education are both contained in the 3-digit NUS codes used. This ensures that comparisons across fields are not confounded by differences in wealth or demographic characteristics. I extend the baseline model (1) by interacting entrepreneurship entry with the field of study indicators, with the other/none category as the omitted group:

$$y_{i,t+h} = \alpha + \sum_{f \in \{\text{Business,Science,Engineering,Multiple}\}} \delta_f \left(\text{New Entrepreneur}_{i,t} \times \mathbf{1}\{\text{Field}_{i,t} = f\}\right) + \lambda_{\text{entry_year}} + \lambda_{\text{municipality}} + \lambda_{\text{education}} + \lambda_{\text{par_q}} + \varepsilon_{i,t,h} \quad (4)$$

where Field_i denotes individual i's educational field and $\mathbf{1}\{\text{Field}_{i,t} = f\}$ is an indicator variable equal to 1 if the highest level of education the person attained belongs to field f. The coefficients δ_f measure the entrepreneurship effect for each field of study relative to the omitted category (Other/None fields). A person is classified as having education in multiple fields only if they fall into more than one of the three explicitly specified categories here. This specification examines whether specialized knowledge domains moderate entrepreneurship's mobility effects. All fixed effects from the baseline model are retained.

The omitted category comprises approximately 84% of the sample (Table B.6) and is highly heterogeneous. The interaction coefficients therefore measure deviations from a broad population average, not from a clean counterfactual.

Table B.27 shows notable differences in intergenerational mobility by field of study. Entrepreneurs in the omitted group advance 6.9 percentile points beyond their parents within five years. The gains are significantly lower for entrepreneurs with a business education: the interaction term is -4.2 percentile points (significant at the 1% level), yielding a total effect of only 2.7 percentile points. The interaction terms for science (-1.5) and engineering (-0.7) are also negative but neither is statistically significant, yielding total effects of 5.3 and 6.2 percentile points, respectively. Engineering graduates thus see intergenerational rank gains comparable to the omitted group, while business graduates see markedly weaker outcomes. The business disadvantage extends to upward quintile mobility, where business graduates are 5.3 percentage points less likely to move to a higher quintile than the omitted group, leaving them with a total effect of only 1.5 percentage points. The most striking field-specific

results appear for the probability of reaching the top decile. Engineers are 6.1 percentage points more likely than the omitted group to reach the top decile (significant at 1%), yielding a total of 20.4 percentage points. The science coefficient is larger in magnitude (+8.2 pp) but only marginally significant, reflecting the small sample of science entrepreneurs (285 individuals, Table B.6). Business graduates show no differential effect on the probability of reaching the top decile (interaction of -0.8, not significant).

The pre-entry results in Table B.31 show notable differences across fields. Entrepreneurs with a business education show a pre-entry rank gap of only 0.3 percentile points relative to their parents, compared with 4.1 for the omitted group. Science graduates are similarly low at 0.8 percentile points. These results suggest that entrepreneurs with business or science backgrounds exhibit essentially no pre-entry wealth mobility advantage. Engineering graduates, by contrast, maintain a substantial pre-entry rank gap (3.6 points) and are 10.8 percentage points more likely to be in the top decile at entry, the highest of any field. Their intergenerational gains thus reflect a combination of pre-existing advantages and post-entry accumulation.

The post-entry results in Table B.35 complete the picture. For rank gains, the omitted group advances 3.5 percentile points, with business graduates showing significantly lower gains (1.7 pp; interaction of -1.7, significant at 1%). The science (-0.3) and engineering (-0.6) interactions are negative but neither is statistically significant, yielding total rank gains of 3.1 and 2.8 percentile points, respectively.

For upward quintile mobility after entry, the patterns diverge. Business graduates are 6.0 percentage points less likely to move to a higher quintile than the omitted group, yielding a total effect of only 3.4 percentage points. Engineering graduates are also significantly lower (-4.1 pp interaction), with a total of 5.3 percentage points. Science graduates, by contrast, show no differential effect relative to the omitted group (interaction of +0.6 pp, not significant), yielding a total of 10.0 percentage points, essentially identical to the omitted group's 9.4.

Looking across the three dimensions, science graduates stand out. They show virtually no pre-entry wealth advantage (a rank gap of 0.8 percentile points), yet achieve large intergenerational gains (5.3 pp) and the largest point estimate for reaching the top decile (+8.2 pp, though imprecisely estimated). This combination suggests that their mobility is driven

primarily by what happens after they start a firm, not by who selects into entrepreneurship. Engineering graduates present a different picture: they already hold strong positions before entry (3.6 pp rank gap, 10.8 pp more likely to be in the top decile at entry) and continue to gain afterward, suggesting that both selection and the entrepreneurial experience contribute. Business graduates show the weakest outcomes across nearly every dimension: low pre-entry mobility, low intergenerational gains, and no differential probability of reaching the top decile.

4.5 Dynamics of wealth accumulation

The regression estimates capture average treatment effects at discrete post-entry horizons but do not reveal how these effects emerge and evolve around the moment of entry. To complement the regression results, I construct evolution plots that trace the paths of key outcomes for entrepreneurs and their matched non-entrepreneur counterparts from five years before entry through ten years after.

Constructing the Evolution Plots I measure all outcomes relative to event time t, where t denotes the year an individual first enters entrepreneurship. For entrepreneurs, event time is based on the actual year of entry: an entrepreneur who enters in 2005 contributes their 2003 outcome to $t = -2$, their 2005 outcome to t, and their 2010 outcome to $t = +5$. I compute the simple mean of each outcome variable across all entrepreneurs observed at each event time.

For the control group, I construct a pseudo-counterfactual trajectory using the entropy balancing weights from my main analysis. Each non-entrepreneur receives a weight in a specific calendar year based on the entropy balancing procedure described in Section 3. The same control individual may enter in multiple years with different weights, as they would in the main regressions. I take each calendar year as the control individual's "pseudo-entry year" and compute their event time relative to the current year. For a non-entrepreneur who receives an entropy balancing weight in 2007, I use their 2002 outcome for $t = -5$, their 2007 outcome for t, and their 2012 outcome for $t = +5$. I then calculate the weighted mean across all control observations at each event time, using the entropy balancing weights. While less tightly identified than the regressions, the plots approximate a control trajectory for

individuals who, at the moment of potential entry, were statistically identical to those who actually became entrepreneurs.

I look at both the level and percentile rank of gross wealth, total income, wage income to look at broad trends in income and wealth. I also look at the level of bank deposits and capital income to compare the saving behavior and potential returns to investment between entrepreneurs and non-entrepreneurs. For each variable, I plot both the entrepreneur trajectory (solid line) and the weighted control trajectory (dashed line) against event time.

The trajectory of mean wealth percentile rank (Figure A.9) shows that entrepreneurs are on a slightly higher wealth path pre-entry, growing at roughly the same rate as non-entrepreneurs until one year before entry. Following entry, the gap widens substantially. This visual pattern is consistent with the regression results in Table B.24: the 6.4 percentile-point rank gap at year 5 and 7.8 at year 10 are visible as a growing wedge between the two trajectories. The trajectory for income percentile ranks differs by measure. When I look at salaries (Figure A.11), entrepreneurs appear to be on a slightly lower path than matched non-entrepreneurs in the pre-entry period, but move marginally ahead after entry. The total income percentile rank (Figure A.10), which includes capital income, is higher for entrepreneurs throughout the fifteen-year window, with a slight dip around entry. The divergence between salary and total income trajectories is consistent with entrepreneurs substituting capital income for wage income as they shift from employment to ownership.

When I turn my focus to the actual level of wealth and income, similar patterns persist for total gross wealth (Figure A.21) and total income (Figure A.22). However, entrepreneurs do not have lower average salary levels than comparable non-entrepreneurs in the pre-entry period (Figure A.23), despite their lower salary percentile ranks. This divergence between levels and ranks can be driven by a small number of future entrepreneurs with very high salaries pushing the mean upward without influencing the rank distribution.

Heterogeneity Analysis I extend the evolution plots to examine how wealth and income trajectories differ across subgroups using the same structure as in sections 4.2, 4.3, and 4.4. Here, I also use the same entropy balancing weights I do in each of the heterogeneity regressions. Each plot displays all subgroup trajectories simultaneously, with solid lines representing entrepreneurs and dashed lines representing non-entrepreneurs.

For parental wealth heterogeneity, I divide individuals into quintiles based on their parents' wealth percentile in the year prior to entry (or the matched year for controls). I compute entrepreneur and control means following the same procedure as above, but separately for each quintile. This reveals whether the returns to entrepreneurship differ systematically by family wealth background.

There are some interesting patterns in the gross wealth percentile rank as illustrated in Figure A.12. The Q5 wealth rank trajectory is the highest throughout for both entrepreneurs and non-entrepreneurs. The more revealing patterns lie elsewhere. For Q1 and Q2 entrepreneurs, the trajectories track their matched controls closely in the pre-entry period, with the gap opening primarily after entry. For Q5 entrepreneurs, by contrast, there is almost no difference prior to entry, and while entrepreneurs gain more after entry, the gap doesn't widen very sharply. Perhaps the most striking feature is that Q1 entrepreneurs eventually surpass non-entrepreneurs from the middle quintiles in average wealth rank, suggesting that firm ownership can ultimately compensate for a substantial initial disadvantage even if the short-run estimates are noisy. The total income trajectories (Figure A.13) tell a broadly similar story, though the gaps between entrepreneurs and controls are more compressed, reinforcing the importance of examining wealth to capture the full extent of entrepreneurial returns. For educational heterogeneity, I split individuals into four groups: those with less than high school education, high school graduates, bachelor's degree holders, and those with a master's degree or PhD. I apply education-specific entropy balancing weights and compute separate trajectories for each education level.

The wealth trajectories (Figure A.15) show that the largest entrepreneur-versus-control gap belongs to those with secondary education. This group starts at the lowest wealth levels but diverges sharply from their controls after entry. For the more educated groups, the levels are higher throughout but the gaps are narrower. The total income trajectories (Figure A.16) make this contrast clearer: for the higher-educated groups, entrepreneurs and non-entrepreneurs move largely in tandem, while for those with secondary education the income gap is wider, consistent with the regression finding that the largest relative rank gains belong to the least educated. The fact that these gaps are wider for wealth than for income across all education groups suggests that entrepreneurial wealth accumulation operates partly through channels other than current income, such as retained business

equity or capital gains.

For field of study heterogeneity, I focus on individuals with higher education and categorize them by their primary field: business, science, engineering, or multiple fields. I again use the education-specific weights and compute field-specific trajectories. I exclude individuals classified as "other" fields from this analysis.

The wealth trajectories (Figure A.18) show that all groups of entrepreneurs pull ahead of their matched controls after entry. Engineering entrepreneurs start at the highest levels and reach the top of the distribution by ten years out. Business entrepreneurs also show a sharp increase in wealth after entry, separating substantially from their controls despite starting at lower levels. Science entrepreneurs start somewhat lower but diverge clearly from their controls, consistent with the regression finding that their mobility is driven primarily by post-entry accumulation. The income trajectories (Figure A.19) reveal a different picture. For science, engineering, and multiple-field graduates, entrepreneurs sit on a slightly higher income trajectory than their controls for most of the period. For business graduates, the pattern reverses: entrepreneurs follow a lower income trajectory than non-entrepreneurs for much of the observation window. This is the only field in which entrepreneurs are consistently outearned by their matched counterparts. The contrast between the wealth and income figures for business graduates is notable: they accumulate wealth at rates comparable to other fields, yet earn less than their non-entrepreneur peers, suggesting that their wealth gains operate through business equity or capital accumulation rather than higher current income.

4.6 Robustness

I conduct three sets of robustness checks. First, I examine the sensitivity of the pre-entry mobility estimates to the timing at which parent and child wealth are measured. Second, I estimate mobility between three years prior to entry and three years after entry to complement the main post-entry results. Third, I replicate the baseline and heterogeneity analyses using net wealth rather than gross wealth. In these tests, the sample composition of entrepreneurs changes slightly because of the availability of data across various horizons that are different in these specifications compared to the main results.

4.6.1 Pre-entry measurement timing

In the main pre-entry specification, I compare the child's wealth rank to the parent's rank measured at the year of entry (t). A concern here is that wealth transfers and inheritance around entry could inflate this comparison from both sides, i.e. a wealth transfer would lower the parent's wealth and increase the child's wealth simultaneously. To address this, I re-estimate the pre-entry specification with both the child's and the parent's wealth measured at $t-1$, one year before entry (Table B.48). I also run an alternative specification in which the child's wealth is measured at $t-1$ and the parent's wealth at $t-5$ (Table B.44). The rank gap drops from 3.9 percentile points in the main specification to 1.5 percentile points when both positions are measured at $t-1$, and to 1.4 percentile points when the parent is measured at $t-5$. The fact that the two estimates are quite close to each other indicate that the decline in mobility compared to the main specification is driven by the child's position, and not by fluctuations in parental wealth over time. The effects in the results concerning top 10% attainment, which entirely depends on the child's rank and not influenced by changes in parental wealth does not decline as sharply, going from 6.6 to 5.2 percentile points. The difference in the results between the main results and these robustness checks is more stark when looking at the rank gap, but more modest when looking at top 10% achievement. This suggests that some of the decrease in mobility observed in the robustness checks could be coming from changes in parental wealth because of intergenerational transfers.

The difference between the pre-entry rank gap at t (3.9 percentile points) and at $t-1$ (1.5 percentile points) provide an upper bound and lower bound on the mobility difference between entrepreneurs and non-entrepreneurs prior to entry. The difference between the two reflect entry-year wealth changes that could be driven by intergenerational wealth transfers as well as the entrepreneurial transition itself, including firm capitalization and asset reallocation. Importantly, the post-entry results where I compare the entrepreneur's wealth position after entry to their position at entry is not subject to these concerns.

The heterogeneous patterns in mobility at $t-1$ are closely aligned with the main results. The results based on level of education (Table B.46 and B.50) show the same pattern as the main pre-entry results: entrepreneurs with secondary education have the largest pre-entry rank gaps (5.5 percentile points), while all other groups have smaller gaps. The fact that

this pattern is already visible at $t-1$, rather than only at t reinforces that selection into entrepreneurship for entrepreneurs with lower levels of education is associated with upward mobility that precede entry into entrepreneurship. Business graduates show near-zero pre-entry gains across both specifications, consistent with the main results (Tables B.47 and B.51).

4.6.2 Mobility around entry

In the main post-entry specification, I compare the entrepreneur's rank at $h=5$ to their own rank at the year of entry. As a complement, I estimate a symmetric specification comparing the individual's rank at $t+3$ to their rank at $t-3$ to estimate mobility in a six-year window centered around entry (Table B.52).

Entrepreneurs gain 4.2 percentile points over this window, compared to 3.3 over the main post-entry specification (t to $t+5$). The larger effect over a shorter post-entry horizon reflects the fact that these estimates also include accumulation of wealth between $t-3$ and t. The difference of roughly one percentile point is consistent with the pre-entry trajectory discussed earlier. Upward quintile mobility in this specification (9.1 percentage points) is nearly identical to the estimates in the main specification (8.6 percentage points) suggesting that a large share of the upward transition effect is concentrated in the years immediately following entry rather than accumulating gradually over the five-year horizon.

In this symmetric window, entrepreneurs from the wealthiest families (Q5) have the largest rank gains (3.6 percentile points), with all the interaction terms negative (Table B.53). This is different from the main specification where the middle quintiles gain the most. When benchmarked against their own wealth, entrepreneurs from the wealthiest families accumulate wealth faster in the short run, consistent with access to more capital and ability to scale their business quickly. The magnitude of the intergenerational rank gains is smaller, but this could reflect the fact that they start closer to their parents in the distribution. The rank gains are relatively flat across education levels (Table B.54) not markedly different from the main post-entry results, but a wider gap in top 10% attainment confirms that highly educated entrepreneurs are much more likely to reach the upper tail of the wealth distribution.

4.6.3 Net wealth

I use gross wealth in my main analysis which captures the scale of economic resources under an individual's control more accurately, but this measure does not account for debt. Entrepreneurs are likely to be more leveraged than matched non-entrepreneurs, particularly in the years around their entry. To see how sensitive the results are to this choice, I replicate my main analysis using net wealth percentiles, defined as gross wealth minus total debt (Tables B.40 - B.43).

The rank gap in the baseline specification is essentially zero at the five-year horizon (-0.04 percentile points, not significant) but grows to 3.1 percentile points by year ten when looking at net wealth (Table B.40). The top 10% effect is roughly half compared to the gross wealth specification, but remains significant (6.4 percentage points at $h = 5$ and 11.7 at $h = 10$). This pattern is consistent with entrepreneurs taking on debt at entry, which reduces their net wealth rank in the short run, followed by a gradual reduction in personal debt as the business grows. The growth in accumulation of net wealth between the five-year and ten-year horizons mirrors the pattern with accumulation of gross wealth, but from a lower starting point. This suggests that the underlying wealth accumulation is not merely an artifact of leverage.

The results based on net wealth also provide some insights on the difference in pre-entry mobility results measured at time t and $t-1$. If the differences were primarily driven by intergenerational transfers, the rank gap should be positive at $h = 5$ as inherited wealth should add directly to net wealth. The insignificant effect on net wealth at $h = 5$ is more in line with the entry-year jump reflecting an increase in personal debt for firm capitalization which would inflate gross wealth, but leave the net wealth approximately unchanged.

There is one notable difference between the gross wealth and net wealth results when looking at heterogeneous effects by level of education (Table B.42). The coefficient for the omitted group (secondary education) is negative at the five-year horizon (-2.7 percentile points), while the interaction terms for all higher education levels are positive and significant. By year ten, the effect for the secondary education group is positive, but small. This suggests that entrepreneurs with less education rely more heavily on debt to finance entry. Highly educated entrepreneurs who may fund ventures with less personal debt, or generate returns

more quickly have positive effects using both measures.

There is no meaningful difference in the results across different groups of parental wealth (Table B.41) with the wealthiest entrepreneurs showing the strongest probability of being in or reaching the top decile.

5 Conclusion

In this paper, I ask whether entrepreneurship serves as a pathway to upward wealth mobility, and if so, for whom. Using Norwegian administrative data on 26,970 entrepreneurs and matched non-entrepreneurs, I decompose the intergenerational wealth rank gap into a pre-entry component, which captures selection, and a post-entry component, which captures accumulation after starting a firm. Both matter. Five years after entry, entrepreneurs advance 6.4 percentile points beyond their parents relative to matched non-entrepreneurs, but roughly half of this gap is already present at the time of entry. The post-entry gains are nonetheless substantial, indicating that entrepreneurship does more than simply attract individuals who were already on the way up.

These findings contradict the view that entrepreneurs do not gain financially relative to comparable employees (Hamilton, 2000), at least when the outcome is gross wealth rather than earnings. When debt is included, the short run effects are smaller, but they recover by year ten indicating that the underlying wealth accumulation is not merely an artifact of leverage. They also complement Lindquist and Vladasel (2025), who document positive intergenerational income mobility among incorporated entrepreneurs in Sweden. The fact that I find substantially higher income mobility than wealth mobility suggests that income gains coexist with more muted, but economically meaningful, mobility along the wealth distribution, consistent with the savings-based mechanism proposed by Quadrini (2000).

The heterogeneity results reveal that the aggregate effects mask important variation. Entrepreneurs from the poorest families show large intergenerational gains, but much of this reflects selection. Those from the middle of the parental distribution show the opposite pattern, with smaller pre-entry gaps and larger post-entry gains, suggesting they have the most to gain from entrepreneurship itself. At the top, entrepreneurship serves primarily as a wealth preservation mechanism, consistent with Fagereng et al. (2020). Education

introduces a further layer: the least educated achieve the largest relative rank gains, but the highly educated are far more likely to reach the top decile. Among fields, business education yields the weakest outcomes while science and engineering yield the strongest.

