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Entrepreneurship and the Discipline of External Finance

Ramana Nanda

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Ramana Nanda
Harvard Business School

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Entrepreneurship and the Discipline of External Finance

I confirm the finding that the propensity to start a new firm rises sharply among those in the top five percentiles of personal wealth. This pattern is more pronounced for entrants in less capital intensive sectors. Prior to entry, founders in this group earn about 6% less compared to those who stay in paid employment. Their firms are more likely to fail early and conditional on survival, less likely to be make money. This pattern is only true for the most-wealthy individuals, and is attenuated for wealthy individuals starting firms in capital intensive industries. Taken together, these findings suggest that the spike in entry at the top end of the wealth distribution is driven by low-ability individuals who can afford to start (and sometimes continue running) weaker firms because they do not face the discipline of external finance.

1. Introduction

One of the most robust findings in the entrepreneurship literature is the strong positive correlation between personal wealth and the propensity to engage in entrepreneurship (Evans and Jovanovic, 1989; Rosen et al 1994; Gentry and Hubbard, 2004). For example, Gentry and Hubbard (2004) find that entrepreneurs comprise just under 9% of households in the US, but hold about 40% of total net worth. Several other studies have documented that entrepreneurs are not just wealthier, but wealthier individuals are also more likely to become entrepreneurs (Hurst and Lusardi, 2004)

The most common explanation for this correlation is that credit constraints pose an important barrier to entry for less wealthy individuals (Evans and Jovanovic, 1989). However, Hurst and Lusardi (2004) use panel data from the US to highlight that the relationship between personal wealth and entrepreneurship is relatively flat for the bottom 80 percent of the wealth distribution and steepest for the wealthiest 5 percent of the population. Since they also find that the wealthy often found *less* capital intensive, service-oriented businesses, the convex relationship between wealth and entry is seen as somewhat of a puzzle when viewed in light of the literature on financing constraints in entrepreneurship. Hurst and Lusardi (2004) infer that the correlation between personal wealth and entrepreneurship may in fact be spurious, driven by unobserved preferences for becoming an entrepreneur that are correlated with personal wealth.

Given that the wealthy constitute a large share of those who become entrepreneurs, understanding the factors driving entry into entrepreneurship for these individuals is important for both theories of entrepreneurship and for public policies aimed at spurring entry. In this paper, therefore, I depart from the prior literature that has largely examined rates of entry into entrepreneurship, to also understand whether the characteristics of the very wealthy who become entrepreneurs differ systematically from the rest of the population selecting into entrepreneurship. In particular, I look at various measures of individual ability of the entrepreneurs, both relative to those who remained employees as well as among those who became entrepreneurs – and see whether they differ systematically across the wealth distribution.

I find that along a number of metrics, individuals in the top 5 percent of the wealth distribution who become entrepreneurs are of lower ability -- particularly those founding businesses in less capital intensive industries. In the years prior to entry, the very wealthiest individuals have lower salaries compared to their counterparts who continue to remain employed. Firms founded by wealthy entrepreneurs have the highest exit rates in the first few years after entry relative to all founders. Conditional on survival, they are the least likely to generate positive returns. These results stand in contrast to less wealthy individuals who become entrepreneurs, who tend to be of higher ability than their counterparts who remain employed.

Even among the wealthiest individuals becoming entrepreneurs, the measures of low ability are primarily due to those entering less capital intensive industries -- which are the industries for which the spike in entry rates is highest at the top end of the wealth distribution. This suggests that the greater propensity for entrepreneurship among the wealthiest individuals may not be due to different preferences for the wealthy *per se*, but rather because wealthy individuals with a desire to start a new business require a lower threshold level of ability to enter -- particularly for entrants in less capital intensive industries. It therefore highlights that while unobserved preferences may play an important role in the decision to become an entrepreneurship, the external capital markets seem to play an important mediating role in determining who can found a business and who cannot, even for the very wealthiest individuals in the economy.

This result highlights that the disciplinary role of external finance can be equally valuable in founder-run businesses, even though such businesses may not face the agency conflicts associated with excessive free cash flow in larger firms (Jensen 1986). Optimism among wealthy individuals with lower ability can lead them to found new ventures when they may not have received capital from external investors for such a project (de Meza and Southey 1996) or to continue running these businesses others may have shut down and reallocated resources to more productive ends. The lack of discipline from the external capital markets for the wealthiest individuals can account for the increasingly high propensity for entry into entrepreneurship among the very wealthy. It may also shed light on why the wealthiest individuals have been found in other settings to be relatively poor entrepreneurs (Hvide and Møen, 2010) or have low returns to the private equity in their businesses relative to returns on public equity markets (Hamilton 2000; Moskowitz and Vissing-Jorgensen, 2002).

While this paper is also related to the large literature on financing constraints in entrepreneurship, the focus of the analysis is on the highly non-linear relationship between personal wealth and entrepreneurship at the top end of the wealth distribution. As such, it does not explicitly examine the issue of whether financing constraints are binding for entrepreneurs at the lower end of the wealth distribution. It is possible, for example, that 'excessive entry' among low-ability individuals at the top end of the wealth distribution can co-exist with credit constraints binding for high-ability individuals at the bottom end of the wealth distribution (de Meza 2002).

The rest of the paper is structured as follows: In Section 2, I put the descriptive evidence on firm foundings and failures across the wealth distribution in context. I outline the data in Section 3 and present the results Section 4. Section 5 has a discussion of the results and Section 6 has conclusions.

2. Personal Wealth and Entrepreneurship

Evans and Jovanovic (1989) provide the canonical model outlining why personal wealth may be related to the propensity to become an entrepreneur: since new businesses require a capital investment, the returns from a new venture can be expected to be an increasing function of the capital invested in the startup, up to an optimal level. If a founder does not face financing constraints, then the amount of capital he invests in his business would be independent of his personal wealth. If however, he did face financing constraints from the external capital markets, then his investment in the business would be limited by his personal wealth and hence likely to be less than the optimal level of capital. This would lower his expected income from entrepreneurship and hence reduce his likelihood of starting the business. For a given capital investment, wealthier individuals are less likely to be constrained. Hence the presence of financing constraints in the capital markets is likely to manifest itself through an association between personal wealth and the propensity to become an entrepreneur.