Entropy balancing achieves exact balance on observables but cannot account for selection on unobservables such as risk tolerance or ambition. The three-dimensional decomposition offers a partial check: if unobserved selection alone drove the intergenerational gap, post-entry gains should be negligible, and they are not. The evolution plots reinforce this interpretation, as the trajectories of entrepreneurs and matched controls move closely together before entry and diverge only afterward. Together with the detailed administrative data used for matching, these results provide stronger evidence against confounding than most earlier work on entrepreneurial returns

A Appendix: Figures

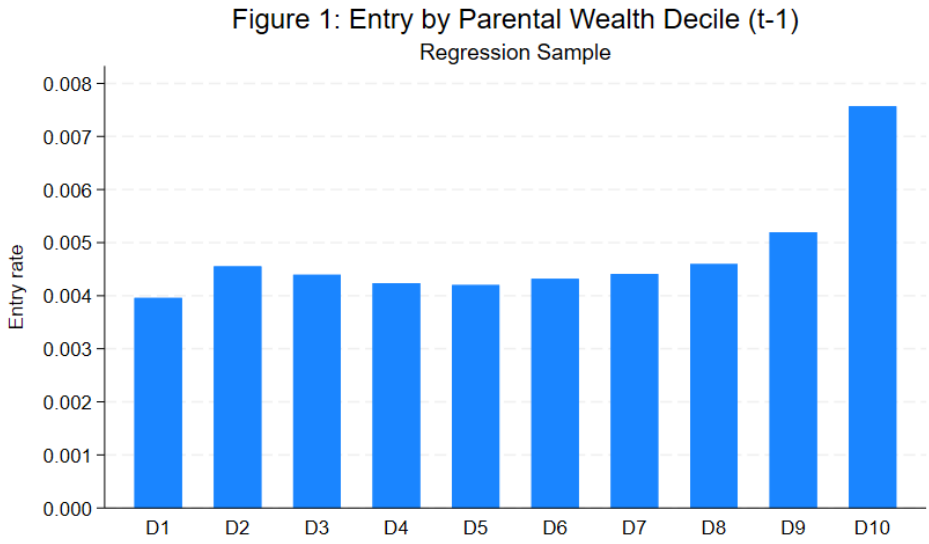


Figure A.1
Entry into Entrepreneurship by Parental Wealth Decile

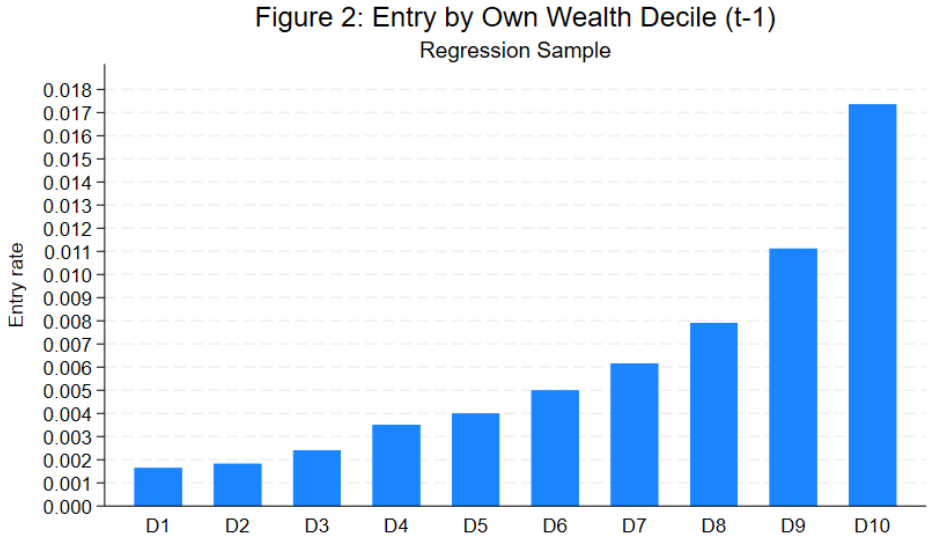


Figure A.2
Entry into Entrepreneurship by Own Wealth Decile

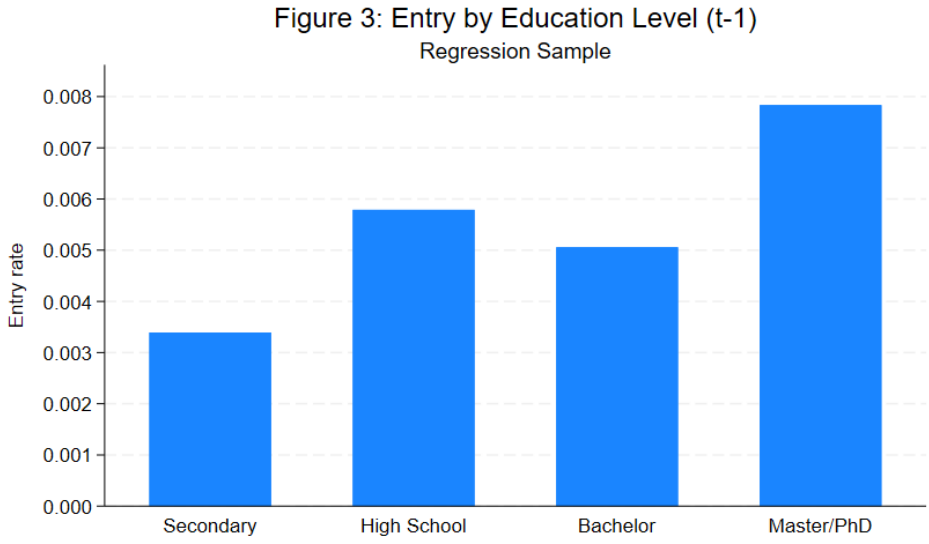


Figure A.3
Entry into Entrepreneurship by Education Level

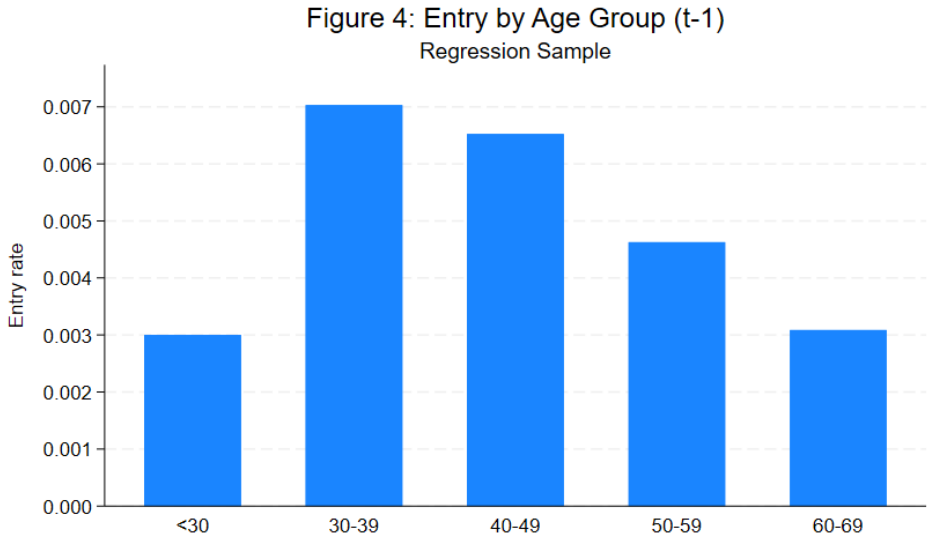


Figure A.4
Entry into Entrepreneurship by Age Group

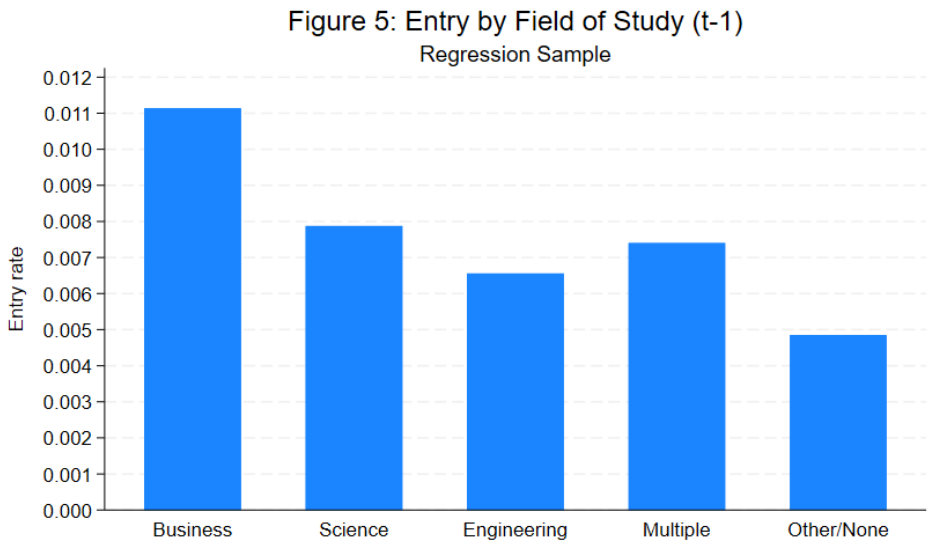


Figure A.5
Entry into Entrepreneurship by Industry Field

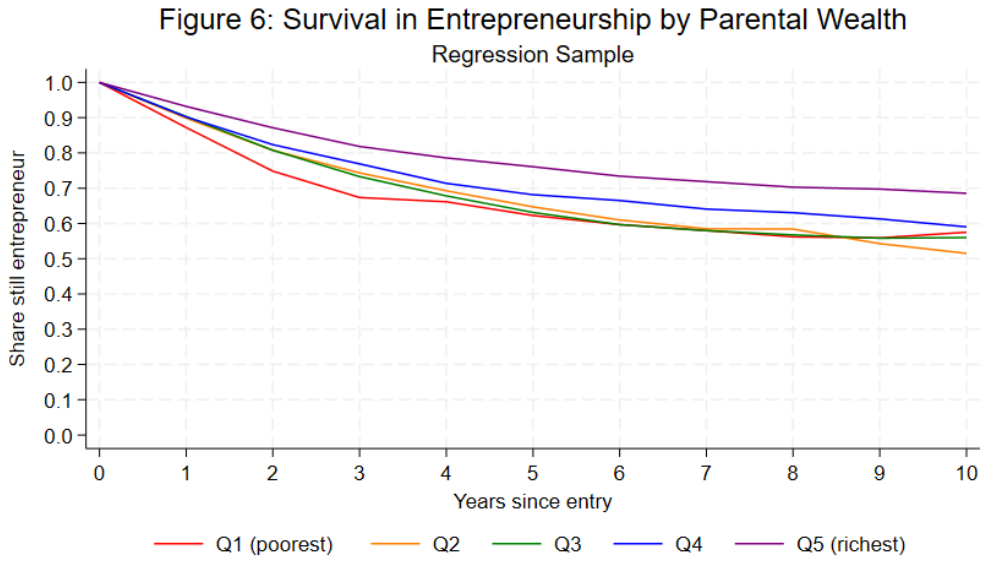


Figure A.6
Survival Curves for Entrepreneurs

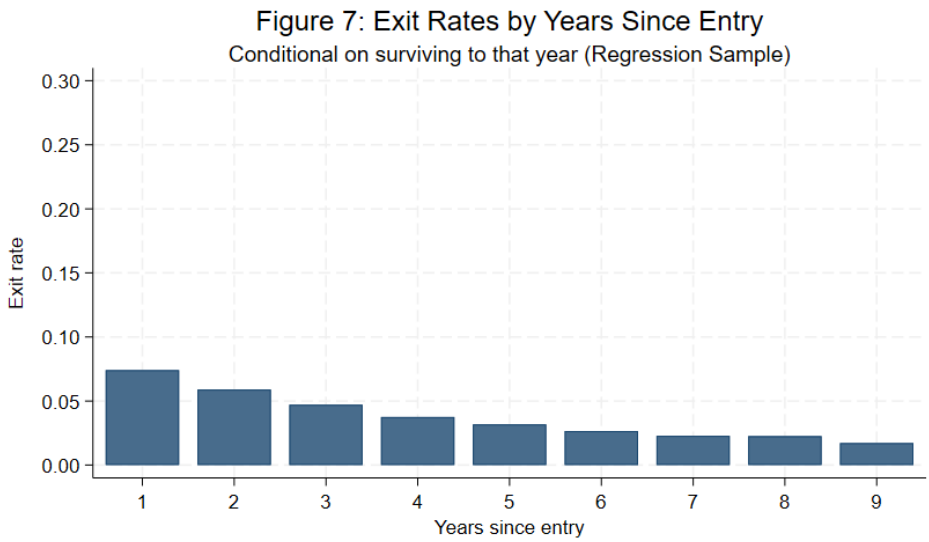


Figure A.7
Exit Rates from Entrepreneurship by Year

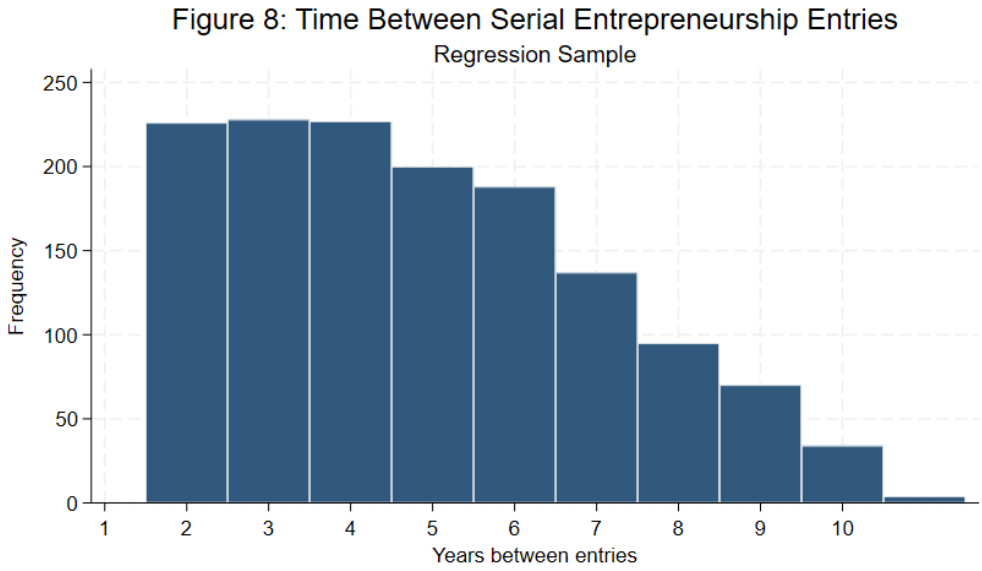


Figure A.8
Serial Entrepreneurship: Time Gaps Between Entries

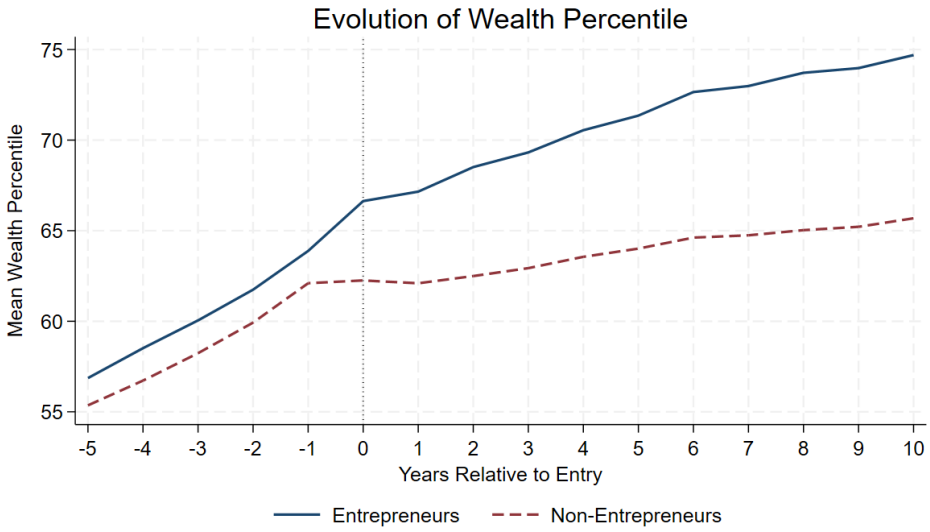


Figure A.9
Evolution of Gross Wealth Percentile: Entrepreneurs vs. Non-Entrepreneurs

Notes: Mean gross wealth percentile by years relative to entrepreneurship entry. Sample restricted to observations with entropy balancing weights.

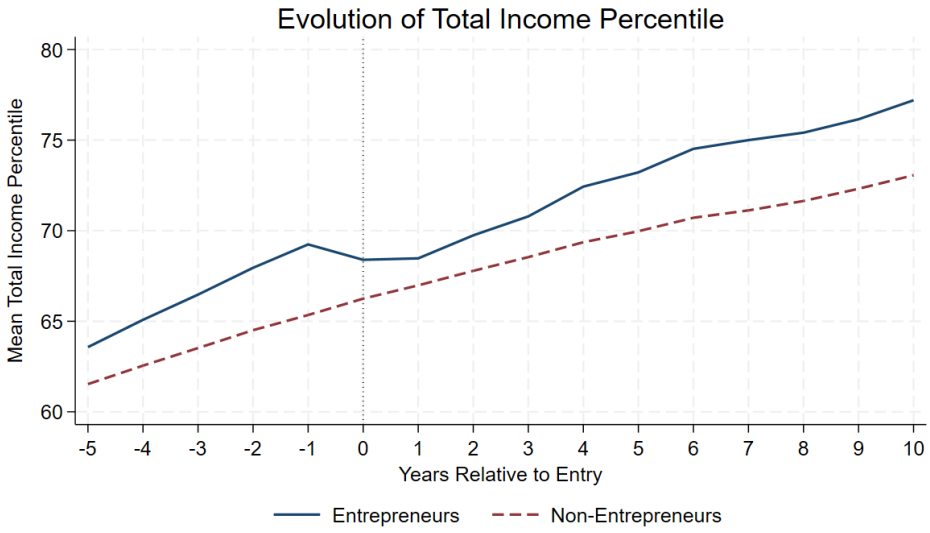


Figure A.10
Evolution of Total Income Percentile: Entrepreneurs vs. Non-Entrepreneurs

Notes: Mean total income percentile by years relative to entrepreneurship entry. Sample restricted to observations with entropy balancing weights.

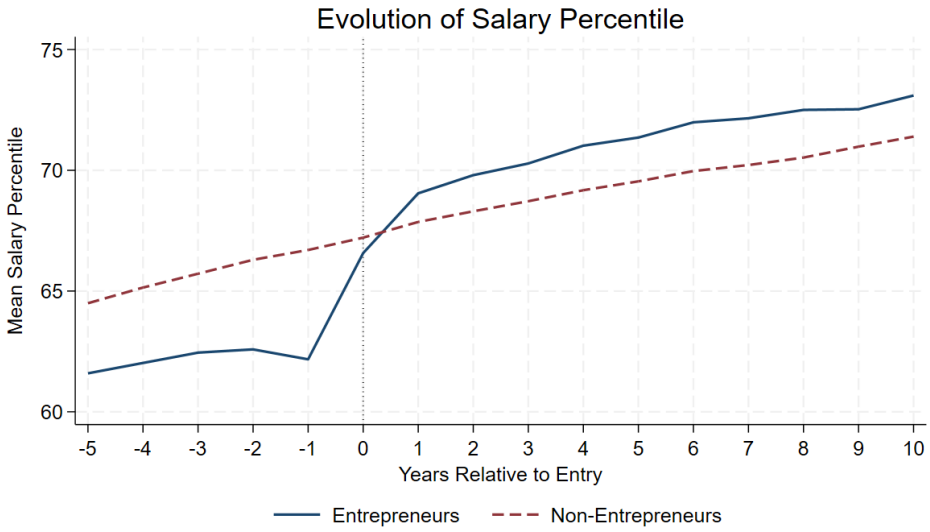


Figure A.11
Evolution of Wage Income Percentile: Entrepreneurs vs. Non-Entrepreneurs

Notes: Mean wage income percentile by years relative to entrepreneurship entry. Sample restricted to observations with entropy balancing weights.

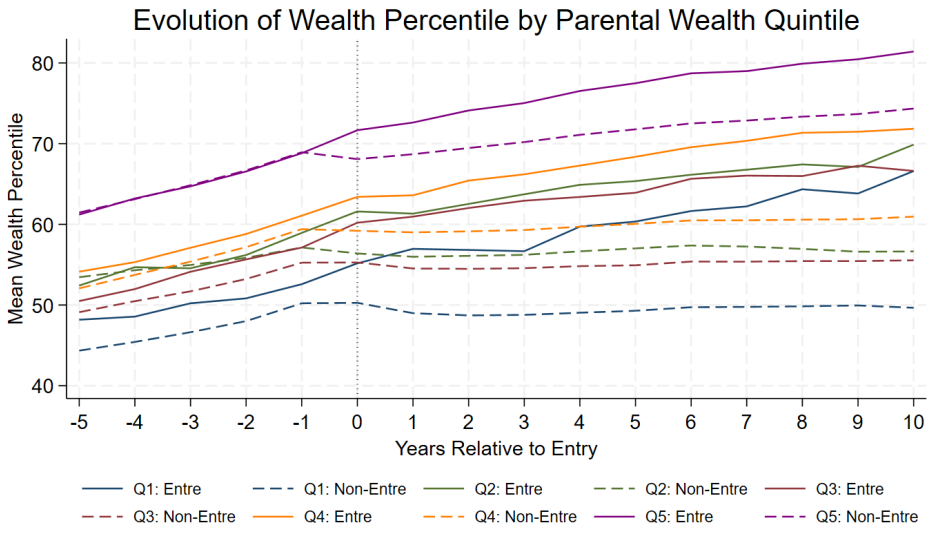


Figure A.12
Evolution of Gross Wealth Percentile by Parental Wealth Quintile

Notes: Mean gross wealth percentile by years relative to entrepreneurship entry, separately by parental wealth quintile. Sample restricted to entrepreneurs with entropy balancing weights.