Aside from this substantive explanation for the relationship between personal wealth and entrepreneurship, two sets of factors may lead to a spurious correlation between wealth the likelihood of becoming an entrepreneur. First, preferences for entrepreneurship could be different for the wealthy. For example, wealthy people may have lower absolute risk aversion, (Evans and Jovanovic,1989; Khilstrom and Laffont, 1979), they may be systematically more optimistic, or they may have a preference for being their own boss that rises with wealth (Hurst and Lusardi, 2004). These factors could lead to an association between wealth and entrepreneurship even in the absence of financing constraints.

Second, the sharp rise in entry at the top end of the wealth distribution could reflect unobserved (or unmeasured) differences in individual ability. Theoretical models of entrepreneurial entry predict that higher ability individuals will select into entrepreneurship (Evans and Jovanovic, 1989; de Meza, 2002). Ability is related to observable measures of human capital such as educational attainment, which are themselves related to personal wealth. In addition, wealthy individuals typically have access to networks of suppliers and customers than make them more productive as entrepreneurs, potentially leading to sorting of wealthy individuals into entrepreneurship along these 'softer' measures of human capital.. The correlation between wealth and entry may thus in fact be due to unobserved differences in human capital rather than substantive financing constraints. In fact, since individuals with higher ability will have higher earnings in paid employment prior to their decision to become an entrepreneurs, this will lead them to accumulate more savings than their counterparts -- causing them to have accumulated more wealth. This fact exacerbates the concern about individual ability being an omitted variable, since it could be driving both personal wealth and entrepreneurship.

In order to more-carefully address these alternative explanations for selection into entrepreneurship, I depart from the literature that has largely focused on entry rates to also examine the ability of entrants across the wealth distribution. I use longitudinal individual-level micro data from Denmark for this analysis. The panel structure of the micro data allow me to create measures of personal wealth in a prior period, reducing concerns about the endogeneity of wealth creation. In addition, the rich micro-data allow me to construct different measures of individual ability as well as accurate control groups of individuals (who remain in paid employment), to better-understand how the ability of those becoming entrepreneurs relative to those who remain employees varies across the wealth distribution.

This approach can be viewed as a complement to studies using exogenous shocks to wealth in order to study entry into entrepreneurship. For example, Lindh and Ohlsson (1999) have shown that those who win lotteries are more likely to be entrepreneurs than those who do not. A related approach has used inheritances as a source of unexpected liquidity that reduces potential financing constraints (Holtz-Eakin, Joulfaian, and Rosen, 1994; Blanchflower and Oswald, 1998). These studies find that unexpected shocks to personal wealth lead to higher rates of entry into entrepreneurship, but do not examine whether those becoming entrepreneurs are those of ‘high’ or ‘low’ ability. For example, it is conceivable that those becoming entrepreneurs after windfall gains are individuals with poor ideas or of lower ability who were appropriately denied credit by the external capital markets, but who can now afford to self-finance their businesses since they do not face the discipline of external finance.

Since several important facets of the data allow me to shed more light on mechanisms behind the decision to select into entrepreneurship. I describe these in greater detail in the section below.

3. Data

3.1 Description of Data

I use a matched employer-employee panel dataset for this study, spanning the period 1980-1997. The data is drawn from the Integrated Database for Labor Market Research in Denmark, which is maintained by the Danish Government and is referred to by its Danish acronym, IDA. IDA has a number of features that makes it very attractive for this study.

First, the data is collected from government registers on an annual basis, and has detailed micro data on the labor market status of individuals, including their primary occupation. An individual's primary occupation in IDA is characterized by the fraction of income earned from that occupation over the prior year. Individuals are therefore identified as business owners if the majority of their income in that year came from their business. This allows me to identify entrepreneurs in a much more precise manner than many prior studies. For example, I can distinguish the truly self-employed from those who are unemployed but may report themselves as self-employed in surveys. I can also distinguish the self-employed from those who employ others in their firm. Finally, since my definition of entrepreneurship is based on an individual's primary occupation code, I am also able to exclude part-time consultants and individuals who may set up a side business in order to shelter taxes from my definition of entrepreneurship.

In addition to the employment codes, IDA has a range of other demographic characteristics such as individuals' age, educational qualifications, marital status, as well as important financial data, including annual salary income, total income, and the value of their assets and debt. These factors allow me to construct useful control groups for individuals selecting into entrepreneurship in order to examine how those who become entrepreneurs differ from the controls across the wealth distribution.

Third, the database is both comprehensive and longitudinal: all legal residents of Denmark and every firm in Denmark is included in the database. This is particularly useful in studying entry into entrepreneurship, where such transitions a rare event. It also allows me to control for many sources of unobserved heterogeneity at the individual level. In this extract, I have annual observations on each individual for the period 1980-1997. For the analysis, I sample 20% of the individuals between 22 and 55 years who are employed, for each year from 1983 to 1990, allowing those who are sampled more than once to remain. I also exclude individuals employed in agriculture, mining and the public sector. I calculate their average assets for each individual in the sample over the period 1980-1982, which I use as the basis for segmenting the population by percentile of assets. For the period 1983 to 1990, I examine whether an individual in the sample became an employer in the following year and for these individuals, I follow their firms until they exit, or until they are censored in 1997.

While there are several benefits to using this data for my study, there may be concerns about the external validity of a study that is based on information from a relatively small country such as Denmark. I address some of these concerns in Table A1 in the Appendix -- by looking at how the rates of self-employment in Denmark compares to the US, and selected European countries . Moreover, as I show later in the analysis, the concentration of wealth and income among entrepreneurs is also present in Denmark, as it is in the US. These comparisons should provide confidence that the data I use has external validity beyond Denmark, at least to other OECD and developed economies.

3.2 Definition of Entrepreneurship

There are two main types of individuals classified as business owners in IDA-- those who are self employed and those who are self employed with at least one employee. In keeping with the spirit of models of entrepreneurship that examine the decision to leave employment to start a firm, I define transitions to entrepreneurship as taking place when an individual who is employed in a given year becomes an entrepreneur in the subsequent year. That is, I study transitions to entrepreneurship when an individual is classified as being in paid employment in year t and becomes an entrepreneur in year t+1. I therefore treat as censored, individuals who were unemployed or students in year t , but became employers in year t+1.[1] To be conservative, I focus my analysis only on business owners with at least one employee, as those with at least one employee probably need to make more capital investment in their businesses than those who are self employed and hence are more likely to be serious about founding the business.

4. Results

4.1 Descriptive Statistics

I first document the bivariate relationship between personal wealth and the propensity to become an entrepreneur. Figures 1 and 2 document the raw correlation between the propensity to become an entrepreneur over the period 1983-1990 and the percentile of personal assets for the same individuals between1980 and1982. Personal assets measure the value of non-property assets, converted to 1990 US dollars. As can be seen from Figure 1, the propensity to become an entrepreneur is relatively flat until the 80th percentile of personal wealth, and then rises sharply, with the steepest relationship being in the top five percent of the wealth distribution. This picture is virtually identical to that documented by Hurst and Lusardi (1984) using the PSID data from the US.

Figure 1 is based on both self employed individuals and employers. As outlined in Section 3.2 above, I choose to be conservative in my definition of entrepreneurship and hence focus only on those who are employers.[2] Figure 2 documents the same relationship as Figure 1, but only including entrepreneurs with at least one employee in the first year of founding. As can be seen from Figure 2, employers exhibit the same sharp rise in entry at the top end of the wealth distribution, although the pattern is less flat below the 80th percentile of wealth than that of self employment.

Given the non-linear relationship between personal wealth and entry documented in Figures 1 and 2, I choose to create buckets of personal wealth within which to examine selection into entrepreneurship. I divide individuals into four buckets, based on their personal wealth in the "pre-period", 1980-1982. Following Hurst and Lusardi (2004), I look at those in the top five percent of the wealth distribution, and those from the 80th to the 95th percentile of wealth. Based on the break points in the wealth distribution, I also categorize those in the lower eighty percent of wealth into two equal sized buckets. In Table 1, I document descriptive statistics on the main dependent variable and important covariates, broken down along these four buckets. The same non-linear propensity to become an entrepreneur, documented in Figures 1 and 2 is apparent from Table 1.

Table 1 also highlights the fact that wealthier individuals differ from less wealthy individuals in important respects aside from having significantly more assets. They are more likely to have a university de-

[1] Transitions from employment account for 85% of all transitions to those becoming an employer.

gree, they are older (and hence have more labor market experience) both of which may lead them to have higher human capital and entrepreneurial ability. They are also more likely to work for smaller firms, suggesting a potential difference in preference for autonomy or less bureaucracy. These factors will be important to control for, given the concerns around unobserved heterogeneity outlined above.

4.2 Personal Wealth and Entrepreneurship

I first explore the association between individual wealth and transition into entrepreneurship in greater detail, by running logit models of transition into entrepreneurship. The basic estimation is:

$$\Pr(E_{it+1} = 1) = F_L(\beta_0 + \beta_1 ASSET_{40-80} + \beta_2 ASSET_{80-95} + \beta_3 ASSET_{95-100} + \gamma_i X_{it} + \phi_t + \psi_j + \varphi_c + \eta_o + \epsilon_{it}) \quad (1)$$

where $\Pr(E_{it+1} = 1)$ is the probability that an individual who is employed in a given year becomes an entrepreneur in the subsequent year conditional on right-hand-side variables, F_L is the cumulative logistic distribution function and $ASSET_x$ is a dummy variable that takes a value of 1 if the individual's assets in 1980-82 correspond to falling in that asset bucket ($ASSET_{0-40}$ is the omitted category). X_{it} is a matrix of individual- and firm-level control variables, and ϕ_t, ψ_j, φ_c, η_o refer to year, industry, county and occupation-code fixed effects, respectively. Standard errors are clustered at the firm-level.

I report the results of equation 1 in Table 2. Model 1 shows the same non-linear pattern observed in Figure 2. The coefficients on logit models facilitate a direct look at the economic magnitude of the coefficients. The coefficient on 95-100th percentile of assets implies that going from the bottom bucket (0-40th

[2] The results are more extreme if I include self-employment in the dependent variable.

percentile in assets) to the top bucket implies a 175% increase in the odds of being an entrepreneur (exp(1.025)).[3]

One possibility for this result is that it is driven by older, wealthier individuals who are "retiring" into entrepreneurship. In order to confirm that these results are not being driven by such individuals, Model 2 runs the same regressions on a subsample of individuals who are 45 years or younger and finds the same relationship. A second possibility is that wealthier individuals are just more likely to move jobs period, and that entrepreneurship just reflects this secular mobility. To account for the possibility that the pattern reflects movers in general, as opposed to those transitioning to entrepreneurship, Model 3 runs the same regression on the subsample of individuals to either move jobs or become entrepreneurs and continues to find this result. Finally Model 4 runs the same regression on the subsample of individuals with a university degree, to check that the result is equally true of wealthy individuals with high levels of human capital. All these models document the same non-linear pattern, highlighting that it is a very robust feature of the data.

As outlined in Section 2, a substantive factor driving the correlations observed in Table 2 could be the presence of financing constraints. If this were the case, we should expect that the propensity to enter more capital intensive industries should be increasing in wealth, since wealthier individuals are less likely to face financing constraints. In Table 3, I therefore examine whether wealthier individuals are systematically founding more capital intensive firms. In order to do so, I segment industries that all individuals (those who remain employed and those who become entrepreneurs) work in year t+1 based on their start-

[3] Note that the coefficients on logit models can be interpreted as the log-odds of becoming an entrepreneur. This is perhaps more intuitive than examining the marginal effects since baseline odds of becoming an entrepreneur are so low. As a comparison, the marginal effect of a unit increase in log assets (computed at the mean) is 0.02%. To put this in perspective, however, the predicted probability of entry is just over 0.4%, implying, as with the odds ratio, that a 1% increase in log assets increases the probability of entry by about 5%.

ing capital requirements.[4] Based on these calculations, I construct dummy variables that take a value of 1 if the industry is above median in the starting capital intensity. The models in Table 3 are similar to the base regression (1), but include an interaction with the dummy variable for being a capital intensive industry.[5]

Table 3 shows that in fact wealthy individuals are *less* likely to found startups in capital intensive industries and that this is even more true for the wealthiest five percent of the population. The fact that the huge spike in entry at the top end of the wealth distribution is driven by entry into less-, rather than more-capital intensive industries suggests that this pattern is not due startups with high capital needs that can only be met by the most wealthy. Rather, it points to one of the other two factors – unobserved ability or preferences at the top end of the wealth distribution – that might be the driver of this highly non-linear relationship.