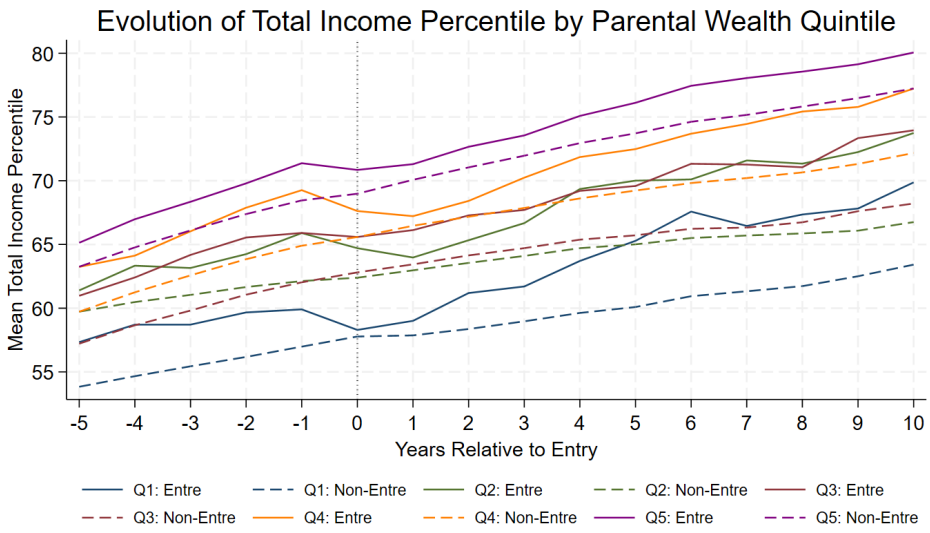


Figure A.13
Evolution of Total Income Percentile by Parental Wealth Quintile

Notes: Mean total income percentile by years relative to entrepreneurship entry, separately by parental wealth quintile. Sample restricted to entrepreneurs with entropy balancing weights.

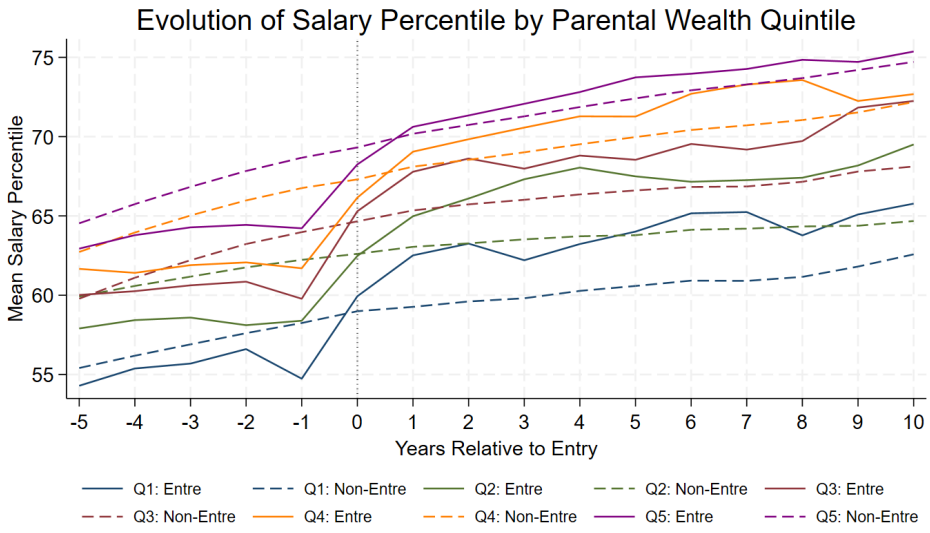


Figure A.14
Evolution of Wage Income Percentile by Parental Wealth Quintile

Notes: Mean wage income percentile by years relative to entrepreneurship entry, separately by parental wealth quintile. Sample restricted to entrepreneurs with entropy balancing weights.

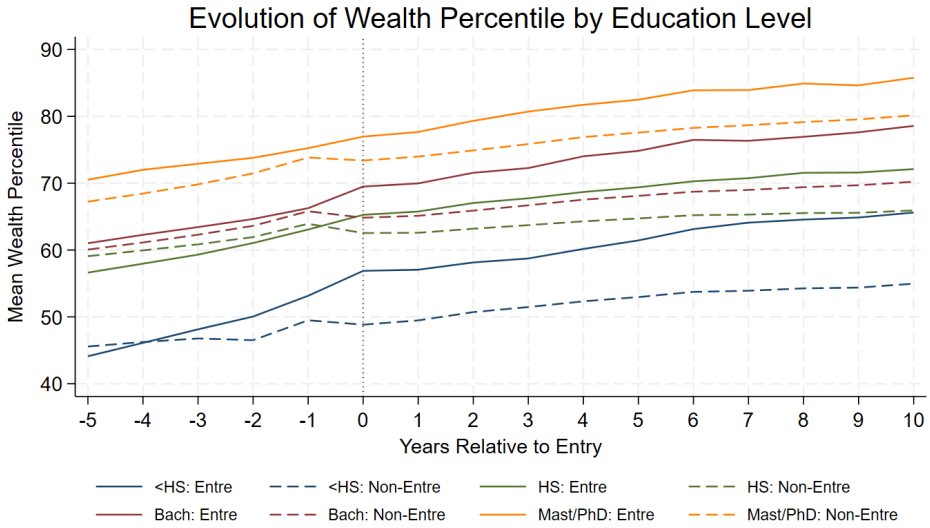


Figure A.15
Evolution of Gross Wealth Percentile by Education Level

Notes: Mean gross wealth percentile by years relative to entrepreneurship entry, separately by education level. Sample restricted to entrepreneurs with entropy balancing weights.

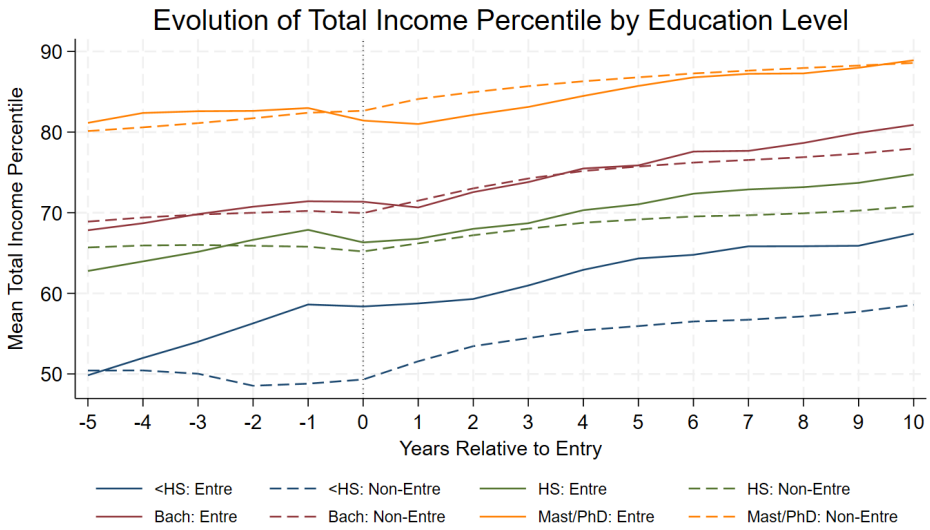


Figure A.16
Evolution of Total Income Percentile by Education Level

Notes: Mean total income percentile by years relative to entrepreneurship entry, separately by education level. Sample restricted to entrepreneurs with entropy balancing weights.

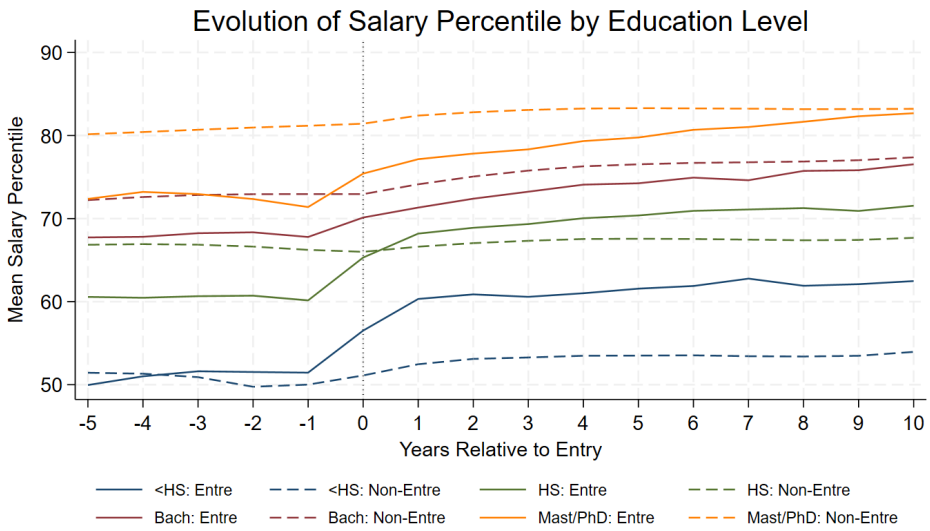


Figure A.17
Evolution of Wage Income Percentile by Education Level

Notes: Mean wage income percentile by years relative to entrepreneurship entry, separately by education level. Sample restricted to entrepreneurs with entropy balancing weights.

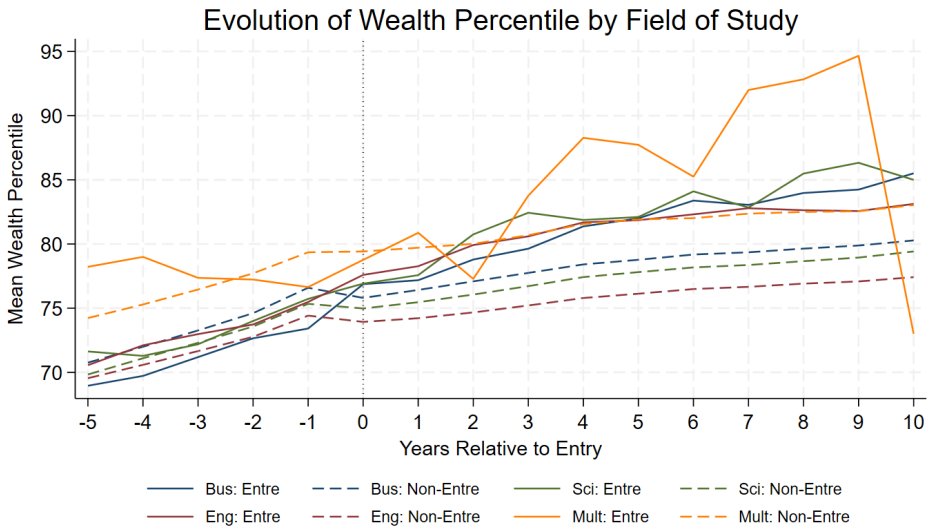


Figure A.18
Evolution of Gross Wealth Percentile by Field of Study

Notes: Mean gross wealth percentile by years relative to entrepreneurship entry, separately by field of study. Sample restricted to entrepreneurs with entropy balancing weights.

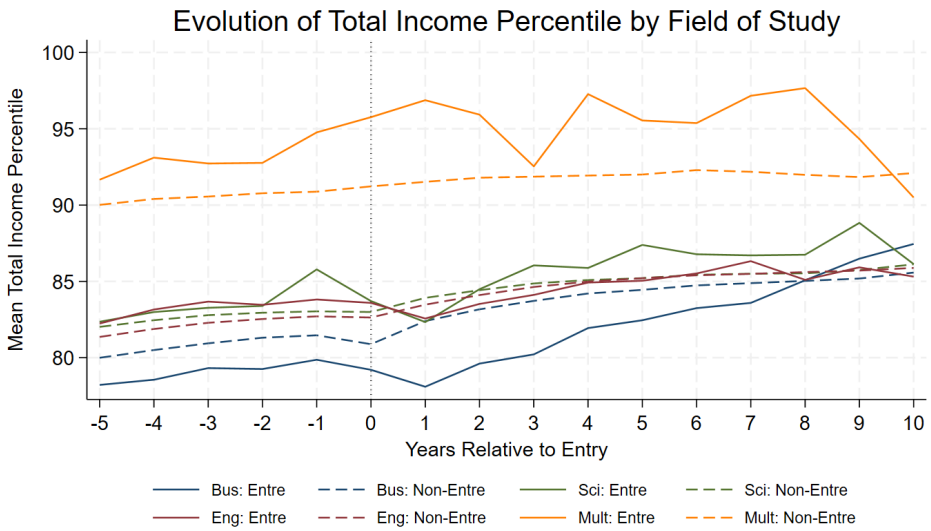


Figure A.19
Evolution of Total Income Percentile by Field of Study

Notes: Mean total income percentile by years relative to entrepreneurship entry, separately by field of study. Sample restricted to entrepreneurs with entropy balancing weights.

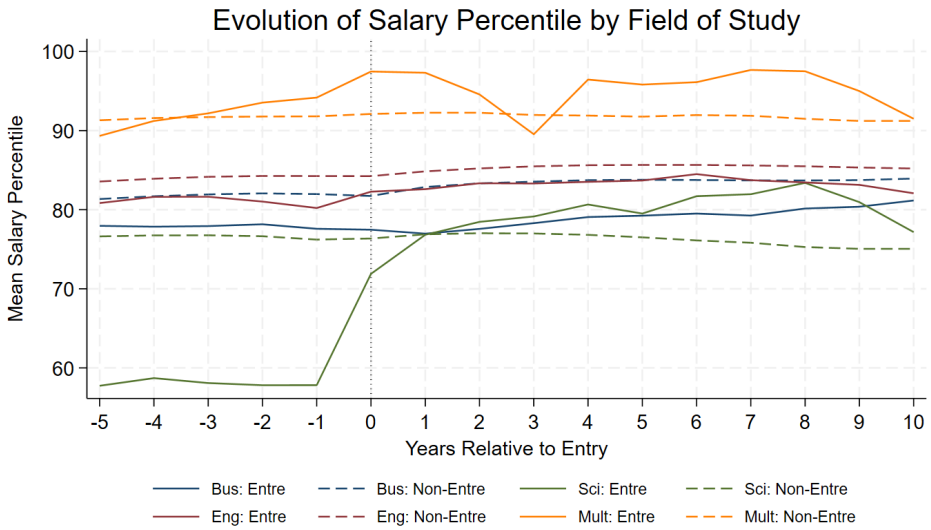


Figure A.20
Evolution of Wage Income Percentile by Field of Study

Notes: Mean wage income percentile by years relative to entrepreneurship entry, separately by field of study. Sample restricted to entrepreneurs with entropy balancing weights.

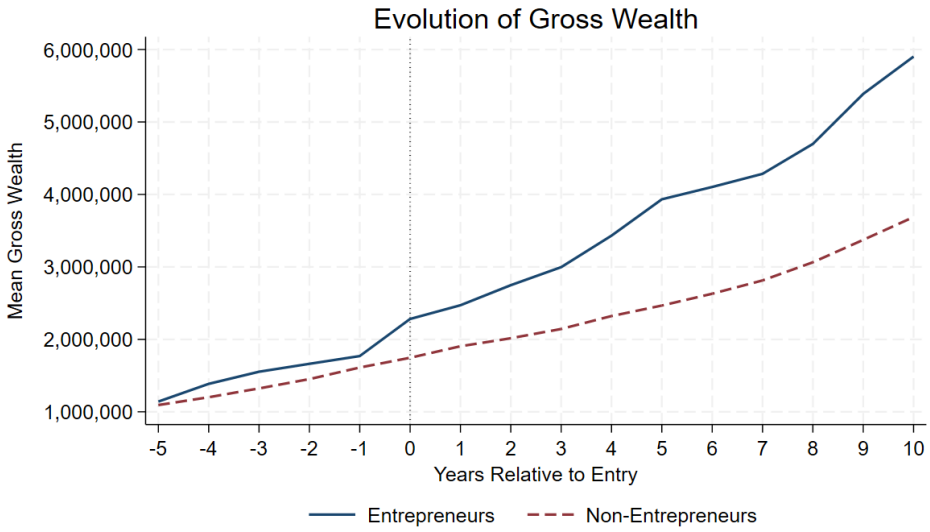


Figure A.21
Evolution of Gross Wealth: Entrepreneurs vs. Non-Entrepreneurs

Notes: Mean gross wealth (NOK) by years relative to entrepreneurship entry. Sample restricted to observations with entropy balancing weights.

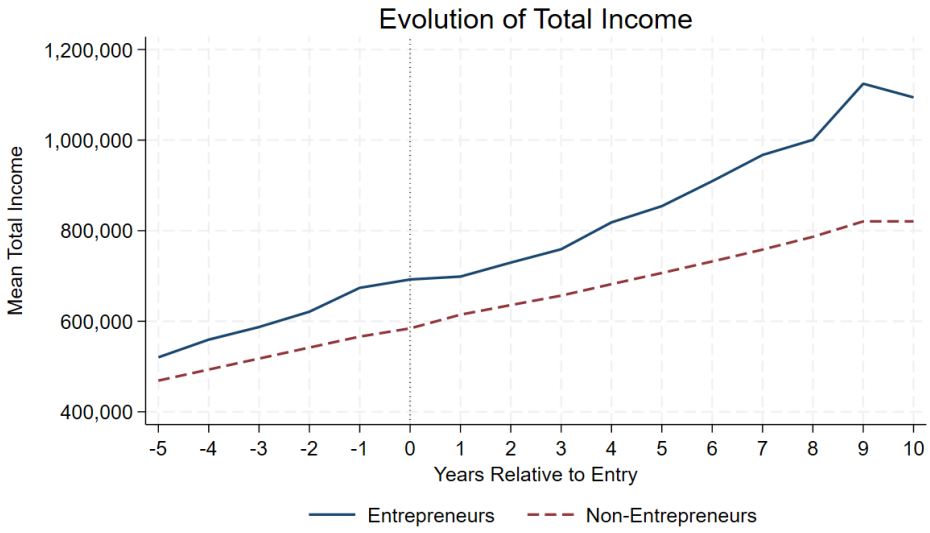


Figure A.22
Evolution of Total Income: Entrepreneurs vs. Non-Entrepreneurs

Notes: Mean total income (NOK) by years relative to entrepreneurship entry. Sample restricted to observations with entropy balancing weights.

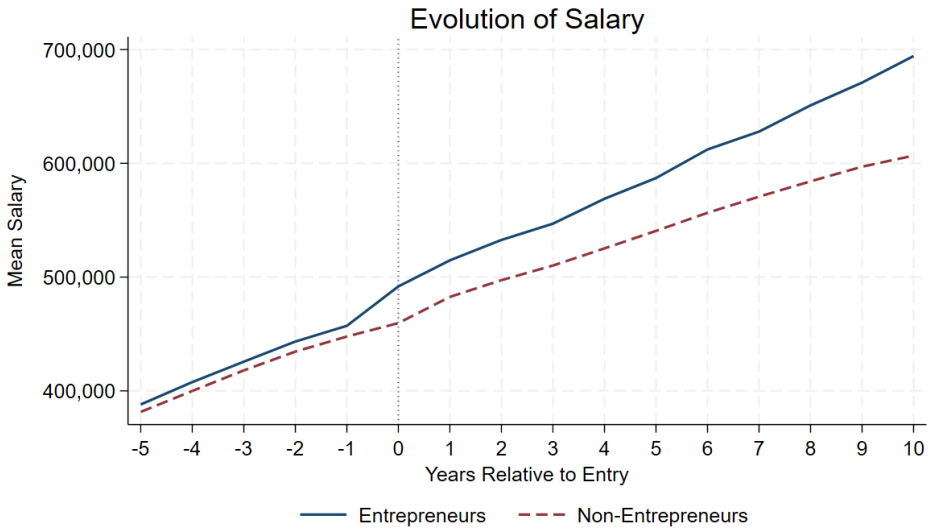


Figure A.23
Evolution of Wage Income: Entrepreneurs vs. Non-Entrepreneurs

Notes: Mean wage income (NOK) by years relative to entrepreneurship entry. Sample restricted to observations with entropy balancing weights.