4.3 Founder Ability relative to Paid-Employees

In order to more explicitly examine the ability of the founders across the wealth buckets, I first turn to a comparison between founders and those who remain in paid employment. Theoretical models of entry into entrepreneurship argue that individuals with higher ability will become entrepreneurs (Evans and Jovanovic 1989; de Meza 2002). For example, de Meza (2002) argues that wages in paid employment typically involve some degree of pooling, so that they reflect a measure of average rather than individual productivity. In this setup, the most productive individuals in wage employment have an incentive to

[4] Following Rajan and Zingales (1994), I use the starting capital requirements for firms in a relatively unconstrained environment (the US), as a proxy for the capital needs for startup firms in Denmark, so as to overcome the potential endogeneity in using capital intensity of Danish startups. Similar to Hurst and Lusardi (2004), I use data from the survey of Small Business Finance to calculate capital intensity of startups at both the SIC1 and the SIC2 level. The calculations at the SIC1-level are taken from Hurst and Lusardi (2004). The calculations at the SIC2 level are calculated from the same source. Based on these calculations, I construct dummy variables that take a value of 1 if the industry is above median in the starting capital intensity. At the SIC2-level, these measures are correlated at 0.56. I use the more granular measure of capital intensity for the analysis, but confirm that the more aggregated measure gives equally consistent results for the analyses.

leave employment and become entrepreneurs, where the returns to their effort would reflect their true, rather than average productivity. In equilibrium, the individuals just indifferent between entrepreneurship and employment are the most able employees and the least able entrepreneurs.

To examine the ability of individuals selecting into entrepreneurship relative to those who remain as employees, I run earnings regressions of the following form:

$$LOGSAL_{it}^{ASSET_x} = \beta_0 + \beta_1 ENT_{t+1} + \gamma_i X_{it} + \phi_t + \psi_j + \varphi_c + \eta_o + \epsilon_{it} \tag{2}$$

where the dependent variable is the log salary income in year t. The coefficient ENT_{t+1} is a dummy variable that takes a value of 1 if the individual becomes an entrepreneur in the following year and 0 if the individual remains in paid employment. The regression therefore compares the "pre-entry" salary income of those who become entrepreneurs with the salary in the same period of those who remain employees in the following year. As before, X_{it} is a matrix of individual- and firm-level control variables, and $\phi_t,\ \psi_j,\ \varphi_c,\ \eta_o$ refer to year, industry, county and occupation-code fixed effects, respectively. The superscript, $ASSET_x$ refers to the fact that I run each regression separately by asset bucket in order to provide "within-bucket" comparisons of the relative ability of entrepreneurs compared to employees.

As those who are becoming entrepreneurs may transition to entrepreneurship in the middle of the year, their salary income may be mechanically lower. I therefore also run regression (2) using a dummy variable ENT_{t+2}. I report the results from this more conservative estimation in Table 4.

Model 1 looks at the results of regression (2) for the full sample. It highlights that those who become entrepreneurs in two years' time earn about 5% more in paid employment in year t than those who continue

[5] Since the regressions also include industry fixed effects, the main effect for the dummy is not identified and hence is not reported.

in paid employment in two years time. This is consistent with the theoretical models outlined above and with the empirical literature in entrepreneurship that finds entrepreneurs could earn more in paid employment that those who are employees (Hamilton 2000).

However, the full sample masks considerable heterogeneity in the relative ability of individuals across the wealth distribution. Those below the 80% percentile of wealth earn upto 11% more than their counterparts who remain employees. On the other hand, those above the 80th percentile of wealth earn less. This is particularly true of those in the top 5 percent of the wealth distribution, who earn about 6% less than their counterparts in paid employment. Figure 3 depicts this pattern graphically, showing that the relative ability of those becoming entrepreneurs falls as individuals get wealthier, ultimately becoming negative in the top five percent of the wealth distribution.

This picture is counter to the view that the spike in entry is due to the high levels of unobserved ability at the top end of the wealth distribution. On the contrary, it suggests that since the financial hurdle to become an entrepreneur falls as individuals get more wealthy, it allows the marginal individual who selects into entrepreneurship to be of lower ability relative to his counterpart who remains employed. This allows a greater proportion of wealthy individuals to become entrepreneurs.

In order to test this hypothesis further, I split the sample based on the capital intensity of the industry in which the individuals work in year t+2. If the results in Table 4 are driven by a lack of discipline from the external capital markets, this would imply that the relationship documented in Figure 3 should be stronger for less capital intensive industries than for those entering more capital intensive industries. In other words, I examine whether the lower relative salary among the wealthiest individuals is driven disproportionately by entrepreneurs entering less capital intensive industries. I therefore run the following specification:

$$
\begin{aligned}
LOGSAL_{it}^{ASSET_x} = \ & \beta_0 + \beta_1 ENT\_DEP_{t+1} + \beta_2 WORK\_DEP_{t+1} \\
& + \beta_3 ENT\_NODEP_{t+1} + \beta_4 WORK\_NODEP_{t+1} \\
& + \gamma_i X_{it} + \phi_t + \psi_j + \varphi_c + \eta_o + \epsilon_{it})
\end{aligned} \tag{3}
$$

and then compare the difference between β_1 and β_2 and the difference between β_3 and β_4. These results are reported in Table 5. For ease of explication, I report the differences of the coefficients and the associated standard errors in each of the cells. That is, Panel A of Table 6 reports the differences between β_1 and β_2. Panel B reports the differences between β_3 and β_4. In addition to the OLS regression outlined in equation (3), I also report the results of quantile regressions at the 25th percentile, median and the 75th percentile.

Figure 4 documents the main result in Table 5. It shows that the salary premium for those becoming entrepreneurs in more capital intensive industries is higher than the salary premium for those becoming entrepreneurs in less capital intensive industries. That is, the line for less capital intensive industries is always below that for more capital intensive industries. This means that the results in Table 4 are driven by founders entering *less* capital intensive industries.

Secondly, it highlights that the gap in relative ability for those entering more vs. less capital intensive industries is higher for the most wealthy. That is, the negative slope for less capital intensive industries is larger than the negative slope for more capital intensive industries. This increasing gap is what accounts for the large negative pre-entry salaries for the wealthiest entrepreneurs – it explains why there is no negative premium for those entering more capital intensive industries, but that the negative premium already emerges at the 80th percentile in personal wealth for individuals becoming entrepreneurs in less capital intensive industries.