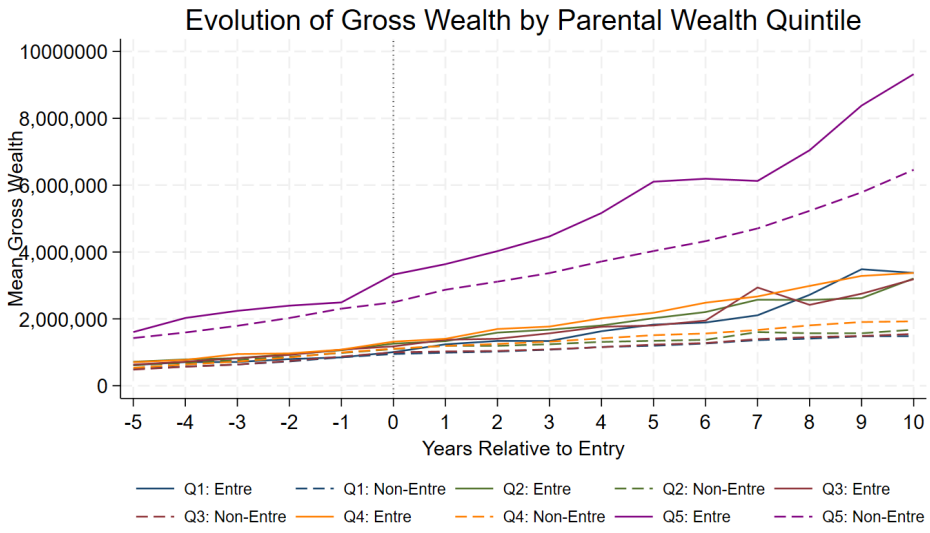


Figure A.24
Evolution of Gross Wealth by Parental Wealth Quintile

Notes: Mean gross wealth (NOK) by years relative to entrepreneurship entry, separately by parental wealth quintile. Sample restricted to entrepreneurs with entropy balancing weights.

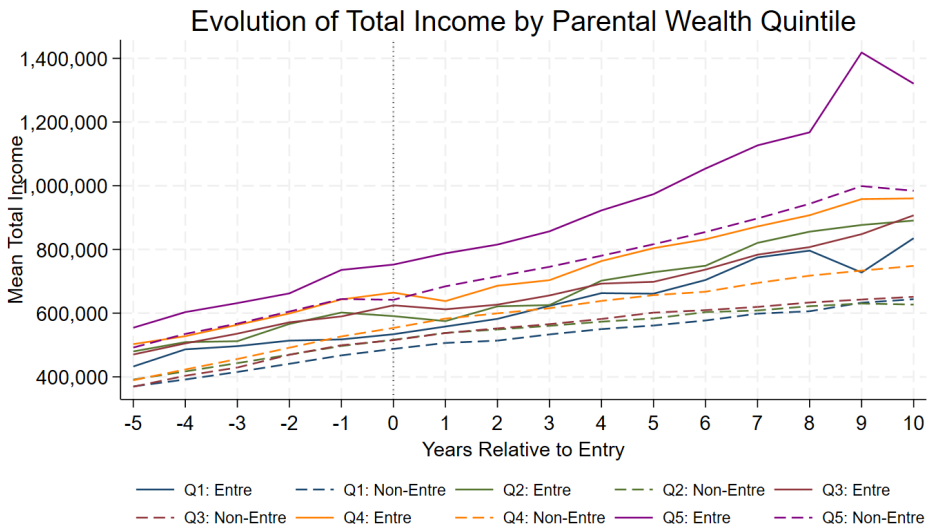


Figure A.25
Evolution of Total Income by Parental Wealth Quintile

Notes: Mean total income (NOK) by years relative to entrepreneurship entry, separately by parental wealth quintile. Sample restricted to entrepreneurs with entropy balancing weights.

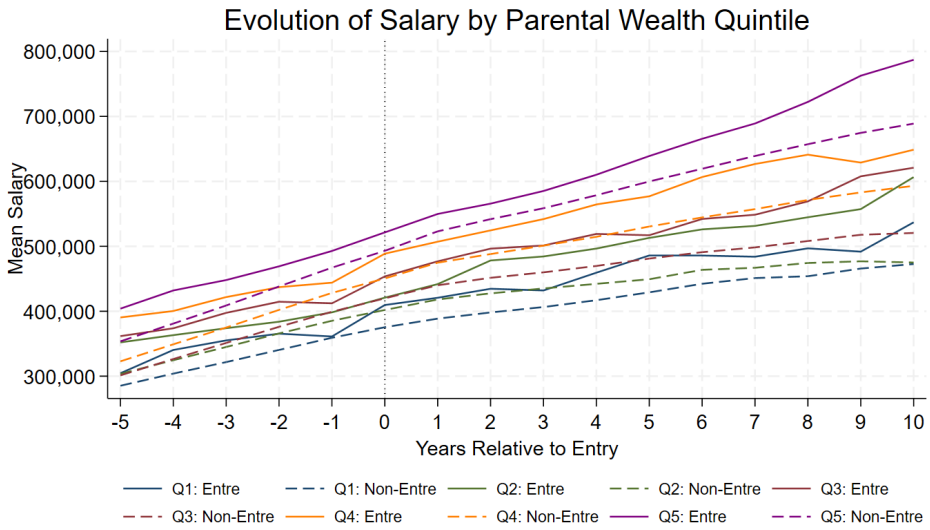


Figure A.26
Evolution of Wage Income by Parental Wealth Quintile

Notes: Mean wage income (NOK) by years relative to entrepreneurship entry, separately by parental wealth quintile. Sample restricted to entrepreneurs with entropy balancing weights.

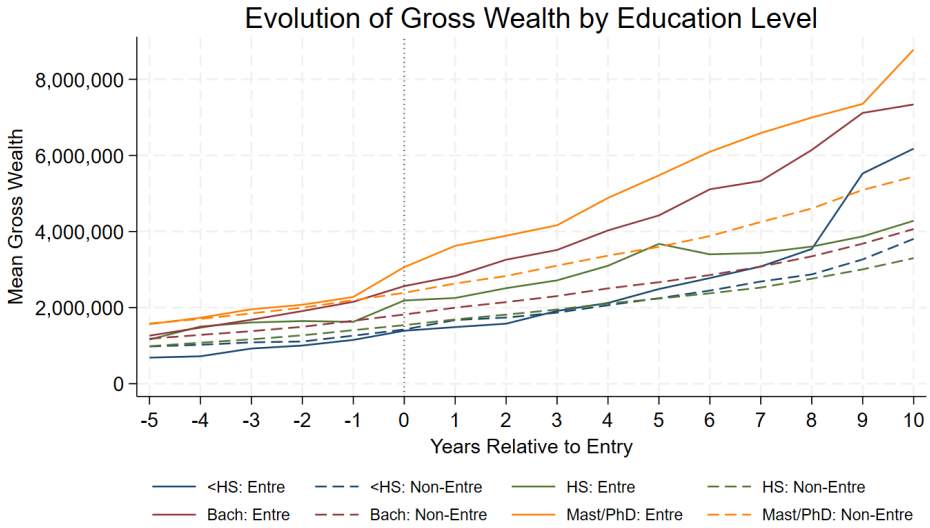


Figure A.27
Evolution of Gross Wealth by Education Level

Notes: Mean gross wealth (NOK) by years relative to entrepreneurship entry, separately by education level. Sample restricted to entrepreneurs with entropy balancing weights.

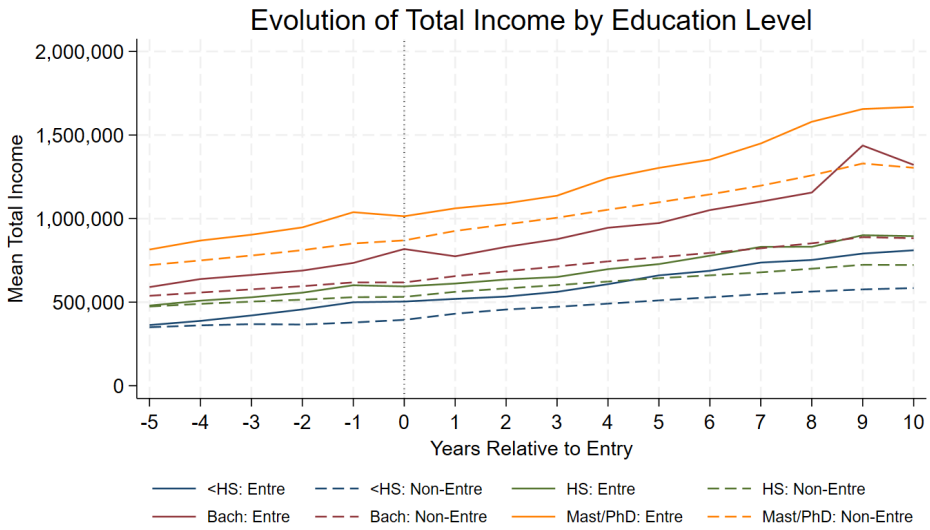


Figure A.28
Evolution of Total Income by Education Level

Notes: Mean total income (NOK) by years relative to entrepreneurship entry, separately by education level. Sample restricted to entrepreneurs with entropy balancing weights.

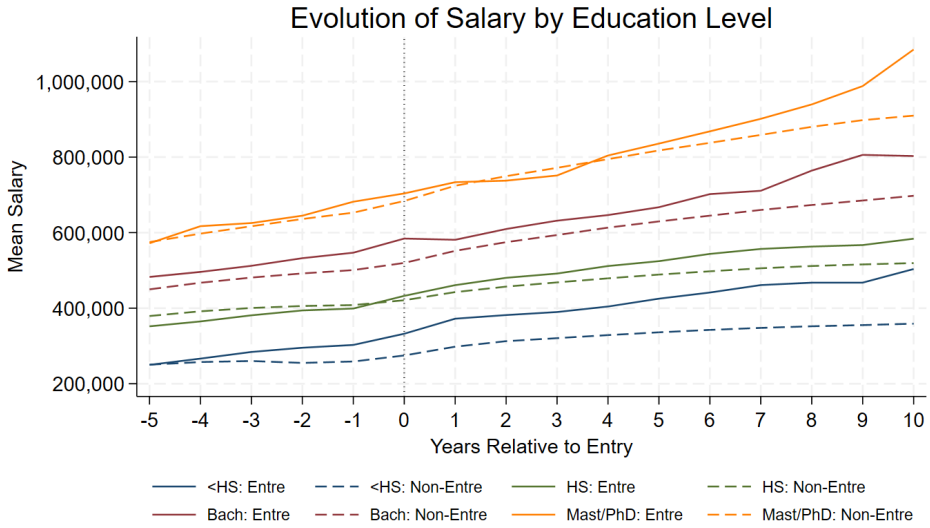


Figure A.29
Evolution of Wage Income by Education Level

Notes: Mean wage income (NOK) by years relative to entrepreneurship entry, separately by education level. Sample restricted to entrepreneurs with entropy balancing weights.

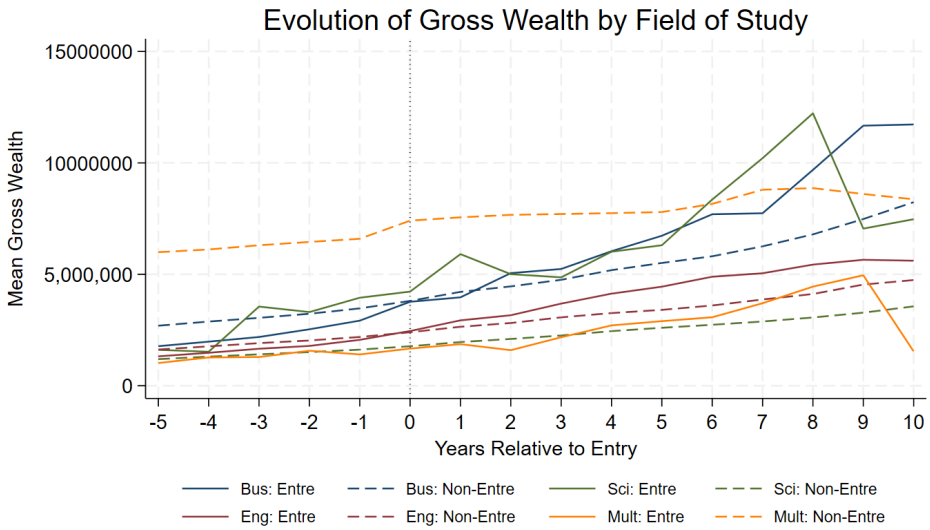


Figure A.30
Evolution of Gross Wealth by Field of Study

Notes: Mean gross wealth (NOK) by years relative to entrepreneurship entry, separately by field of study. Sample restricted to entrepreneurs with entropy balancing weights.

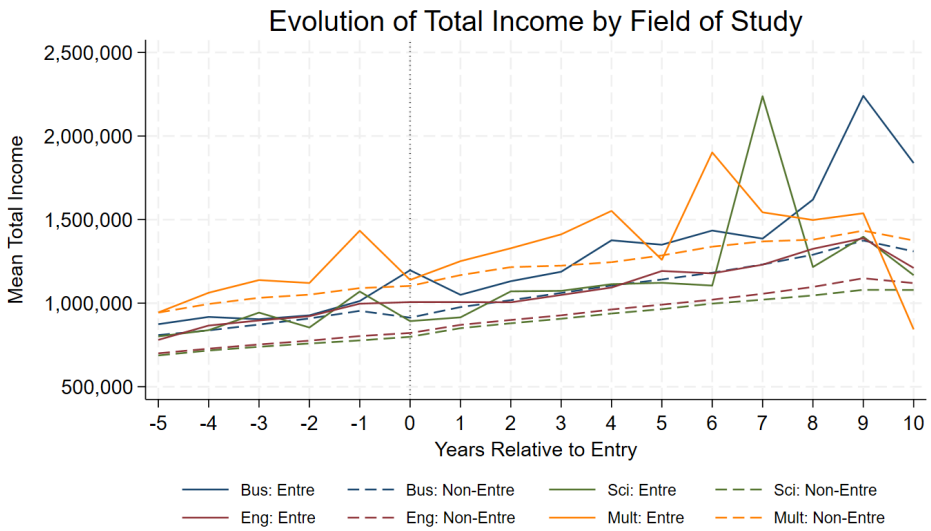


Figure A.31
Evolution of Total Income by Field of Study

Notes: Mean total income (NOK) by years relative to entrepreneurship entry, separately by field of study. Sample restricted to entrepreneurs with entropy balancing weights.

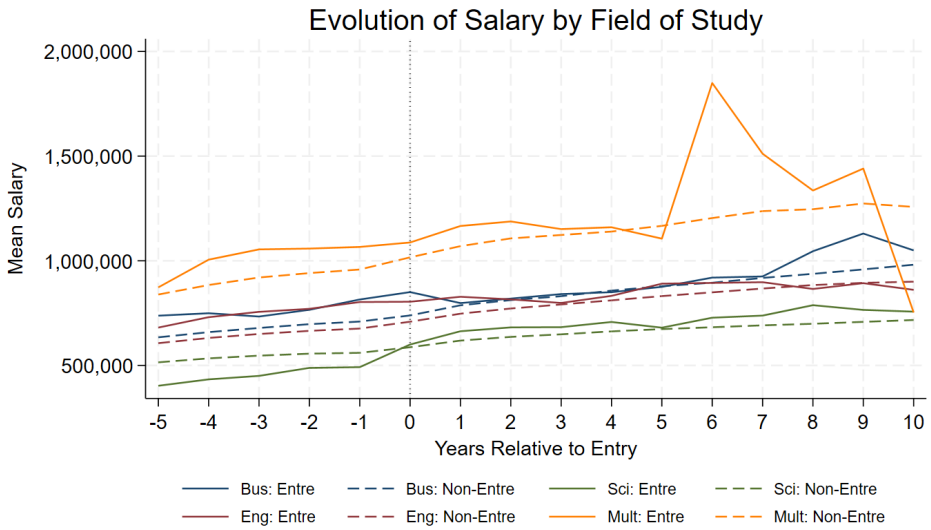


Figure A.32
Evolution of Wage Income by Field of Study

Notes: Mean wage income (NOK) by years relative to entrepreneurship entry, separately by field of study. Sample restricted to entrepreneurs with entropy balancing weights.

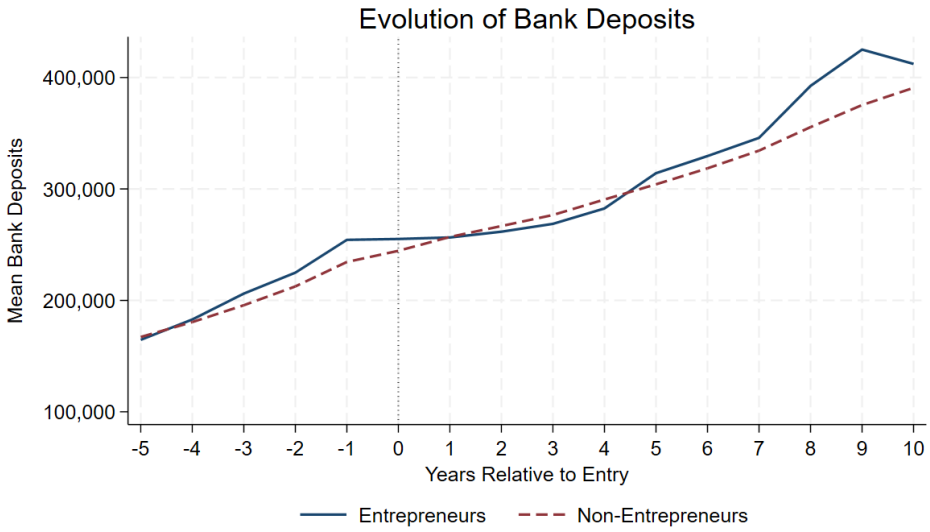


Figure A.33
Evolution of Bank Deposits: Entrepreneurs vs. Non-Entrepreneurs

Notes: Mean bank deposits (NOK) by years relative to entrepreneurship entry. Sample restricted to observations with entropy balancing weights.

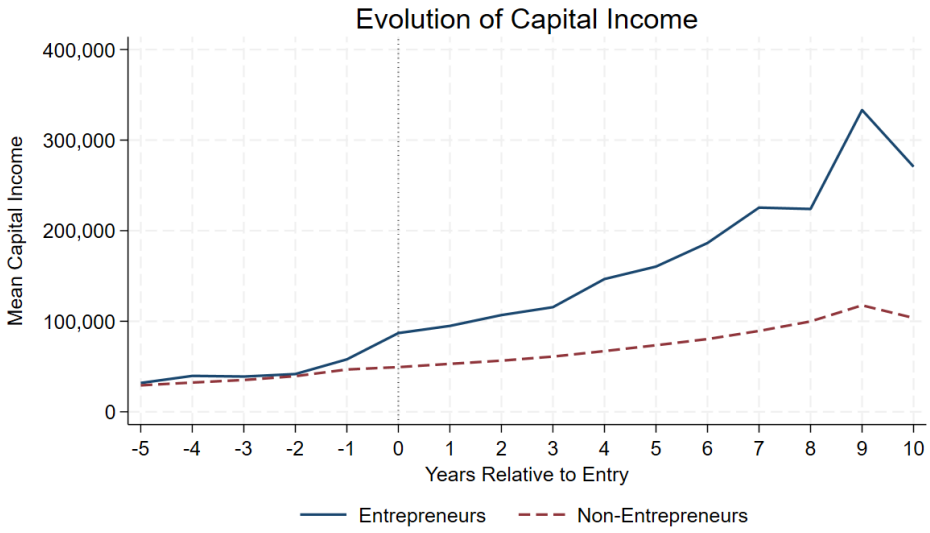


Figure A.34
Evolution of Capital Income: Entrepreneurs vs. Non-Entrepreneurs

Notes: Mean capital income (NOK) by years relative to entrepreneurship entry. Sample restricted to observations with entropy balancing weights.

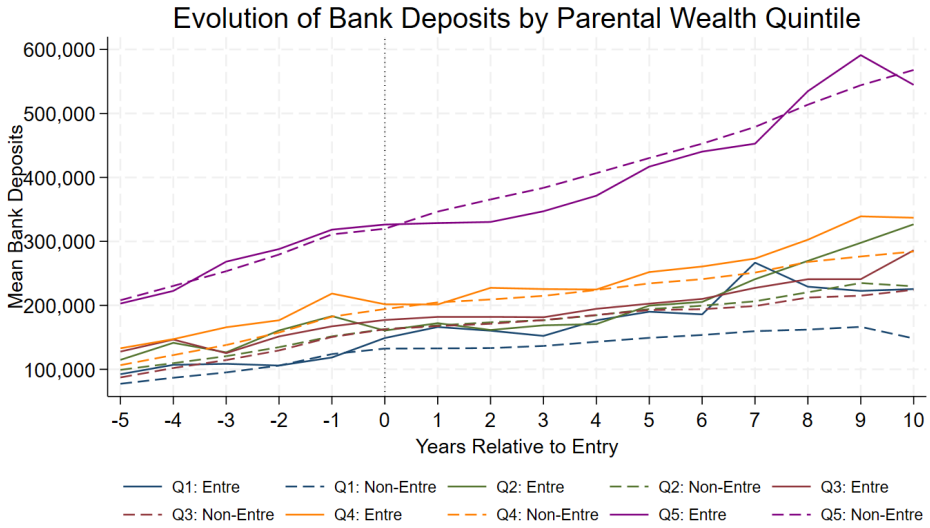


Figure A.35
Evolution of Bank Deposits by Parental Wealth Quintile

Notes: Mean bank deposits (NOK) by years relative to entrepreneurship entry, separately by parental wealth quintile. Sample restricted to entrepreneurs with entropy balancing weights.

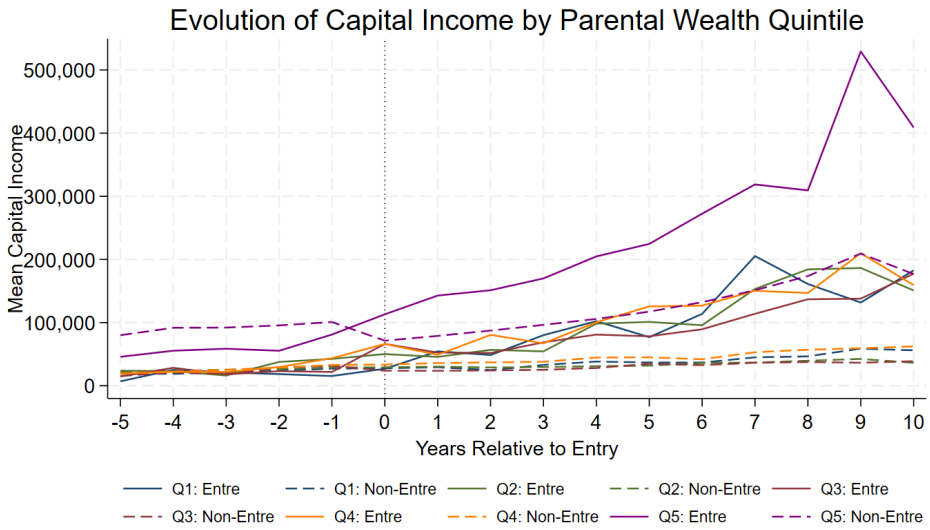


Figure A.36
Evolution of Capital Income by Parental Wealth Quintile

Notes: Mean capital income (NOK) by years relative to entrepreneurship entry, separately by parental wealth quintile. Sample restricted to entrepreneurs with entropy balancing weights.

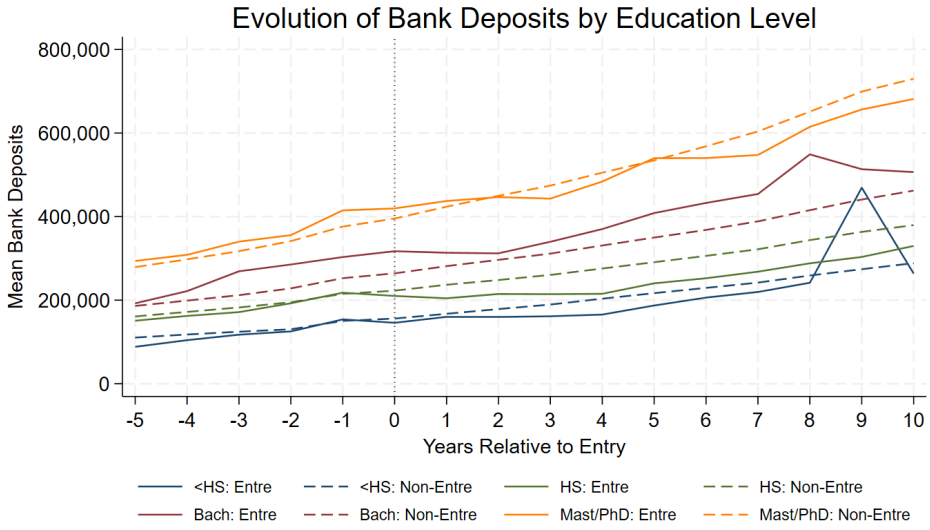


Figure A.37
Evolution of Bank Deposits by Education Level

Notes: Mean bank deposits (NOK) by years relative to entrepreneurship entry, separately by education level. Sample restricted to entrepreneurs with entropy balancing weights.

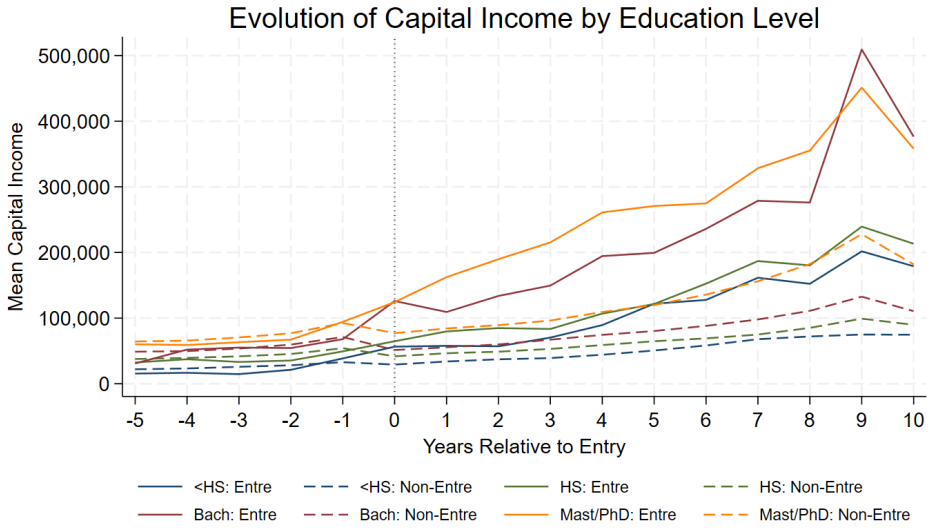


Figure A.38
Evolution of Capital Income by Education Level

Notes: Mean capital income (NOK) by years relative to entrepreneurship entry, separately by education level. Sample restricted to entrepreneurs with entropy balancing weights.

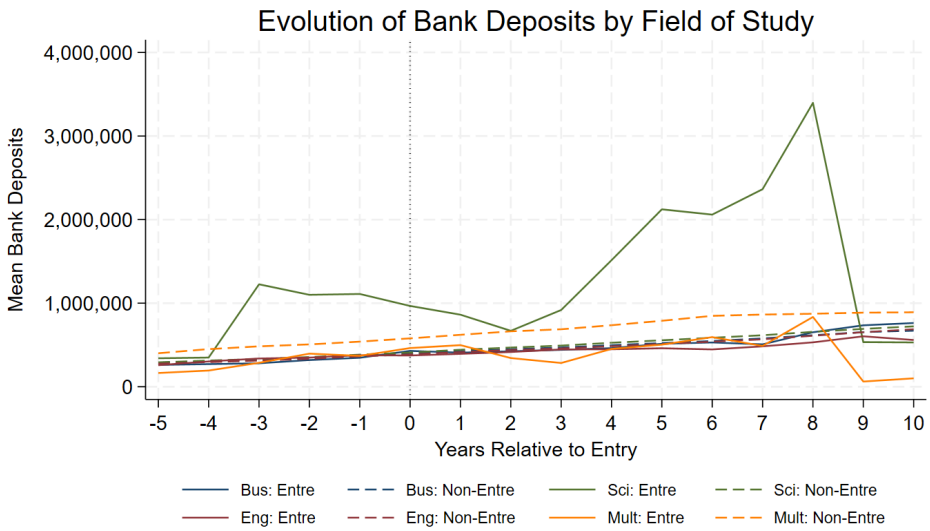


Figure A.39
Evolution of Bank Deposits by Field of Study

Notes: Mean bank deposits (NOK) by years relative to entrepreneurship entry, separately by field of study. Sample restricted to entrepreneurs with entropy balancing weights.

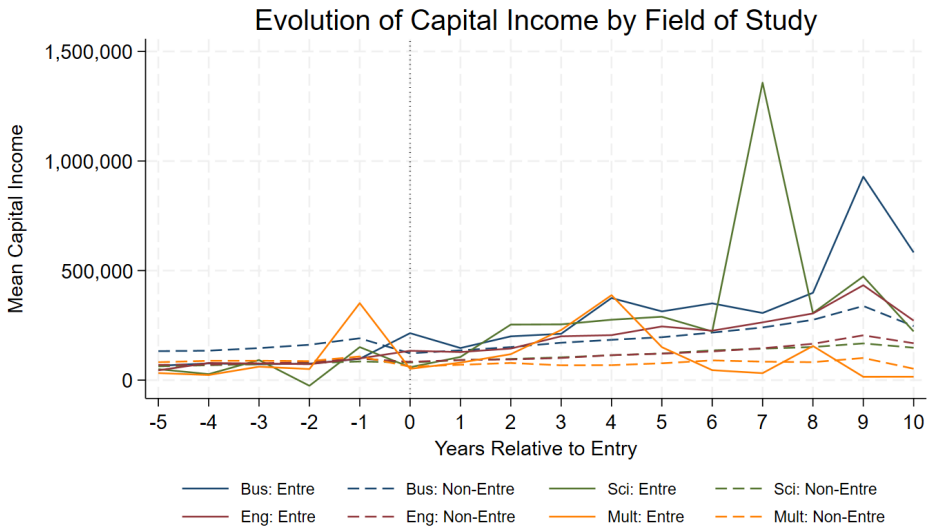


Figure A.40
Evolution of Capital Income by Field of Study

Notes: Mean capital income (NOK) by years relative to entrepreneurship entry, separately by field of study. Sample restricted to entrepreneurs with entropy balancing weights.

B Appendix: Tables

Year	New Entrepreneurs
2006	3,109
2007	2,576
2008	2,080
2009	1,683
2010	1,829
2011	2,031
2012	2,971
2013	2,690
2014	2,572
2015	2,570
2016	2,642
2017	217
Total	26,970

Table B.1
Number of New Entrepreneurs by Year

	Entrepreneurs	Non-Entrepreneurs	Difference	p-value
Gross wealth (NOK)	3,003,196.32	1,259,084.61	-1744111.71	0.000
Gross wealth percentile	64.86	44.45	-20.41	0.000
Wage income (NOK)	494,627.93	345,620.77	-149,007.16	0.000
Wage income percentile	66.57	58.60	-7.97	0.000
Capital income (NOK)	98,638.45	17,897.85	-80,740.60	0.000
Total income (NOK)	702,171.84	420,832.95	-281,338.89	0.000
Total income percentile	68.69	51.84	-16.86	0.000
Parental wealth percentile	72.01	67.49	-4.53	0.000
Age	39.75	36.63	-3.13	0.000
Female	0.26	0.52	0.26	0.000
Education level	2.34	2.20	-0.14	0.000
Business field	0.09	0.04	-0.05	0.000
Science field	0.01	0.01	-0.00	0.000
Engineering field	0.06	0.05	-0.01	0.000
Multiple fields	0.00	0.00	-0.00	0.001
Observations	318,600	4,971,802		

Notes: Pooled person-year observations. Entrepreneurs defined as ever entering entrepreneurship. Standard errors not clustered. Education level is a categorical variable with the values 2 (Secondary school), 3 (High school), 4 (Bachelor), and 5 (Master/PhD). The variables for field of education are binary variables that take the value 1 if the person has completed a degree that is linked to the fields mentioned.

Table B.2
Summary Statistics

	Mean	Median	P25	P75
Panel A: Wealth and Income				
Gross wealth (NOK)	2,254,096	822,488	407,344	1,657,000
Net wealth (NOK)	398,469	-338,760	-1,387,286	383,946
Parental wealth (NOK)	3,621,637	1,278,872	644,401	2,620,888
Parental wealth percentile	73	79	58	93
Total income (NOK)	689,612	507,548	347,596	758,072
Panel B: Education Level (shares)				
Secondary (%)	14.4			
High school (%)	47.1			
Bachelor (%)	25.9			
Master/PhD (%)	12.6			
Panel C: Field of Study (shares)				
Business (%)	8.8			
Science (%)	1.1			
Engineering (%)	6.2			
Other/None (%)	83.9			
Observations	26,970			

Notes: Sample restricted to entrepreneurs at entry year with entropy balancing weights. Wealth and income in NOK. Net wealth is gross wealth minus debt. Parental wealth is the sum of both parents' gross wealth. Education and field shares sum to 100%.

Table B.3
Entrepreneur Characteristics at Entry

	Q1		Q2		Q3		Q4		Q5	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Panel A: Wealth and Income										
Gross wealth (NOK)	1,033,989	586,871	1,201,730	675,256	1,259,681	673,483	1,240,079	715,703	3,333,185	1,007,000
Net wealth (NOK)	-681,331	-451,979	-536,721	-467,514	-440,231	-445,805	-508,017	-468,141	1,346,158	-194,918
Parental wealth (NOK)	20,129	11,222	245,584	198,392	617,543	570,784	1,064,016	979,715	6,655,247	2,675,984
Parental wealth percentile	12	13	31	31	50	51	70	71	92	93
Total income (NOK)	531,014	436,123	564,690	461,783	628,335	481,631	646,204	496,908	762,701	542,930
Panel B: Education Level (%)										
Secondary (%)	32.8		23.9		18.2		15.0		9.9	
High school (%)	48.1		51.8		53.6		49.5		43.1	
Bachelor (%)	15.0		19.7		20.6		25.2		29.7	
Master/PhD (%)	4.1		4.6		7.5		10.3		17.3	
Panel C: Field of Study (%)										
Business (%)	4.8		4.8		5.6		6.9		11.8	
Science (%)	0.0		0.5		0.6		1.0		1.4	
Engineering (%)	2.2		3.9		5.0		6.1		7.2	
Other/None (%)	93.0		90.7		88.8		86.0		79.5	
N	912		2,282		3,991		6,625		13,160	

Notes: Sample restricted to entrepreneurs at entry year with entropy balancing weights. Wealth and income in NOK. Net wealth is gross wealth minus debt. Parental wealth is the sum of both parents' gross wealth. Q1 = poorest parental quintile, Q5 = richest. Education and field shares sum to approximately 100% within each quintile.

Table B.4
Entrepreneur Characteristics at Entry by Parental Wealth Quintile

Education Level	*N*	%
Secondary	3,871	14.4
High School	12,711	47.1
Bachelor	6,992	25.9
Master/PhD	3,396	12.6
Total	26,970	100.0

Notes: Sample restricted to entrepreneurs with entropy balancing weights at entry year.

Table B.5
Distribution of Entrepreneurs by Education Level

Field of Study	*N*	%
Business	2,385	8.8
Science	285	1.0
Engineering	1,664	6.2
Multiple Fields	16	0.1
Other	22,620	83.9
Total	26,970	100.0

Notes: Sample restricted to entrepreneurs with entropy balancing weights at entry year.

Table B.6
Distribution of Entrepreneurs by Field of Study

Parental Wealth Decile	*N*	%
D1 (0–10)	288	1.1
D2 (10–20)	624	2.3
D3 (20–30)	934	3.5
D4 (30–40)	1,348	5.0
D5 (40–50)	1,724	6.4
D6 (50–60)	2,267	8.4
D7 (60–70)	2,930	10.9
D8 (70–80)	3,695	13.7
D9 (80–90)	4,694	17.4
D10 (90–100)	8,466	31.4
Total	26,970	100.0

Notes: Sample restricted to entrepreneurs with entropy balancing weights at entry year. Excludes observations with missing parental wealth.

Table B.7
Distribution of Entrepreneurs by Parental Wealth Decile

Parental Wealth Quintile	*N*	%
Q1 (0–20)	912	3.4
Q2 (20–40)	2,282	8.5
Q3 (40–60)	3,991	14.8
Q4 (60–80)	6,625	24.6
Q5 (80–100)	13,160	48.8
Total	26,970	100.0

Notes: Sample restricted to entrepreneurs with entropy balancing weights at entry year. Excludes observations with missing parental wealth. Q1 = poorest quintile, Q5 = richest quintile.

Table B.8
Distribution of Entrepreneurs by Parental Wealth Quintile

Parental Quintile	Secondary	High School	Bachelor	Master/PhD	Total
Q1 (0–20)	299	439	137	37	912
Q2 (20–40)	545	1,182	450	105	2,282
Q3 (40–60)	728	2,140	823	300	3,991
Q4 (60–80)	991	3,281	1,670	683	6,625
Q5 (80–100)	1,308	5,669	3,912	2,271	13,160
Total	3,871	12,711	6,992	3,396	26,970

Notes: Sample restricted to entrepreneurs with entropy balancing weights at entry year. Q1 = poorest quintile, Q5 = richest quintile.

Table B.9
Number of Entrepreneurs by Parental Wealth Quintile and Education Level

Education Level	Mean	Median	Std. Dev.
Secondary	38.6	39.0	9.6
High school	39.0	39.0	9.0
Bachelor	39.7	40.0	8.7
Master/PhD	40.6	40.0	8.4
Total	39.3	39.0	9.0

Notes: Sample restricted to entrepreneurs with entropy balancing weights at entry year.

Table B.10
Age at Entrepreneurship Entry by Education Level

Field of Study	Mean	Median	Std. Dev.
Business	40.4	41.0	8.1
Science	42.4	42.0	8.0
Engineering	43.0	43.0	8.0
Multiple fields	42.9	45.0	6.7
Other/None	38.9	39.0	9.0
Total	39.3	39.0	9.0

Notes: Sample restricted to entrepreneurs with entropy balancing weights at entry year.

Table B.11
Age at Entrepreneurship Entry by Field of Study

Parental Wealth Quintile	Mean	Median	Std. Dev.
Q1 (0–20)	39.2	40.0	9.8
Q2 (20–40)	41.4	42.0	9.2
Q3 (40–60)	40.1	40.0	9.2
Q4 (60–80)	39.7	40.0	8.9
Q5 (80–100)	38.5	38.0	8.7
Total	39.3	39.0	9.0

Notes: Sample restricted to entrepreneurs with entropy balancing weights at entry year. Q1 = poorest quintile, Q5 = richest quintile.

Table B.12
Age at Entrepreneurship Entry by Parental Wealth Quintile

	Age Quartile			
Parental Wealth Quintile	Q1	Q2	Q3	Q4
Q1 (0–20)	38.17	39.45	39.15	43.68
Q2 (20–40)	40.19	41.41	42.37	44.29
Q3 (40–60)	38.51	40.00	41.17	42.30
Q4 (60–80)	39.40	39.02	40.33	41.37
Q5 (80–100)	37.39	38.01	38.81	39.90

Notes: Sample restricted to entrepreneurs with entropy balancing weights at entry year. Q1 = poorest parental wealth quintile, Q5 = richest parental wealth quintile. Age quartiles are computed within the sample.

Table B.13
Mean Age at Entrepreneurship Entry by Parental Wealth Quintile and Age Quartile

Years Since Founding	Survival Rate	*N*
0	1.000	27,282
1	0.915	26,700
2	0.840	23,813
3	0.781	20,994
4	0.738	18,226
5	0.705	15,420
6	0.679	12,429
7	0.659	10,381
8	0.646	8,543
9	0.634	6,923
10	0.618	4,977

Notes: Sample restricted to entrepreneurs with entropy balancing weights at entry year. Survival is defined as the startup remaining active. *N* reflects the number of startups observed at each horizon (decreases due to both exits and right-censoring).

Table B.14
Startup Survival Rates by Years Since Founding

Parental Wealth Quintile	% Serial Entrepreneurs	Mean Entries	*N*
Q1 (0–20)	5.37	1.055	912
Q2 (20–40)	5.57	1.057	2,282
Q3 (40–60)	4.59	1.049	3,991
Q4 (60–80)	5.03	1.053	6,625
Q5 (80–100)	5.45	1.057	13,160
Total	5.18	1.054	26,970

Notes: Sample restricted to entrepreneurs with entropy balancing weights at entry year. Serial entrepreneurs are defined as founders with more than one startup entry during the sample period. Mean entries reflects the average number of startups founded per entrepreneur. Q1 = poorest quintile, Q5 = richest quintile.

Table B.15
Serial Entrepreneurship by Parental Wealth Quintile

	Education Level			
Parental Wealth Quintile	Secondary	High School	Bachelor	Master/PhD
Q1 (0–20)	38.17	39.45	39.15	43.68
Q2 (20–40)	40.19	41.41	42.37	44.29
Q3 (40–60)	38.51	40.00	41.17	42.30
Q4 (60–80)	39.40	39.02	40.33	41.37
Q5 (80–100)	37.39	38.01	38.81	39.90

Notes: Sample restricted to entrepreneurs with entropy balancing weights at entry year. Q1 = poorest quintile, Q5 = richest quintile.