Table 5 also reports the coefficients of quantile regressions, which confirm that the OLS results are not driven by outliers. It shows that for the more capital intensive industries, the only negative coefficient is for the 25^{th} percentile of salary income in the top asset bucket. However, for less capital intensive industries, the 25^{th} percentile is negative for the top two asset buckets. Moreover, even the median entrepreneur in the top asset bucket who starts a business in a less capital intensive industry earns 3% less than his counterpart who remains in paid employment.

Tables 4 and 5 suggest that the wealthiest individuals who become entrepreneurs seem to be of lower ability than their counterparts who remain employed, particularly for those who start firms in less capital intensive industries. These are the same individuals who were documented in Table 3 to account for the large spike in entry at the top end of the wealth distribution.

However, Tables 4 and 5 measure ability in the wage sector. That is, they document that wealthy individuals who become entrepreneurs are worse employees than their counterparts who remain employed. While theoretical models tend to equate ability in the wage sector with that in the entrepreneurship sector, it is possible that wealthy individuals make good entrepreneurs despite being relatively bad employees. I therefore next examine within-founder ability across the wealth distribution.

4.4 Within-Founder Ability across the Wealth Distribution

In order to examine "within-founder" ability, I first examine the exit rates of new ventures, by wealth bucket. I define exit as the first year when the individual is no longer either an employer or self-employed. That is, I do not count the firm as having failed even if the founder "downsizes" from having at least one employee to having no employees. In Figure 5, I plot the raw correlation between the personal assets of the founder and the probability he will exit within 3 years of entry.

As can be seen from Figure 5, the propensity to exit within the first three years of entry falls until the 80th percentile of assets and then again rises sharply. In fact, founders in the top 5 percent of the wealth distribution have the highest failure rates of all founders. While this picture of exit rates is consistent with the prior results, and indicative of lower ability among the wealthiest founders, it is difficult to infer low ability looking just at exit rates. First, exits may involve a successful sale or transfer of the firm, so that not all exits are failures. Secondly, those with poor ability may continue to persist in entrepreneurship because of non-pecuniary benefits (Hamilton 2000) or because they do not face the hard constraints on exit. Third, wealthier individuals may be more willing to experiment or take on riskier projects, so that their initial failure rates might be higher, but conditional on survival, they may do a lot better. I therefore look at the share of exits that were successful in order to shed light on the relative ability of founders.

The IDA data does not have detailed firm-level financial data over the period of my analysis. However, I do have a measure of the individual's total income in every year. I define a successful exit as one where the founder's total income in the year following the exit was at least as high as the total income in the year prior to entry. This is clearly an imperfect measure since the "threshold" for success differs by individual. Moreover, since individuals who are wealthier are more likely to have a higher income, it also systematically raises the bar for wealthier individuals relative to less wealthy individuals in terms of the requirement for a successful outcome. On the other hand, however, this measure provides some benchmark for the opportunity cost for individuals founding new businesses. Wealthier individuals with higher incomes are also more likely to have higher salary incomes that they would give up to start a new venture. They would thus likely only enter businesses with greater potential. The measure used in this analysis implicitly controls for this 'unobserved' opportunity cost.

Figure 6 documents the share of individuals who have a "successful" exit by wealth bucket and by whether the exit was within 3 years or after 3 years.[6] As can be seen from Figure 6, about 45% of those who exit within 3 years of entry have a "successful" exit. Despite the fact that wealthier individuals are more likely to exit within 3 years (as noted from Figure 5), the share of successful exits is the same. That is, wealthier individuals have a greater *number* of "failures" early on.

On the other hand, about 60% of those who survive at least 4 years have successful exits; however wealthier individuals have a lower probability of having a successful exit. That is, wealthier individuals have more failures early on, but conditional on surviving are *less* likely to have a successful exit. This pattern suggests that the higher exit rates among the wealthy are not due to more risk taking or better experimentation, but rather because they are founding relatively "weaker" firms which either fail early, or continue to persist without being closed down despite not generating large positive returns for the founders.

Since Figure 6 reports bivariate correlations without controlling for covariates, I examine this pattern in greater detail in Table 6, using an estimation similar to that in Table 2. Table 6 reports the results of logit regressions where the dependent variable is a dummy that takes a value of 1 if the founder's total income in the year following the exit (or the income in 1997 for those that do not exit by then) is greater than his income in the year prior to entry. As can be seen from Model 1, the probability of a successful outcome for those in the middle two buckets of wealth is no different from those in the bottom (omitted category). However, the odds of the wealthiest individuals having a successful exit are about 25% less than those in the 0-40 percentile of wealth. As can be seen from Models 3 and 5, this is particularly likely to occur for those founding businesses that are less capital intensive, and for those persisting as entrepreneurs. These results are consistent with a view that many of the founders in the top wealth bucket found weaker or

[6] Since about 50% of entrants exit with 3 years of entry, this is a useful breakpoint at which to measure success at exit.

"lifestyle businesses", and are likely to persist in entrepreneurship even if they are generating poor financial returns (Hamilton 2000; Scott Morton and Podolny 2002).

5. Discussion

The results from Tables 2 to 6 highlight that the spike in entry at the top end of the wealth distribution is due primarily to founders entering less capital industries. This suggests that it is not driven by substantive financing constraints, but due to some other factor that is correlated with personal wealth. In addition, they suggest that the wealthiest individuals are on average of lower ability than their counterparts who remain as employees, as well as even relative to other founders, implying that unobserved ability is also not the driver of the large spike in entry among the wealthiest individuals.

Rather, unobserved preferences for entrepreneurship or optimism about the prospects of the startup might play an important role in the explaining this correlation. However, the large differences in the results that vary by the capital intensity of the businesses also highlight that unobserved preferences do not paint the complete picture. While preferences clearly play role, the discipline of the external capital markets seems to play an important mediating role in determining who can found a business, even for the very wealthiest individuals in the economy.

Taken together, the results in this paper provide an alternative explanation for the strong positive association between individual wealth and entrepreneurship among the very wealthy (Evans and Jovanovic 1989) and the finding that even wealthy individuals (with liquid assets well beyond the needs to start a typical business) respond to unexpected increases in their assets by choosing to become entrepreneurs (Holtz-Eakin, Joulfaian and Rosen, 1994). While prior work has argued that this finding was evidence of a lower bound for financing constraints in entrepreneurship, the results from this paper suggest that at least part of the entry in entrepreneurship following large windfall gains for already-wealthy individuals may be driven by the fact that these individuals can now undertake lower value entrepreneurial ventures that they aspired to found but may not have been able to self-finance before. This result can also explain the strong positive association between wealth and entrepreneurship in the cross section even among the top 5% of the wealth distribution (Hurst and Lusardi, 2004) and is consistent with the finding that private equity returns seem to be too low relative to expectations (Moskowitz and Vissing Jorgensen, 2002). It is also consistent with findings that wealth and ability may be negatively correlated in certain populations (Jovanovic and Evans, 1989) and that returns to capital can be decreasing for the very wealthy (Hvide and Møen, 2010).