Table B.16
Mean Age at Entrepreneurship Entry by Parental Wealth Quintile and Education Level

	Entrepreneurs					Non-Entrepreneurs				
Parent Quintile	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
Q1 (0–20)	13.0	19.7	17.6	18.2	31.5	38.1	23.7	18.9	11.7	7.5
Q2 (20–40)	10.9	12.6	17.7	20.7	38.1	27.2	25.8	22.2	14.7	10.0
Q3 (40–60)	9.8	13.4	18.1	21.6	37.0	23.5	27.0	24.7	15.6	9.3
Q4 (60–80)	7.1	11.1	18.5	23.9	39.4	17.4	25.2	26.9	19.1	11.5
Q5 (80–100)	4.0	7.6	11.1	20.1	57.2	10.4	19.0	24.4	24.3	22.0

Notes: Row percentages (each row sums to 100). Cells show the percentage of individuals from each parental wealth quintile (rows) who reach each own-wealth quintile 5 years after entrepreneurship (columns). Entrepreneurs measured at entry year; non-entrepreneurs averaged across psuedo entry years.

Table B.17
Intergenerational Wealth Transition Matrix: 5-Year Horizon

	Entrepreneurs					Non-Entrepreneurs				
Parent Quintile	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
Q1 (0–20)	13.5	21.6	13.5	10.8	40.5	34.8	23.7	19.7	12.8	8.9
Q2 (20–40)	7.8	13.6	16.9	23.4	38.3	25.8	25.6	22.7	15.3	10.6
Q3 (40–60)	9.8	10.2	17.5	16.8	45.6	21.0	25.8	25.8	17.0	10.4
Q4 (60–80)	7.3	10.7	18.9	19.1	43.9	15.3	24.1	27.8	20.0	12.8
Q5 (80–100)	3.2	6.7	11.0	16.9	62.2	9.0	16.6	24.6	25.2	24.5

Notes: Row percentages (each row sums to 100). Cells show the percentage of individuals from each parental wealth quintile (rows) who reach each own-wealth quintile 10 years after entrepreneurship (columns). Entrepreneurs measured at entry year; non-entrepreneurs averaged across psuedo entry years.

Table B.18
Intergenerational Wealth Transition Matrix: 10-Year Horizon

	Entrepreneurs					Non-Entrepreneurs				
Parent Quintile	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
Q1 (0–20)	8.5	9.1	18.8	21.8	41.8	16.8	22.0	24.0	22.3	14.9
Q2 (20–40)	6.9	9.7	14.4	24.9	44.0	12.9	18.4	23.8	25.7	19.2
Q3 (40–60)	6.8	9.1	15.6	21.3	47.2	13.0	16.7	23.3	26.8	20.2
Q4 (60–80)	6.9	7.9	12.6	22.0	50.5	11.6	14.2	21.8	28.3	24.1
Q5 (80–100)	6.6	6.2	10.2	18.5	58.4	10.9	11.1	17.8	27.7	32.4

Notes: Row percentages (each row sums to 100). Cells show the percentage of individuals from each parental wealth quintile (rows) who reach each total income quintile 5 years after entrepreneurship (columns). Entrepreneurs measured at entry year; non-entrepreneurs averaged across psuedo entry years.

Table B.19
Transition Matrix: Parent Wealth to Child Total Income (5-Year Horizon)

	Entrepreneurs					Non-Entrepreneurs				
Parent Quintile	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
Q1 (0–20)	11.2	4.2	22.7	21.8	40.0	16.7	7.9	27.7	28.6	19.1
Q2 (20–40)	9.1	5.3	17.8	23.7	44.2	13.1	7.0	25.2	30.7	24.0
Q3 (40–60)	8.4	5.2	18.1	22.0	46.4	10.6	6.4	25.3	32.0	25.7
Q4 (60–80)	7.4	4.9	16.0	21.4	50.3	8.8	5.7	23.2	32.1	30.2
Q5 (80–100)	6.6	4.4	14.4	19.1	55.6	8.0	5.5	20.2	29.1	37.2

Notes: Row percentages (each row sums to 100). Cells show the percentage of individuals from each parental wealth quintile (rows) who reach each salary quintile 5 years after entrepreneurship (columns). Entrepreneurs measured at entry year; non-entrepreneurs averaged across psuedo entry years.

Table B.20
Transition Matrix: Parent Wealth to Child Wage Income (5-Year Horizon)

	Full Sample (%)					Entrepreneurs (%)				
Field	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
Other/None	95.0	93.9	91.9	89.1	85.9	91.1	88.4	86.4	83.0	78.1
Business	1.7	2.2	3.0	4.2	6.2	4.3	5.5	6.4	8.6	12.3
Science	0.3	0.4	0.6	0.9	1.2	0.5	0.7	0.9	1.3	1.6
Engineering	2.9	3.6	4.5	5.8	6.7	4.1	5.3	6.3	7.1	7.9
Multiple	0.0	0.0	0.0	0.1	0.1	0.0	0.1	0.1	0.1	0.1

Notes: Column percentages within each parental wealth quintile. Q1 = bottom quintile, Q5 = top quintile.

Table B.21
Field of Education by Parental Wealth Quintile

	Full Sample (%)					Entrepreneurs (%)				
Education	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
Secondary	47.7	44.2	37.5	31.8	30.8	30.1	25.0	20.7	17.5	14.9
High School	36.4	36.4	37.4	36.6	32.6	48.8	49.2	48.2	46.4	40.6
Bachelor	13.2	16.2	20.3	24.4	26.3	16.3	19.7	22.1	25.0	29.2
Master/PhD	2.6	3.2	4.8	7.2	10.3	4.8	6.1	8.9	11.1	15.3

Notes: Column percentages within each parental wealth quintile. Q1 = bottom quintile, Q5 = top quintile.

Table B.22
Education Level by Parental Wealth Quintile

	Mobility Dimensions		
Mobility Metrics	**Intergenerational** *(vs. Parents)*	**Pre-Entry** *(Selection Test)*	**Post-Entry** *(Self-Improvement)*
Rank Gap	Child rank - Parent rank (at horizon h)	Child rank - Parent rank (at t)	Own rank (h) - Own rank (t)
Upward Shift	Child quintile > Parent quintile (at horizon h)	Child quintile > Parent quintile (at t)	Own quintile (h) > Own quintile (t)
Top 10%	Child ≥ 90th percentile (at h or t) – *Identical across dimensions*		

Notes: Framework for analyzing entrepreneurial mobility effects across three dimensions using three metrics. **Intergenerational:** Traditional mobility vs. parental wealth. **Pre-Entry:** Mobility at entry (t) to test selection vs. treatment. **Post-Entry:** Self-improvement vs. own baseline. Top 10% Achievement is an absolute threshold measured identically across dimensions.

Table B.23
Mobility Dimensions and Metrics Framework

	(1) Rank Gap $h = 5$	(2) Rank Gap $h = 10$	(3) Upward $h = 5$	(4) Upward $h = 10$	(5) Top 10% $h = 5$	(6) Top 10% $h = 10$
Entrepreneur	6.428^{***}	7.792^{***}	0.062^{***}	0.071^{***}	0.145^{***}	0.188^{***}
	(0.253)	(0.406)	(0.003)	(0.005)	(0.005)	(0.008)
Constant	-10.018^{***}	-9.622^{***}	0.196^{***}	0.188^{***}	0.207^{***}	0.246^{***}
	(0.098)	(0.187)	(0.001)	(0.003)	(0.002)	(0.003)
Observations	2,554,462	681,951	2,554,462	681,951	2,554,462	681,951
R^2	0.370	0.359	0.435	0.459	0.132	0.170
Fixed Effects						
Entry year	Yes	Yes	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes	Yes	Yes
Education (3-digit)	Yes	Yes	Yes	Yes	Yes	Yes
Parental wealth quintile	Yes	Yes	Yes	Yes	Yes	Yes
Entropy balancing	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors clustered by entry year × municipality in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.24
Baseline Treatment Effects of Entrepreneurship on Wealth Mobility

	(1) Rank Gap $h=5$	(2) Rank Gap $h=10$	(3) Upward $h=5$	(4) Upward $h=10$	(5) Top 10% $h=5$	(6) Top 10% $h=10$
Entrepreneur	5.505^{***}	6.760^{***}	0.000	−0.001	0.166^{***}	0.211^{***}
	(0.327)	(0.477)	(0.001)	(0.001)	(0.006)	(0.010)
Entrepreneur × Q1	1.519	0.811	0.039^{**}	−0.005	-0.041^{*}	−0.064
	(1.556)	(2.878)	(0.016)	(0.036)	(0.022)	(0.047)
Entrepreneur × Q2	1.784^{**}	2.595^{*}	0.061^{***}	0.054^{***}	-0.038^{***}	-0.044^{*}
	(0.784)	(1.503)	(0.011)	(0.020)	(0.014)	(0.023)
Entrepreneur × Q3	2.032^{***}	2.945^{***}	0.133^{***}	0.159^{***}	-0.045^{***}	-0.056^{***}
	(0.623)	(1.122)	(0.010)	(0.018)	(0.011)	(0.019)
Entrepreneur × Q4	1.215^{**}	1.193	0.150^{***}	0.193^{***}	-0.048^{***}	-0.051^{***}
	(0.514)	(0.744)	(0.008)	(0.013)	(0.009)	(0.016)
Parental wealth Q1	64.195^{***}	63.093^{***}	0.866^{***}	0.875^{***}	-0.106^{***}	-0.127^{***}
	(0.230)	(0.411)	(0.004)	(0.005)	(0.003)	(0.007)
Parental wealth Q2	50.269^{***}	49.367^{***}	0.741^{***}	0.743^{***}	-0.089^{***}	-0.109^{***}
	(0.193)	(0.261)	(0.004)	(0.007)	(0.003)	(0.005)
Parental wealth Q3	29.886^{***}	29.395^{***}	0.492^{***}	0.515^{***}	-0.106^{***}	-0.125^{***}
	(0.165)	(0.252)	(0.005)	(0.010)	(0.003)	(0.005)
Parental wealth Q4	12.574^{***}	12.088^{***}	0.281^{***}	0.309^{***}	-0.100^{***}	-0.113^{***}
	(0.106)	(0.158)	(0.004)	(0.008)	(0.002)	(0.004)
Observations	2,554,462	681,951	2,554,462	681,951	2,554,462	681,951
R^2	0.373	0.363	0.442	0.468	0.134	0.172
Fixed Effects						
Entry year	Yes	Yes	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes	Yes	Yes
Education (3-digit)	Yes	Yes	Yes	Yes	Yes	Yes
Entropy balancing	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Omitted category: Q5 (top quintile). Standard errors clustered by entry year × municipality in parentheses. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

Table B.25
Heterogeneous Effects by Parental Wealth

	(1) Rank Gap $h=5$	(2) Rank Gap $h=10$	(3) Upward $h=5$	(4) Upward $h=10$	(5) Top 10% $h=5$	(6) Top 10% $h=10$
Entrepreneur	9.939***	10.652***	0.088***	0.103***	0.125***	0.171***
	(0.664)	(1.160)	(0.009)	(0.013)	(0.010)	(0.018)
Entrepreneur × High school	−4.142***	−3.438***	−0.022**	−0.029**	0.001	−0.009
	(0.677)	(1.149)	(0.010)	(0.013)	(0.012)	(0.020)
Entrepreneur × Bachelor	−2.980***	−1.485	−0.032***	−0.037***	0.061***	0.088***
	(0.746)	(1.343)	(0.010)	(0.013)	(0.013)	(0.020)
Entrepreneur × Master/PhD	−4.655***	−4.286***	−0.051***	−0.063***	0.076***	0.056**
	(0.772)	(1.240)	(0.011)	(0.016)	(0.015)	(0.026)
High school	11.385***	10.256***	0.095***	0.086***	0.060***	0.065***
	(0.129)	(0.203)	(0.001)	(0.002)	(0.002)	(0.004)
Bachelor	14.174***	13.456***	0.115***	0.113***	0.065***	0.079***
	(0.271)	(0.458)	(0.002)	(0.003)	(0.004)	(0.008)
Master/PhD	22.200***	21.598***	0.175***	0.170***	0.172***	0.205***
	(0.221)	(0.263)	(0.002)	(0.003)	(0.004)	(0.007)
Observations	2,554,462	681,952	2,554,462	681,952	2,554,462	681,952
R^2	0.344	0.331	0.425	0.448	0.101	0.138
Fixed Effects						
Entry year	Yes	Yes	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes	Yes	Yes
Parental wealth quintile	Yes	Yes	Yes	Yes	Yes	Yes
Entropy balancing	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Omitted category: Secondary education. Standard errors clustered by entry year × municipality in parentheses. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

Table B.26
Heterogeneous Effects by Education Level

	(1) Rank Gap $h = 5$	(2) Rank Gap $h = 10$	(3) Upward $h = 5$	(4) Upward $h = 10$	(5) Top 10% $h = 5$	(6) Top 10% $h = 10$
Entrepreneur	6.870***	8.291***	0.068***	0.079***	0.143***	0.186***
	(0.271)	(0.446)	(0.003)	(0.006)	(0.005)	(0.009)
Entrepreneur × Business	−4.204***	−3.602***	−0.053***	−0.065***	−0.008	0.000
	(0.632)	(0.905)	(0.008)	(0.013)	(0.015)	(0.019)
Entrepreneur × Science	−1.528	−1.515	−0.038*	0.007	0.082*	0.004
	(1.494)	(2.060)	(0.023)	(0.037)	(0.042)	(0.077)
Entrepreneur × Engineering	−0.662	−0.471	−0.011	−0.027	0.061***	0.076***
	(0.640)	(1.115)	(0.009)	(0.018)	(0.016)	(0.023)
Entrepreneur × Multiple	5.672	−5.095	0.002	0.049	0.180	−0.095
	(5.698)	(20.862)	(0.119)	(0.147)	(0.166)	(0.405)
Business	12.751***	12.354***	0.092***	0.090***	0.168***	0.176***
	(0.141)	(0.195)	(0.002)	(0.003)	(0.004)	(0.007)
Science	11.635***	11.203***	0.093***	0.094***	0.118***	0.126***
	(0.226)	(0.456)	(0.003)	(0.006)	(0.005)	(0.010)
Engineering	11.086***	10.334***	0.084***	0.076***	0.101***	0.105***
	(0.125)	(0.195)	(0.001)	(0.002)	(0.003)	(0.005)
Multiple fields	16.183***	14.991***	0.130***	0.132***	0.191***	0.220***
	(0.517)	(0.938)	(0.009)	(0.015)	(0.016)	(0.033)
Observations	2,554,462	681,952	2,554,462	681,952	2,554,462	681,952
R^2	0.331	0.319	0.421	0.444	0.100	0.135
Fixed Effects						
Entry year	Yes	Yes	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes	Yes	Yes
Parental wealth quintile	Yes	Yes	Yes	Yes	Yes	Yes
Entropy balancing	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Omitted category: Other fields. Standard errors clustered by entry year × municipality in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.27
Heterogeneous Effects by Field of Study

	(1) Rank Gap t	(2) Upward t	(3) Top 10% t
Entrepreneur	3.883***	0.036***	0.066***
	(0.214)	(0.002)	(0.004)
Constant	-10.556***	0.203***	0.174***
	(0.078)	(0.001)	(0.001)
Observations	4,587,452	4,634,137	4,634,137
R^2	0.344	0.415	0.098
Fixed Effects			
Entry year	Yes	Yes	Yes
Municipality	Yes	Yes	Yes
Education (3-digit)	Yes	Yes	Yes
Parental wealth quintile	Yes	Yes	Yes
Entropy balancing	Yes	Yes	Yes

Notes: Outcomes measured at entrepreneurship entry year (t) to assess pre-existing mobility patterns. Standard errors clustered by entry year × municipality in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.28
Pre-Entry Mobility: Effects at Entrepreneurship Entry (t)

	(1) Rank Gap t	(2) Upward t	(3) Top 10% t
Entrepreneur	2.797***	-0.000	0.085***
	(0.295)	(0.001)	(0.005)
Entrepreneur × Q1	2.312**	0.067***	-0.035**
	(1.121)	(0.011)	(0.015)
Entrepreneur × Q2	2.432***	0.049***	-0.037***
	(0.640)	(0.009)	(0.009)
Entrepreneur × Q3	1.886***	0.079***	-0.040***
	(0.522)	(0.008)	(0.007)
Entrepreneur × Q4	1.636***	0.070***	-0.040***
	(0.411)	(0.007)	(0.006)
Parental wealth Q1	61.700***	0.854***	-0.084***
	(0.214)	(0.004)	(0.002)
Parental wealth Q2	47.793***	0.729***	-0.067***
	(0.200)	(0.004)	(0.002)
Parental wealth Q3	28.178***	0.471***	-0.088***
	(0.156)	(0.004)	(0.002)
Parental wealth Q4	12.836***	0.259***	-0.083***
	(0.095)	(0.002)	(0.001)
Observations	4,587,452	4,634,137	4,634,137
R^2	0.348	0.419	0.099
Fixed Effects			
Entry year	Yes	Yes	Yes
Municipality	Yes	Yes	Yes
Education (3-digit)	Yes	Yes	Yes
Entropy balancing	Yes	Yes	Yes

Notes: Omitted category: Q5 (top quintile). Outcomes measured at entry year (t) to assess heterogeneous pre-existing mobility patterns by parental wealth background. Standard errors clustered by entry year × municipality in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.29
Pre-Entry Heterogeneity by Parental Wealth (t)

	(1) Rank Gap t	(2) Upward t	(3) Top 10% t
Entrepreneur	8.472***	0.071***	0.059***
	(0.490)	(0.006)	(0.006)
Entrepreneur × High school	-5.819***	-0.043***	-0.020***
	(0.514)	(0.007)	(0.007)
Entrepreneur × Bachelor	-4.541***	-0.035***	0.045***
	(0.572)	(0.007)	(0.009)
Entrepreneur × Master/PhD	-5.669***	-0.049***	0.055***
	(0.639)	(0.008)	(0.010)
High school	11.809***	0.098***	0.051***
	(0.128)	(0.001)	(0.001)
Bachelor	12.801***	0.106***	0.040***
	(0.230)	(0.002)	(0.002)
Master/PhD	19.789***	0.157***	0.116***
	(0.312)	(0.002)	(0.003)
Observations	4,587,455	4,634,140	4,634,140
R^2	0.321	0.407	0.071
Fixed Effects			
Entry year	Yes	Yes	Yes
Municipality	Yes	Yes	Yes
Parental wealth quintile	Yes	Yes	Yes
Entropy balancing	Yes	Yes	Yes

Notes: Omitted category: Secondary education. Outcomes measured at entry year (t) to assess heterogeneous pre-existing mobility patterns by education level. Standard errors clustered by entry year × municipality in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.30
Pre-Entry Heterogeneity by Education Level (t)

	(1) Rank Gap t	(2) Upward t	(3) Top 10% t
Entrepreneur	4.086***	0.039***	0.061***
	(0.231)	(0.002)	(0.003)
Entrepreneur × Business only	-3.760***	-0.038***	0.014
	(0.534)	(0.006)	(0.013)
Entrepreneur × Science only	-3.278**	-0.043**	0.027
	(1.369)	(0.019)	(0.030)
Entrepreneur × Engineering only	-0.511	-0.002	0.047***
	(0.601)	(0.009)	(0.013)
Entrepreneur × Multiple fields	-2.916	0.031	0.040
	(4.591)	(0.100)	(0.141)
Business only	11.890***	0.084***	0.143***
	(0.187)	(0.002)	(0.003)
Science only	10.754***	0.081***	0.097***
	(0.309)	(0.003)	(0.005)
Engineering only	10.714***	0.080***	0.086***
	(0.172)	(0.002)	(0.003)
Multiple fields	15.153***	0.118***	0.148***
	(0.505)	(0.008)	(0.013)
Observations	4,587,455	4,634,140	4,634,140
R^2	0.314	0.403	0.074
Fixed Effects			
Entry year	Yes	Yes	Yes
Municipality	Yes	Yes	Yes
Parental wealth quintile	Yes	Yes	Yes
Entropy balancing	Yes	Yes	Yes

Notes: Omitted category: Other fields. Outcomes measured at entry year (t) to assess heterogeneous pre-existing mobility patterns by field of study. Standard errors clustered by entry year × municipality in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.31
Pre-Entry Heterogeneity by Field of Study (t)

	(1) Rank Change $h = 5$	(2) Rank Change $h = 10$	(3) Upward $h = 5$	(4) Upward $h = 10$
Entrepreneur	3.260***	5.047***	0.086***	0.090***
	(0.192)	(0.415)	(0.003)	(0.007)
Constant	-0.509***	-0.860***	0.193***	0.224***
	(0.105)	(0.204)	(0.002)	(0.003)
Observations	2,554,462	681,951	2,554,462	681,951
R^2	0.152	0.229	0.250	0.342
Fixed Effects				
Entry year	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes
Education (3-digit)	Yes	Yes	Yes	Yes
Own wealth quintile at t-1	Yes	Yes	Yes	Yes
Entropy balancing	Yes	Yes	Yes	Yes