One potential concern with the results presented above is that they may reflect tax shelters by wealthy individuals rather than substantive firms that are weaker. Several factors point to the fact that this is not the case. First, the proportion of wealthy individuals becoming entrepreneurs is high relative to the population, but still extremely small in absolute terms. As can be seen from Figure 2, even among those in the 99th percentile of wealth, the share of employers is under 2%. The measure of firm starts used here is an exception rather than the norm, as opposed to what might be expected if they reflected tax shelters. This is due to the conservative measure used to study entrepreneurship -- it only counts an individual as an entrepreneur if the business is their primary source of income. In addition, I deliberately focus on individuals with at least one employee, in order to exclude less-serious businesses.

Second, the businesses founded by wealthy individuals are distributed across a number of industries, rather than clustering around a particular industrial classification as may be expected if individuals were using these businesses purely as tax shelters. Finally, the fact that these patterns are only driven by those in the top 5% of the wealth distribution but not those who are somewhat less wealthy but in the same tax bracket (such as those from the 80-95th percentile of wealth) -- and hence with the same incentives -- also points to the fact that these are substantive businesses, rather than those with an aim to reduce taxes.

5. Conclusions

The relationship between individual wealth and entry into entrepreneurship is highly non-linear. In this paper, I examine whether the characteristics of individuals selecting into entrepreneurship vary across the wealth distribution, to shed light on the reasons for the spike in entrepreneurship among the wealthiest individuals in society. I find that below the 80th percentile of personal wealth, those selecting into entrepreneurship had either the same, or higher pre-entry salaries than their counterparts who stayed in paid employment. On the other hand, wealthy individuals who became entrepreneurs earned about 6% less in the years prior to entry than their counterparts who stayed as employees. Those entering less capital intensive industries earned even less relative to their counterparts. This is not just driven by outliers at the bottom of the salary distribution: even the median entrepreneur above the 95th percentile of wealth earns 3% less than his or her counterpart who remained employed. The wealthiest founders exhibit the highest exit rates in the first three years following entry, with no difference in the share of successful exits than less-wealthy founders. Conditional on survival, they are much less likely to be successful than their less-wealthy counterparts, particularly among those entering less-capital intensive industries.

These findings suggest that the spike in entry at the top end of the wealth distribution is not due to their ability to found more capital intensive businesses or due to unobserved human capital, but is driven by low-ability individuals who can afford to start (and sometimes continue running) weaker firms because they do not face the discipline of external finance.

This result has important implications for policy makers aiming to stimulate entrepreneurship by providing cheap credit for new ventures. A growing literature supports the view that entrepreneurs are not only critical for their role in creating new markets, technologies and products, but are equally important for their role in the process of "creative destruction" (King and Levine, 1993a; 1993b; Foster, Haltiwanger and Syverson 2008; Kerr and Nanda, 2009). While these potential positive externalities could justify a role for the government to stimulate entrepreneurship, the results from this paper suggest that a simple scheme of providing cheap credit for new ventures may lead to adverse selection among entrepreneurs, where individuals who choose to select into entrepreneurship based on these subsidies may not always be talented individuals who lack funding for their ventures. A significant portion might instead include individuals with large non-pecuniary private benefits from entrepreneurship, rather than the projects that are typically seen as those that suffer from market failure (Hamilton 2000; Scott Morton and Podolny, 1998).

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Figure 1: Probability of Entry, by Percentile of Assets (Self Employed and Employers)

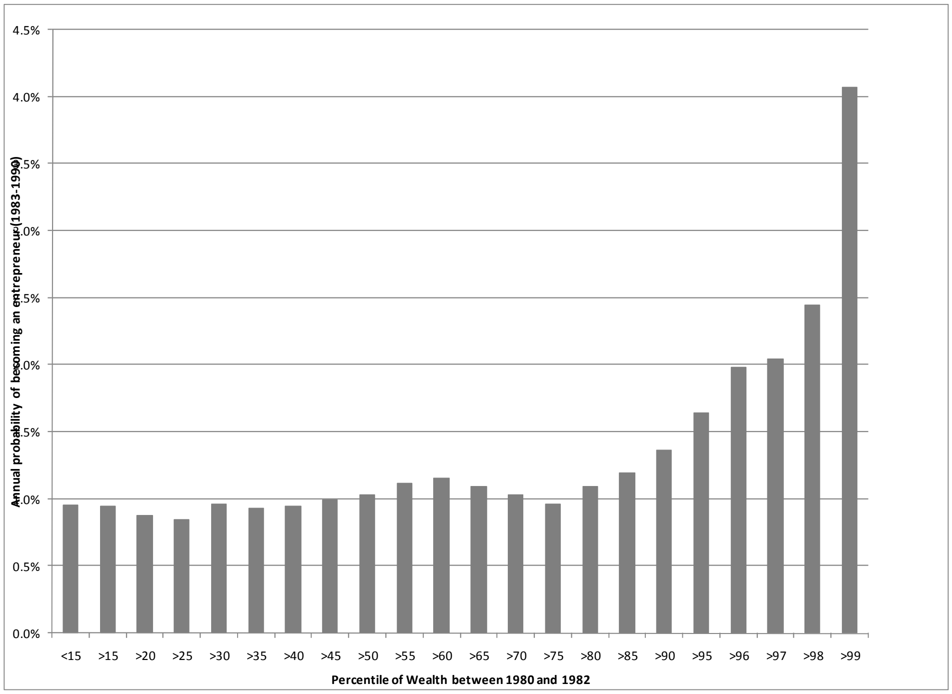

Figure 2: Probability of Entry, by Percentile of Assets (Only Employers)

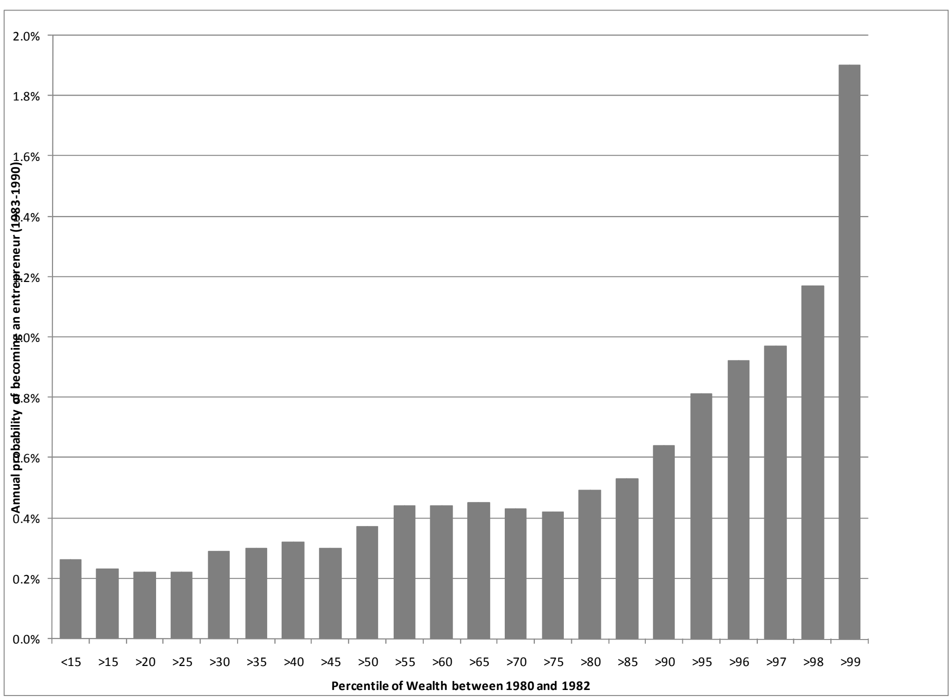

Figure 3: Pre-entry salary of those who become entrepreneurs relative to those who remain employees

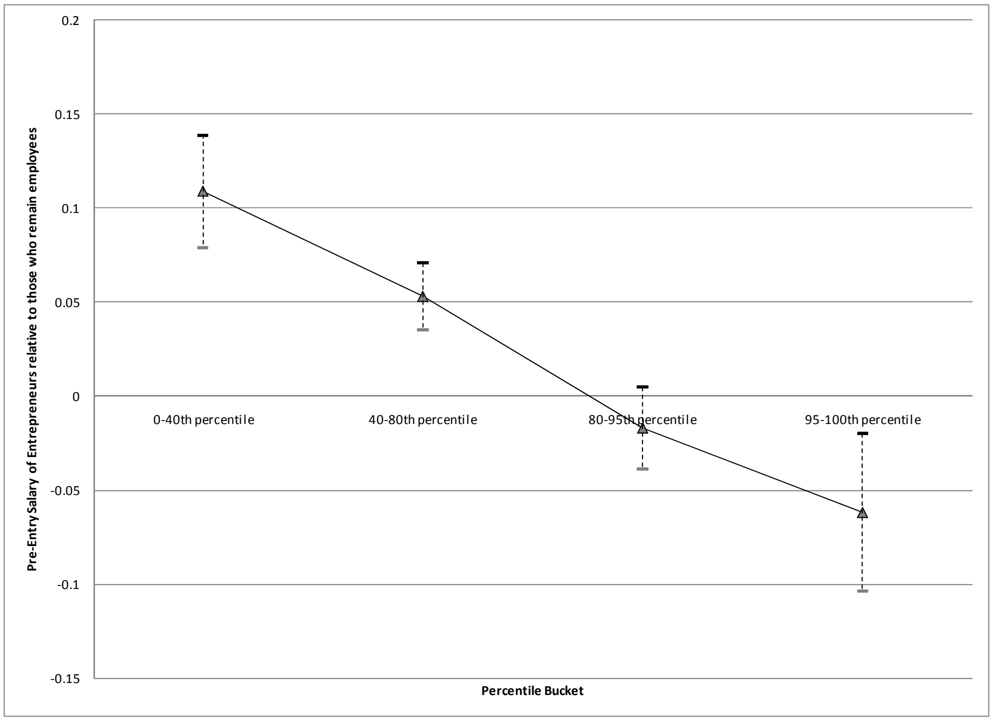

Figure 4: Pre-entry salary of those who become entrepreneurs relative to those who remain employees, by type of industry