Notes: Outcomes measure changes relative to person's own wealth position at t. Rank Change shows percentile point improvement from baseline. Upward indicates movement to higher wealth quintile relative to own starting position. Standard errors clustered by entry year × municipality in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.32
Self-Benchmarked Mobility: Personal Wealth Trajectory Effects

	(1) Rank Change $h = 5$	(2) Rank Change $h = 10$	(3) Upward $h = 5$	(4) Upward $h = 10$
Entrepreneur	2.378***	3.037***	0.032***	0.017
	(0.247)	(0.565)	(0.006)	(0.013)
Entrepreneur × Q1	-1.502	-0.590	0.019	0.003
	(1.273)	(3.098)	(0.022)	(0.047)
Entrepreneur × Q2	-1.040	0.611	0.028*	0.058**
	(0.769)	(1.576)	(0.015)	(0.029)
Entrepreneur × Q3	0.008	1.853	0.032***	0.044**
	(0.534)	(1.151)	(0.011)	(0.022)
Entrepreneur × Q4	-0.703*	0.476	0.021**	0.041**
	(0.420)	(0.739)	(0.009)	(0.017)
Parental wealth Q1	-2.596***	-4.807***	-0.025***	-0.037***
	(0.142)	(0.364)	(0.003)	(0.006)
Parental wealth Q2	-2.295***	-4.609***	-0.028***	-0.042***
	(0.119)	(0.230)	(0.003)	(0.004)
Parental wealth Q3	-1.288***	-2.914***	-0.003	-0.014***
	(0.108)	(0.186)	(0.002)	(0.004)
Parental wealth Q4	-0.883***	-1.875***	0.005***	-0.003
	(0.072)	(0.132)	(0.002)	(0.003)
Observations	2,554,462	681,951	2,554,462	681,951
R^2	0.034	0.068	0.026	0.047
Fixed Effects				
Entry year	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes
Education (3-digit)	Yes	Yes	Yes	Yes
Entropy balancing	Yes	Yes	Yes	Yes

Notes: Omitted category: Q5 (top quintile). Outcomes measure changes relative to person's own wealth position at t to assess heterogeneous personal wealth trajectory improvements by parental wealth background. Standard errors clustered by entry year × municipality in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.33
Self-Benchmarked Heterogeneity by Parental Wealth

	(1) Rank Change $h = 5$	(2) Rank Change $h = 10$	(3) Upward $h = 5$	(4) Upward $h = 10$
Entrepreneur	3.410***	6.408***	0.111***	0.124***
	(0.548)	(1.012)	(0.008)	(0.015)
Entrepreneur × High school	0.431	-0.708	-0.010	-0.020
	(0.578)	(1.063)	(0.009)	(0.018)
Entrepreneur × Bachelor	-0.284	-1.521	-0.040***	-0.037*
	(0.591)	(1.200)	(0.010)	(0.020)
Entrepreneur × Master/PhD	-0.997	-3.044***	-0.067***	-0.103***
	(0.652)	(1.176)	(0.013)	(0.018)
High school	3.992***	5.373***	0.068***	0.072***
	(0.125)	(0.217)	(0.002)	(0.003)
Bachelor	6.958***	9.721***	0.117***	0.129***
	(0.173)	(0.372)	(0.003)	(0.006)
Master/PhD	10.682***	15.060***	0.185***	0.213***
	(0.227)	(0.301)	(0.003)	(0.004)
Observations	2,554,462	681,952	2,554,462	681,952
R^2	0.142	0.213	0.242	0.330
Fixed Effects				
Entry year	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes
Own wealth quintile at t	Yes	Yes	Yes	Yes
Entropy balancing	Yes	Yes	Yes	Yes

Notes: Omitted category: Secondary education. Outcomes measure changes relative to person's own wealth position at t to assess heterogeneous personal wealth trajectory improvements by education level. Standard errors clustered by entry year × municipality in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.34
Self-Benchmarked Heterogeneity by Education Level

	(1) Rank Change $h = 5$	(2) Rank Change $h = 10$	(3) Upward $h = 5$	(4) Upward $h = 10$
Entrepreneur	3.460***	5.581***	0.094***	0.103***
	(0.212)	(0.436)	(0.004)	(0.007)
Entrepreneur × Business only	-1.715***	-3.273***	-0.060***	-0.084***
	(0.493)	(0.795)	(0.010)	(0.013)
Entrepreneur × Science only	-0.327	-2.928	0.006	-0.047
	(1.341)	(2.181)	(0.030)	(0.035)
Entrepreneur × Engineering only	-0.612	-1.240	-0.041***	-0.053***
	(0.517)	(0.894)	(0.011)	(0.019)
Entrepreneur × Multiple fields	3.634	-2.770	-0.002	-0.010
	(3.498)	(7.742)	(0.121)	(0.112)
Business only	5.347***	7.869***	0.089***	0.108***
	(0.123)	(0.176)	(0.002)	(0.003)
Science only	5.519***	8.333***	0.093***	0.120***
	(0.185)	(0.425)	(0.004)	(0.006)
Engineering only	4.746***	6.777***	0.077***	0.090***
	(0.105)	(0.152)	(0.002)	(0.003)
Multiple fields	7.227***	10.251***	0.125***	0.144***
	(0.414)	(0.728)	(0.010)	(0.017)
Observations	2,554,462	681,952	2,554,462	681,952
R^2	0.130	0.198	0.236	0.324
Fixed Effects				
Entry year	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes
Own wealth quintile at t	Yes	Yes	Yes	Yes
Entropy balancing	Yes	Yes	Yes	Yes

Notes: Omitted category: Other fields. Outcomes measure changes relative to person's own wealth position at t to assess heterogeneous personal wealth trajectory improvements by field of study. Standard errors clustered by entry year × municipality in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.35
Self-Benchmarked Heterogeneity by Field of Study

	(1) Rank Gap $h = 5$	(2) Rank Gap $h = 10$	(3) Upward $h = 5$	(4) Upward $h = 10$	(5) Top 10% $h = 5$	(6) Top 10% $h = 10$
Entrepreneur	16.406^{***}	16.465^{***}	0.120^{***}	0.119^{***}	0.242^{***}	0.297^{***}
	(0.287)	(0.495)	(0.003)	(0.007)	(0.006)	(0.010)
Constant	-21.698^{***}	-19.772^{***}	0.137^{***}	0.144^{***}	0.076^{***}	0.094^{***}
	(0.051)	(0.031)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	2,554,462	681,951	2,554,462	681,951	2,554,462	681,951
R^2	0.408	0.357	0.276	0.273	0.083	0.091
Fixed Effects						
Entry year	Yes	Yes	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes	Yes	Yes
Education (3-digit)	Yes	Yes	Yes	Yes	Yes	Yes
Parental wealth quintile	Yes	Yes	Yes	Yes	Yes	Yes
Entropy balancing	No	No	No	No	No	No

Notes: Standard errors clustered by entry year × municipality in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.36
Baseline Treatment Effects (Without Entropy Balancing)

	(1) Rank Gap $h = 5$	(2) Rank Gap $h = 10$	(3) Upward $h = 5$	(4) Upward $h = 10$	(5) Top 10% $h = 5$	(6) Top 10% $h = 10$
Entrepreneur	15.495^{***}	15.195^{***}	-0.026^{***}	-0.028^{***}	0.294^{***}	0.349^{***}
	(0.376)	(0.600)	(0.001)	(0.002)	(0.008)	(0.011)
Entrepreneur × Q1	3.403^{**}	4.897^{*}	0.230^{***}	0.178^{***}	-0.117^{***}	-0.135^{***}
	(1.634)	(2.916)	(0.016)	(0.036)	(0.023)	(0.045)
Entrepreneur × Q2	3.662^{***}	5.175^{***}	0.300^{***}	0.269^{***}	-0.099^{***}	-0.117^{***}
	(0.801)	(1.603)	(0.012)	(0.021)	(0.015)	(0.023)
Entrepreneur × Q3	2.315^{***}	4.108^{***}	0.349^{***}	0.369^{***}	-0.117^{***}	-0.132^{***}
	(0.672)	(1.201)	(0.011)	(0.018)	(0.011)	(0.019)
Entrepreneur × Q4	1.073^{**}	1.579^{**}	0.299^{***}	0.350^{***}	-0.109^{***}	-0.111^{***}
	(0.524)	(0.768)	(0.009)	(0.014)	(0.009)	(0.016)
Parental wealth Q1	64.357^{***}	61.227^{***}	0.677^{***}	0.702^{***}	-0.054^{***}	-0.067^{***}
	(0.172)	(0.266)	(0.004)	(0.004)	(0.002)	(0.003)
Parental wealth Q2	49.726^{***}	47.846^{***}	0.503^{***}	0.526^{***}	-0.048^{***}	-0.060^{***}
	(0.143)	(0.207)	(0.003)	(0.007)	(0.001)	(0.003)
Parental wealth Q3	30.308^{***}	29.159^{***}	0.274^{***}	0.309^{***}	-0.054^{***}	-0.066^{***}
	(0.121)	(0.161)	(0.003)	(0.008)	(0.002)	(0.003)
Parental wealth Q4	13.305^{***}	12.571^{***}	0.132^{***}	0.155^{***}	-0.050^{***}	-0.060^{***}
	(0.097)	(0.133)	(0.002)	(0.005)	(0.002)	(0.003)
Observations	2,554,462	681,951	2,554,462	681,951	2,554,462	681,951
R^2	0.408	0.357	0.277	0.275	0.083	0.092
Fixed Effects						
Entry year	Yes	Yes	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes	Yes	Yes
Education (3-digit)	Yes	Yes	Yes	Yes	Yes	Yes
Entropy balancing	No	No	No	No	No	No

Notes: Omitted category: Q5 (top quintile). Standard errors clustered by entry year × municipality in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.37
Heterogeneous Effects by Parental Wealth (Without Entropy Balancing)

	(1) Rank Gap $h = 5$	(2) Rank Gap $h = 10$	(3) Upward $h = 5$	(4) Upward $h = 10$	(5) Top 10% $h = 5$	(6) Top 10% $h = 10$
Entrepreneur	25.795***	24.165***	0.193***	0.194***	0.208***	0.267***
	(0.708)	(1.174)	(0.009)	(0.014)	(0.011)	(0.018)
Entrepreneur × High school	−6.410***	−4.892***	−0.042***	−0.043***	0.032***	0.022
	(0.697)	(1.184)	(0.010)	(0.015)	(0.012)	(0.019)
Entrepreneur × Bachelor	−8.786***	−5.886***	−0.088***	−0.085***	0.093***	0.120***
	(0.776)	(1.359)	(0.010)	(0.015)	(0.014)	(0.020)
Entrepreneur × Master/PhD	−13.693***	−11.941***	−0.127***	−0.139***	0.123***	0.098***
	(0.778)	(1.252)	(0.012)	(0.018)	(0.016)	(0.028)
High school	13.558***	11.736***	0.092***	0.085***	0.037***	0.042***
	(0.101)	(0.186)	(0.001)	(0.002)	(0.001)	(0.002)
Bachelor	19.908***	17.614***	0.119***	0.116***	0.050***	0.062***
	(0.238)	(0.388)	(0.001)	(0.002)	(0.002)	(0.006)
Master/PhD	30.997***	28.677***	0.178***	0.177***	0.150***	0.187***
	(0.174)	(0.183)	(0.002)	(0.002)	(0.004)	(0.008)
Observations	2,554,462	681,952	2,554,462	681,952	2,554,462	681,952
R^2	0.373	0.329	0.264	0.264	0.055	0.066
Fixed Effects						
Entry year	Yes	Yes	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes	Yes	Yes
Parental wealth quintile	Yes	Yes	Yes	Yes	Yes	Yes
Entropy balancing	No	No	No	No	No	No

Notes: Omitted category: Secondary education. Standard errors clustered by entry year × municipality in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.38
Heterogeneous Effects by Education Level (Without Entropy Balancing)

	(1) Rank Gap $h = 5$	(2) Rank Gap $h = 10$	(3) Upward $h = 5$	(4) Upward $h = 10$	(5) Top 10% $h = 5$	(6) Top 10% $h = 10$
Entrepreneur	20.755***	20.644***	0.153***	0.157***	0.249***	0.306***
	(0.318)	(0.488)	(0.003)	(0.007)	(0.006)	(0.010)
Entrepreneur × Business	−9.905***	−8.869***	−0.109***	−0.120***	0.047***	0.046**
	(0.645)	(0.946)	(0.010)	(0.015)	(0.016)	(0.020)
Entrepreneur × Science	−9.234***	−8.654***	−0.096***	−0.048	0.082*	0.007
	(1.478)	(2.047)	(0.027)	(0.047)	(0.043)	(0.076)
Entrepreneur × Engineering	−6.063***	−4.967***	−0.049***	−0.065***	0.080***	0.090***
	(0.646)	(1.141)	(0.011)	(0.021)	(0.016)	(0.023)
Entrepreneur × Multiple	−4.026	−13.126	−0.046	0.036	0.132	−0.136
	(5.523)	(22.846)	(0.137)	(0.251)	(0.159)	(0.381)
Business	18.319***	17.054***	0.102***	0.099***	0.135***	0.147***
	(0.126)	(0.177)	(0.002)	(0.003)	(0.004)	(0.008)
Science	19.112***	17.353***	0.105***	0.103***	0.135***	0.140***
	(0.179)	(0.343)	(0.003)	(0.006)	(0.004)	(0.007)
Engineering	16.316***	14.112***	0.095***	0.087***	0.096***	0.098***
	(0.144)	(0.194)	(0.001)	(0.002)	(0.002)	(0.004)
Multiple fields	26.266***	23.622***	0.169***	0.165***	0.229***	0.245***
	(0.539)	(0.929)	(0.010)	(0.016)	(0.012)	(0.023)
Observations	2,554,462	681,952	2,554,462	681,952	2,554,462	681,952
R^2	0.322	0.288	0.250	0.251	0.054	0.060
Fixed Effects						
Entry year	Yes	Yes	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes	Yes	Yes
Parental wealth quintile	Yes	Yes	Yes	Yes	Yes	Yes
Entropy balancing	No	No	No	No	No	No

Notes: Omitted category: Other fields. Standard errors clustered by entry year × municipality in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.39
Heterogeneous Effects by Field of Study (Without Entropy Balancing)

	(1) Rank Gap $h = 5$	(2) Rank Gap $h = 10$	(3) Upward $h = 5$	(4) Upward $h = 10$	(5) Top 10% $h = 5$	(6) Top 10% $h = 10$
Entrepreneur	−0.040	3.078***	0.011***	0.018***	0.064***	0.117***
	(0.321)	(0.556)	(0.002)	(0.004)	(0.004)	(0.007)
Constant	−31.077***	−28.608***	0.107***	0.110***	0.141***	0.182***
	(0.106)	(0.256)	(0.001)	(0.002)	(0.001)	(0.003)
Observations	2,554,462	681,951	2,554,462	681,951	2,554,462	681,951
R^2	0.217	0.215	0.221	0.265	0.090	0.133
Fixed Effects						
Entry year	Yes	Yes	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes	Yes	Yes
Education (3-digit)	Yes	Yes	Yes	Yes	Yes	Yes
Parental net wealth quintile	Yes	Yes	Yes	Yes	Yes	Yes
Entropy balancing	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table re-estimates the main specification using net wealth percentiles rather than gross wealth percentiles. Net wealth is defined as gross wealth minus debt. Regressions compare entrepreneurs to entropy-balanced non-entrepreneurs using the baseline weighting design. Standard errors clustered by entry year × municipality in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.40
Baseline Treatment Effects of Entrepreneurship on Net-Wealth Mobility

	(1) Rank Gap $h=5$	(2) Rank Gap $h=10$	(3) Upward $h=5$	(4) Upward $h=10$	(5) Top 10% $h=5$	(6) Top 10% $h=10$
Entrepreneur	0.146	3.963***	0.001	0.000	0.076***	0.141***
	(0.446)	(0.745)	(0.001)	(0.001)	(0.006)	(0.009)
Entrepreneur × Q1	2.783*	0.894	−0.030	−0.030	−0.021	−0.041*
	(1.632)	(2.429)	(0.023)	(0.035)	(0.014)	(0.025)
Entrepreneur × Q2	−1.935*	−3.799**	−0.029**	−0.014	−0.044***	−0.069***
	(1.015)	(1.704)	(0.012)	(0.021)	(0.009)	(0.018)
Entrepreneur × Q3	−1.762*	−4.840**	0.004	0.017	−0.039***	−0.083***
	(0.945)	(2.015)	(0.012)	(0.027)	(0.009)	(0.020)
Entrepreneur × Q4	−0.467	−2.131*	0.057***	0.079***	−0.020**	−0.050***
	(0.720)	(1.290)	(0.007)	(0.014)	(0.008)	(0.014)
Parental wealth Q1	63.069***	62.182***	0.546***	0.552***	−0.111***	−0.133***
	(0.247)	(0.437)	(0.004)	(0.008)	(0.003)	(0.005)
Parental wealth Q2	46.718***	45.281***	0.348***	0.386***	−0.111***	−0.136***
	(0.200)	(0.344)	(0.003)	(0.007)	(0.002)	(0.005)
Parental wealth Q3	24.936***	23.154***	0.270***	0.301***	−0.103***	−0.124***
	(0.203)	(0.305)	(0.003)	(0.007)	(0.002)	(0.004)
Parental wealth Q4	10.724***	9.932***	0.161***	0.192***	−0.090***	−0.109***
	(0.127)	(0.224)	(0.003)	(0.006)	(0.002)	(0.004)
Observations	2,554,462	681,951	2,554,462	681,951	2,554,462	681,951
R^2	0.219	0.217	0.221	0.266	0.091	0.135
Fixed Effects						
Entry year	Yes	Yes	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes	Yes	Yes
Education (3-digit)	Yes	Yes	Yes	Yes	Yes	Yes
Parental net wealth quintile	Yes	Yes	Yes	Yes	Yes	Yes
Entropy balancing	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Omitted category: Q5 (top quintile). This table uses net wealth percentiles for all outcome measures and net-wealth-based fixed effects. Net wealth is defined as gross wealth minus debt. For comparability with the main specification, the interaction groups in H1 are based on parental gross wealth quintiles rather than parental net wealth quintiles. Regressions compare entrepreneurs to entropy-balanced non-entrepreneurs using the H1 weighting design, which excludes parental wealth from the balancing constraints. Standard errors clustered by entry year × municipality in parentheses. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

Table B.41
Heterogeneous Effects on Net-Wealth Mobility by Parental Wealth

	(1) Rank Gap $h=5$	(2) Rank Gap $h=10$	(3) Upward $h=5$	(4) Upward $h=10$	(5) Top 10% $h=5$	(6) Top 10% $h=10$
Entrepreneur	-2.725^{***}	0.727	0.004	0.015	0.046^{***}	0.113^{***}
	(0.708)	(1.401)	(0.007)	(0.013)	(0.008)	(0.014)
Entrepreneur × High school	2.258^{***}	1.122	0.009	-0.003	0.004	-0.015
	(0.819)	(1.451)	(0.008)	(0.014)	(0.009)	(0.017)
Entrepreneur × Bachelor	3.268^{***}	4.847^{***}	0.012	0.015	0.051^{***}	0.050^{***}
	(0.914)	(1.715)	(0.008)	(0.013)	(0.010)	(0.018)
Entrepreneur × Master/PhD	5.205^{***}	4.809^{**}	0.002	0.011	0.043^{***}	0.031
	(1.037)	(1.910)	(0.010)	(0.016)	(0.013)	(0.024)
High school	0.470^{***}	2.230^{***}	0.015^{***}	0.027^{***}	0.029^{***}	0.038^{***}
	(0.122)	(0.270)	(0.001)	(0.002)	(0.002)	(0.003)
Bachelor	1.453^{***}	4.317^{***}	0.024^{***}	0.040^{***}	0.039^{***}	0.058^{***}
	(0.173)	(0.399)	(0.001)	(0.002)	(0.003)	(0.007)
Master/PhD	2.383^{***}	7.400^{***}	0.037^{***}	0.058^{***}	0.099^{***}	0.143^{***}
	(0.185)	(0.362)	(0.002)	(0.003)	(0.003)	(0.007)
Observations	2,554,462	681,952	2,554,462	681,952	2,554,462	681,952
R^2	0.204	0.198	0.215	0.256	0.074	0.111
Fixed Effects						
Entry year	Yes	Yes	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes	Yes	Yes
Parental net wealth quintile	Yes	Yes	Yes	Yes	Yes	Yes
Entropy balancing	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Omitted category: Less than high school. This table uses net wealth percentiles for all outcome measures and net-wealth-based fixed effects. Net wealth is defined as gross wealth minus debt. Regressions compare entrepreneurs to entropy-balanced non-entrepreneurs using the H2 weighting design, which excludes education from the balancing constraints. Standard errors clustered by entry year × municipality in parentheses. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

Table B.42
Heterogeneous Effects on Net-Wealth Mobility by Education Level

	(1) Rank Gap $h = 5$	(2) Rank Gap $h = 10$	(3) Upward $h = 5$	(4) Upward $h = 10$	(5) Top 10% $h = 5$	(6) Top 10% $h = 10$
Entrepreneur	−0.303	2.773***	0.011***	0.016***	0.062***	0.118***
	(0.312)	(0.595)	(0.003)	(0.004)	(0.004)	(0.007)
Entrepreneur × Business	−1.077	−0.060	−0.006	0.005	−0.001	−0.022
	(1.077)	(1.718)	(0.006)	(0.011)	(0.013)	(0.023)
Entrepreneur × Science	1.041	−6.802	−0.004	0.015	0.060	−0.001
	(3.781)	(7.810)	(0.022)	(0.043)	(0.046)	(0.103)
Entrepreneur × Engineering	2.528*	4.202**	0.015	0.022	0.042**	0.061***
	(1.343)	(1.878)	(0.009)	(0.014)	(0.016)	(0.023)
Entrepreneur × Multiple	16.712	25.872	0.119	0.356	0.128	0.064
	(11.987)	(18.764)	(0.121)	(0.268)	(0.164)	(0.380)
Business	3.985***	5.640***	0.025***	0.030***	0.105***	0.122***
	(0.223)	(0.425)	(0.001)	(0.002)	(0.003)	(0.006)
Science	6.818***	8.075***	0.037***	0.041***	0.094***	0.110***
	(0.381)	(0.568)	(0.003)	(0.005)	(0.004)	(0.007)
Engineering	6.756***	7.507***	0.033***	0.034***	0.088***	0.097***
	(0.172)	(0.299)	(0.001)	(0.002)	(0.002)	(0.004)
Multiple fields	11.763***	12.557***	0.036***	0.036***	0.161***	0.186***
	(1.052)	(1.710)	(0.006)	(0.011)	(0.015)	(0.030)
Observations	2,554,462	681,952	2,554,462	681,952	2,554,462	681,952
R^2	0.206	0.198	0.216	0.255	0.076	0.110
Fixed Effects						
Entry year	Yes	Yes	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes	Yes	Yes
Parental net wealth quintile	Yes	Yes	Yes	Yes	Yes	Yes
Entropy balancing	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Omitted category: Other fields. This table uses net wealth percentiles for all outcome measures and net-wealth-based fixed effects. Net wealth is defined as gross wealth minus debt. Regressions compare entrepreneurs to entropy-balanced non-entrepreneurs using the H2 weighting design, which excludes education from the balancing constraints. Standard errors clustered by entry year × municipality in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.43
Heterogeneous Effects on Net-Wealth Mobility by Field of Study

	(1) Rank Gap	(2) Upward	(3) Top 10%
Entrepreneur	1.410***	0.024***	0.052***
	(0.188)	(0.002)	(0.003)
Constant	−12.461***	0.180***	0.174***
	(0.077)	(0.001)	(0.001)
Observations	4,576,147	4,576,147	4,576,147
R^2	0.355	0.392	0.092
Fixed Effects			
Entry year	Yes	Yes	Yes
Municipality	Yes	Yes	Yes
Education (3-digit)	Yes	Yes	Yes
Parental wealth quintile (t−5)	Yes	Yes	Yes
Entropy balancing	Yes	Yes	Yes

Notes: This alternative specification tests whether entrepreneurs already exhibit higher intergenerational mobility before entry. The child's wealth percentile is measured at $t-1$ (one year before entry), while the parent's wealth percentile is measured at $t-5$. Regressions compare entrepreneurs to entropy-balanced non-entrepreneurs using the baseline weighting design. Standard errors clustered by entry year × municipality in parentheses. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

Table B.44
Pre-Entry Alternative Test: Parent–Child Mobility Before Entrepreneurship

	(1) Rank Gap	(2) Upward	(3) Top 10%
Entrepreneur	0.120	−0.001	0.060***
	(0.255)	(0.001)	(0.005)
Entrepreneur × Q1	1.774	0.022	−0.038***
	(1.274)	(0.017)	(0.015)
Entrepreneur × Q2	3.644***	0.038***	−0.007
	(0.654)	(0.010)	(0.009)
Entrepreneur × Q3	2.199***	0.034***	−0.027***
	(0.484)	(0.008)	(0.007)
Entrepreneur × Q4	2.231***	0.062***	−0.015**
	(0.390)	(0.006)	(0.006)
Parental wealth Q1	65.410***	0.852***	−0.094***
	(0.200)	(0.004)	(0.003)
Parental wealth Q2	50.677***	0.725***	−0.084***
	(0.173)	(0.004)	(0.002)
Parental wealth Q3	29.755***	0.471***	−0.097***
	(0.148)	(0.004)	(0.002)
Parental wealth Q4	12.531***	0.248***	−0.094***
	(0.088)	(0.003)	(0.002)
Observations	4,576,147	4,576,147	4,576,147
R^2	0.360	0.395	0.092
Fixed Effects			
Entry year	Yes	Yes	Yes
Municipality	Yes	Yes	Yes
Education (3-digit)	Yes	Yes	Yes
Entropy balancing	Yes	Yes	Yes

Notes: Omitted category: Q5 (richest parents). Child wealth measured at $t-1$, parental wealth measured at $t-5$. Entropy balancing weights exclude parental wealth from the balancing constraints (H1 design). Standard errors clustered by entry year × municipality. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

Table B.45
Pre-Entry Alternative: Heterogeneous Effects by Parental Wealth

	(1) Rank Gap	(2) Upward	(3) Top 10%
Entrepreneur	5.540***	0.051***	0.053***
	(0.474)	(0.006)	(0.006)
Entrepreneur × High school	−5.241***	−0.031***	−0.020***
	(0.502)	(0.006)	(0.007)
Entrepreneur × Bachelor	−4.563***	−0.029***	0.023***
	(0.553)	(0.007)	(0.009)
Entrepreneur × Master/PhD	−4.515***	−0.040***	0.033***
	(0.581)	(0.007)	(0.011)
High school	12.066***	0.089***	0.048***
	(0.128)	(0.001)	(0.001)
Bachelor	13.053***	0.093***	0.033***
	(0.213)	(0.001)	(0.002)
Master/PhD	19.799***	0.136***	0.106***
	(0.279)	(0.002)	(0.003)
Observations	4,576,147	4,576,147	4,576,147
R^2	0.330	0.384	0.065
Fixed Effects			
Entry year	Yes	Yes	Yes
Municipality	Yes	Yes	Yes
Parental wealth quintile (t−5)	Yes	Yes	Yes
Entropy balancing	Yes	Yes	Yes

Notes: Omitted category: Secondary education. Child wealth measured at $t-1$, parental wealth measured at $t-5$. Entropy balancing weights exclude education from the balancing constraints (H2 design). Standard errors clustered by entry year × municipality. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

Table B.46
Pre-Entry Alternative: Heterogeneous Effects by Education Level

	(1) Rank Gap	(2) Upward	(3) Top 10%
Entrepreneur	1.536***	0.026***	0.051***
	(0.203)	(0.002)	(0.003)
Entrepreneur × Business	−3.922***	−0.034***	−0.022**
	(0.490)	(0.006)	(0.011)
Entrepreneur × Science	−0.817	−0.027	0.052*
	(1.452)	(0.017)	(0.031)
Entrepreneur × Engineering	−0.210	−0.012	0.021
	(0.626)	(0.008)	(0.014)
Entrepreneur × Multiple	−2.724	0.134	0.064
	(6.492)	(0.094)	(0.144)
Business	11.815***	0.074***	0.139***
	(0.173)	(0.002)	(0.002)
Science	10.676***	0.071***	0.096***
	(0.286)	(0.003)	(0.004)
Engineering	10.552***	0.069***	0.080***
	(0.167)	(0.001)	(0.003)
Multiple fields	15.271***	0.104***	0.133***
	(0.499)	(0.008)	(0.014)
Observations	4,576,147	4,576,147	4,576,147
R^2	0.320	0.381	0.068
Fixed Effects			
Entry year	Yes	Yes	Yes
Municipality	Yes	Yes	Yes
Parental wealth quintile (t−5)	Yes	Yes	Yes
Entropy balancing	Yes	Yes	Yes

Notes: Omitted category: Other fields. Child wealth measured at $t-1$, parental wealth measured at $t-5$. Entropy balancing weights exclude education from the balancing constraints (H3 design). Standard errors clustered by entry year × municipality. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

Table B.47
Pre-Entry Alternative: Heterogeneous Effects by Field of Study

	(1) Rank Gap	(2) Upward	(3) Top 10%
Entrepreneur	1.470***	0.023***	0.052***
	(0.189)	(0.002)	(0.003)
Constant	−10.439***	0.207***	0.174***
	(0.067)	(0.001)	(0.001)
Observations	4,634,137	4,634,137	4,634,137
R^2	0.392	0.408	0.090
Fixed Effects			
Entry year	Yes	Yes	Yes
Municipality	Yes	Yes	Yes
Education (3-digit)	Yes	Yes	Yes
Parental wealth quintile (t−1)	Yes	Yes	Yes
Entropy balancing	Yes	Yes	Yes

Notes: This table reports a contemporaneous pre-entry snapshot in which both the child's wealth percentile and the parent's wealth percentile are measured at $t-1$, one year before entrepreneurship entry. This shifts the main pre-entry comparison back one year so that both measures are fully pre-entry. Regressions compare entrepreneurs to entropy-balanced non-entrepreneurs using the baseline weighting design. Standard errors clustered by entry year × municipality in parentheses. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

Table B.48
Contemporaneous Pre-Entry Snapshot: Parent–Child Wealth Mobility Before Entrepreneurship

	(1) Rank Gap	(2) Upward	(3) Top 10%
Entrepreneur	0.144	−0.001	0.062***
	(0.269)	(0.001)	(0.005)
Entrepreneur × Q1	3.122***	0.024**	−0.024*
	(0.995)	(0.012)	(0.014)
Entrepreneur × Q2	2.695***	0.020**	−0.016*
	(0.638)	(0.010)	(0.009)
Entrepreneur × Q3	2.498***	0.038***	−0.022***
	(0.496)	(0.008)	(0.007)
Entrepreneur × Q4	1.991***	0.056***	−0.022***
	(0.387)	(0.006)	(0.006)
Parental wealth Q1	67.187***	0.861***	−0.086***
	(0.180)	(0.004)	(0.003)
Parental wealth Q2	51.886***	0.737***	−0.067***
	(0.176)	(0.004)	(0.002)
Parental wealth Q3	30.756***	0.482***	−0.089***
	(0.127)	(0.004)	(0.002)
Parental wealth Q4	13.562***	0.264***	−0.083***
	(0.075)	(0.003)	(0.001)
Observations	4,634,137	4,634,137	4,634,137
R^2	0.397	0.411	0.090
Fixed Effects			
Entry year	Yes	Yes	Yes
Municipality	Yes	Yes	Yes
Education (3-digit)	Yes	Yes	Yes
Entropy balancing	Yes	Yes	Yes

Notes: Omitted category: Q5 (top quintile). Both the child's wealth percentile and the parent's wealth percentile are measured at $t-1$, one year before entrepreneurship entry. Entropy balancing weights exclude parental wealth from the balancing constraints (H1 design). Standard errors clustered by entry year × municipality in parentheses. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

Table B.49
Contemporaneous Pre-Entry Snapshot: Heterogeneous Effects by Parental Wealth

	(1) Rank Gap	(2) Upward	(3) Top 10%
Entrepreneur	5.659***	0.052***	0.052***
	(0.491)	(0.006)	(0.006)
Entrepreneur × High school	−5.381***	−0.036***	−0.020***
	(0.519)	(0.007)	(0.007)
Entrepreneur × Bachelor	−4.418***	−0.031***	0.023***
	(0.580)	(0.007)	(0.009)
Entrepreneur × Master/PhD	−4.756***	−0.039***	0.036***
	(0.605)	(0.008)	(0.011)
High school	12.296***	0.095***	0.050***
	(0.133)	(0.001)	(0.001)
Bachelor	13.360***	0.099***	0.037***
	(0.228)	(0.002)	(0.002)
Master/PhD	20.148***	0.146***	0.110***
	(0.294)	(0.002)	(0.003)
Observations	4,634,140	4,634,140	4,634,140
R^2	0.369	0.399	0.062
Fixed Effects			
Entry year	Yes	Yes	Yes
Municipality	Yes	Yes	Yes
Parental wealth quintile (t−1)	Yes	Yes	Yes
Entropy balancing	Yes	Yes	Yes

Notes: Omitted category: Secondary education. Both the child's wealth percentile and the parent's wealth percentile are measured at $t-1$, one year before entrepreneurship entry. Entropy balancing weights exclude education from the balancing constraints (H2 design). Standard errors clustered by entry year × municipality in parentheses. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

Table B.50
Contemporaneous Pre-Entry Snapshot: Heterogeneous Effects by Education Level

	(1) Rank Gap	(2) Upward	(3) Top 10%
Entrepreneur	1.621***	0.026***	0.051***
	(0.203)	(0.002)	(0.003)
Entrepreneur × Business	−4.054***	−0.038***	−0.021**
	(0.492)	(0.006)	(0.011)
Entrepreneur × Science	−0.993	−0.019	0.052
	(1.439)	(0.021)	(0.032)
Entrepreneur × Engineering	−0.370	−0.010	0.022
	(0.635)	(0.009)	(0.014)
Entrepreneur × Multiple	−0.071	0.126	0.061
	(6.196)	(0.104)	(0.138)
Business	12.058***	0.079***	0.141***
	(0.185)	(0.002)	(0.002)
Science	10.932***	0.075***	0.098***
	(0.296)	(0.003)	(0.005)
Engineering	10.796***	0.075***	0.082***
	(0.174)	(0.002)	(0.003)
Multiple fields	15.327***	0.108***	0.135***
	(0.496)	(0.008)	(0.013)
Observations	4,634,140	4,634,140	4,634,140
R^2	0.360	0.396	0.065
Fixed Effects			
Entry year	Yes	Yes	Yes
Municipality	Yes	Yes	Yes
Parental wealth quintile (t−1)	Yes	Yes	Yes
Entropy balancing	Yes	Yes	Yes

Notes: Omitted category: Other fields. Both the child's wealth percentile and the parent's wealth percentile are measured at $t-1$, one year before entrepreneurship entry. Entropy balancing weights exclude education from the balancing constraints (H3 design). Standard errors clustered by entry year × municipality in parentheses. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

Table B.51
Contemporaneous Pre-Entry Snapshot: Heterogeneous Effects by Field of Study

	(1) Rank Change	(2) Upward	(3) Top 10%
Entrepreneur	4.227***	0.091***	0.094***
	(0.168)	(0.003)	(0.003)
Constant	3.330***	0.283***	0.204***
	(0.102)	(0.002)	(0.002)
Observations	3,357,442	3,357,442	3,357,442
R^2	0.232	0.288	0.321
Fixed Effects			
Entry year	Yes	Yes	Yes
Municipality	Yes	Yes	Yes
Education (3-digit)	Yes	Yes	Yes
Own wealth quintile (t−3)	Yes	Yes	Yes
Entropy balancing	Yes	Yes	Yes

Notes: This table reports a symmetric self-benchmarked specification comparing the individual's own wealth percentile at $t+3$ to their own wealth percentile at $t-3$, creating a six-year window centered on entrepreneurship entry. The outcome measures are rank change, upward movement to a higher own-wealth quintile, and top 10% achievement at $t+3$. Regressions compare entrepreneurs to entropy-balanced non-entrepreneurs using the baseline weighting design. Standard errors clustered by entry year × municipality in parentheses. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

Table B.52
Symmetric Self-Benchmarked Mobility Around Entrepreneurship Entry

	(1) Rank Change	(2) Upward	(3) Top 10%
Entrepreneur	3.634***	0.060***	0.143***
	(0.258)	(0.005)	(0.006)
Entrepreneur × Q1	−1.445	−0.001	−0.047**
	(1.144)	(0.020)	(0.020)
Entrepreneur × Q2	0.039	0.027**	−0.056***
	(0.688)	(0.013)	(0.011)
Entrepreneur × Q3	−0.814*	0.002	−0.057***
	(0.492)	(0.011)	(0.009)
Entrepreneur × Q4	−0.586	−0.002	−0.046***
	(0.427)	(0.009)	(0.008)
Parental wealth Q1	−3.804***	−0.051***	−0.092***
	(0.133)	(0.003)	(0.003)
Parental wealth Q2	−3.607***	−0.055***	−0.076***
	(0.118)	(0.002)	(0.002)
Parental wealth Q3	−2.347***	−0.028***	−0.095***
	(0.108)	(0.002)	(0.002)
Parental wealth Q4	−1.461***	−0.008***	−0.092***
	(0.077)	(0.002)	(0.002)
Observations	3,357,442	3,357,442	3,358,671
R^2	0.040	0.032	0.125
Fixed Effects			
Entry year	Yes	Yes	Yes
Municipality	Yes	Yes	Yes
Education (3-digit)	Yes	Yes	Yes
Entropy balancing	Yes	Yes	Yes

Notes: Omitted category: Q5 (top quintile). The outcome compares the individual's own wealth percentile at $t+3$ to their own wealth percentile at $t-3$. Parental wealth heterogeneity is measured using parental wealth quintiles at $t-1$. Entropy balancing weights exclude parental wealth from the balancing constraints (H1 design). Standard errors clustered by entry year × municipality in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.53
Symmetric Self-Benchmarked Mobility: Heterogeneous Effects by Parental Wealth

	(1) Rank Change	(2) Upward	(3) Top 10%
Entrepreneur	3.975***	0.112***	0.057***
	(0.490)	(0.009)	(0.007)
Entrepreneur × High school	0.509	−0.008	0.022***
	(0.510)	(0.009)	(0.008)
Entrepreneur × Bachelor	0.393	−0.033***	0.067***
	(0.567)	(0.010)	(0.009)
Entrepreneur × Master/PhD	−0.601	−0.063***	0.093***
	(0.567)	(0.012)	(0.011)
High school	3.815***	0.077***	0.010***
	(0.080)	(0.002)	(0.001)
Bachelor	6.694***	0.130***	0.022***
	(0.140)	(0.003)	(0.002)
Master/PhD	11.790***	0.226***	0.075***
	(0.171)	(0.003)	(0.003)
Observations	3,357,444	3,357,444	3,357,444
R^2	0.222	0.280	0.311
Fixed Effects			
Entry year	Yes	Yes	Yes
Municipality	Yes	Yes	Yes
Own wealth quintile (t−3)	Yes	Yes	Yes
Entropy balancing	Yes	Yes	Yes

Notes: Omitted category: Secondary education. The outcome compares the individual's own wealth percentile at $t+3$ to their own wealth percentile at $t-3$. Entropy balancing weights exclude education from the balancing constraints (H2 design). Standard errors clustered by entry year × municipality in parentheses. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

Table B.54
Symmetric Self-Benchmarked Mobility: Heterogeneous Effects by Education Level

	(1) Rank Change	(2) Upward	(3) Top 10%
Entrepreneur	4.254***	0.095***	0.086***
	(0.194)	(0.004)	(0.004)
Entrepreneur × Business	−1.495***	−0.046***	0.028**
	(0.459)	(0.009)	(0.011)
Entrepreneur × Science	−0.997	−0.048*	0.049*
	(1.140)	(0.026)	(0.029)
Entrepreneur × Engineering	−0.406	−0.022**	0.075***
	(0.459)	(0.011)	(0.013)
Entrepreneur × Multiple	4.765	0.093	0.247*
	(4.771)	(0.120)	(0.133)
Business	6.160***	0.107***	0.080***
	(0.099)	(0.002)	(0.002)
Science	5.810***	0.107***	0.047***
	(0.153)	(0.003)	(0.004)
Engineering	5.078***	0.087***	0.035***
	(0.083)	(0.002)	(0.002)
Multiple fields	7.920***	0.157***	0.073***
	(0.404)	(0.011)	(0.013)
Observations	3,357,444	3,357,444	3,357,444
R^2	0.209	0.272	0.309
Fixed Effects			
Entry year	Yes	Yes	Yes
Municipality	Yes	Yes	Yes
Own wealth quintile (t−3)	Yes	Yes	Yes
Entropy balancing	Yes	Yes	Yes

Notes: Omitted category: Other fields. The outcome compares the individual's own wealth percentile at $t+3$ to their own wealth percentile at $t-3$. Entropy balancing weights exclude education from the balancing constraints (H3 design). Standard errors clustered by entry year × municipality in parentheses. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

Table B.55
Symmetric Self-Benchmarked Mobility: Heterogeneous Effects by Field of Study

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