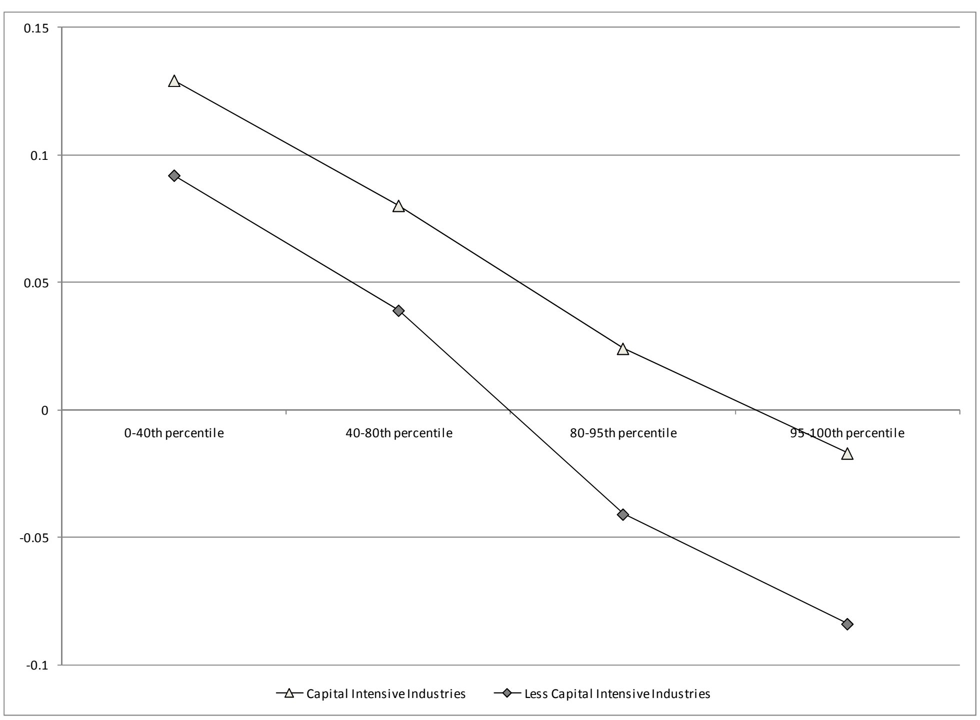

Figure 5: Share of Founders who Exit within 3 years of Entry, by Assets

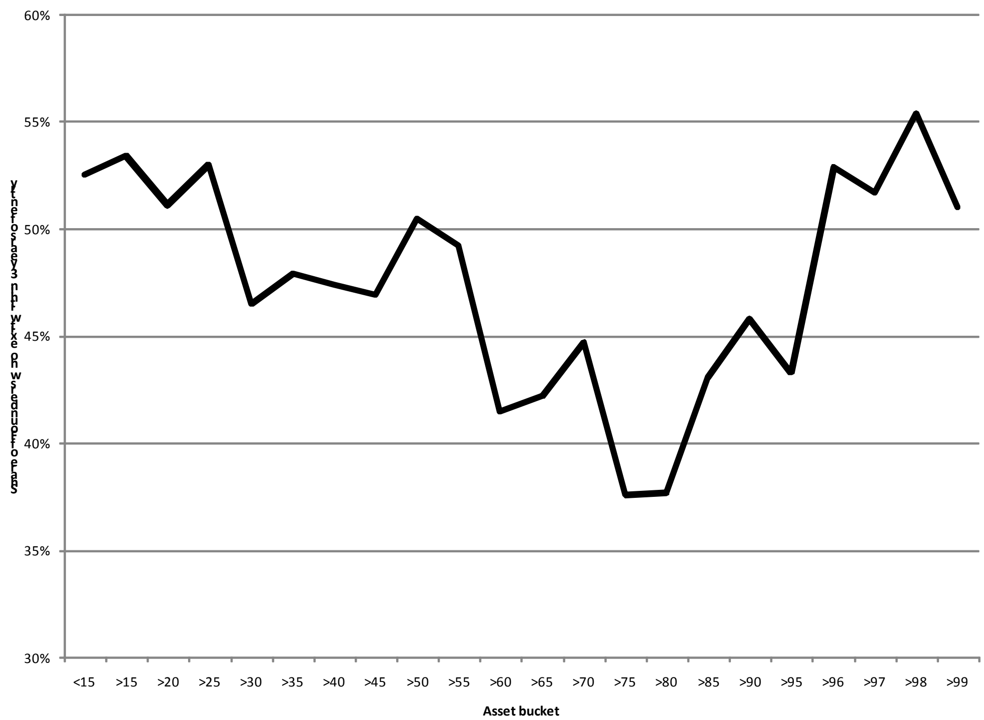

Figure 6: Share of founders with a "Successful" outcome

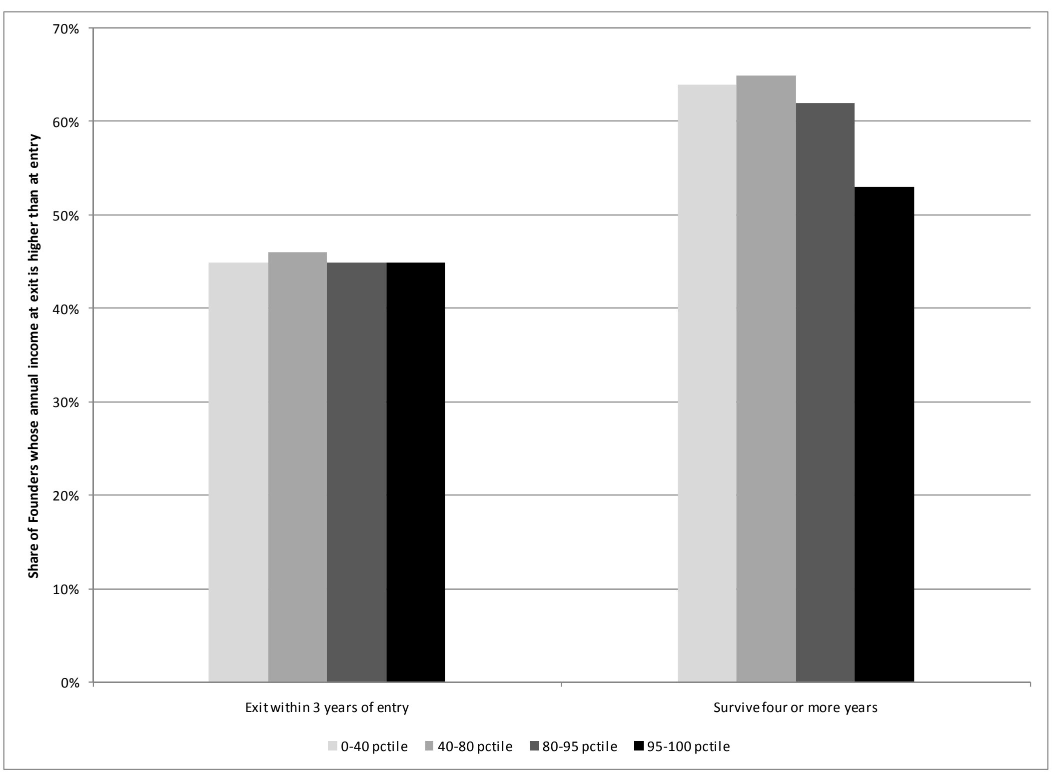

Table 1: Descriptive Statistics, by percentile of personal assets from 1980-82

	Full Sample	*0-40 pctile*	*40-80 pctile*	*80-95 pctile*	*95-100 pctile*
Number of Observations	1,468,504	482,566	619,034	274,588	92,316
Share that become entrepreneurs each year	1.1%	0.9%	1.0%	1.1%	2.2%
Of which self employed	0.7%	0.6%	0.6%	0.6%	1.2%
Of which those with at least one employee	0.4%	0.3%	0.4%	0.5%	1.0%
Individual-level covariates					
Median Assets$_{1980\text{-}1982}$ (1990 US $)	44,450	1,077	25,050	103,043	231,135
Median Salary Income (1990 US $)	29,378	22,375	29,011	36,315	42,042
Average age in years	37	35	35	42	44
Highest degree is high school	54%	51%	55%	58%	50%
Have a college or higher degree	12%	7%	11%	15%	29%
Share that are married	61%	56%	49%	85%	88%
Share with Children	51%	46%	46%	66%	62%
Firm-level covariates					
Median size of firm at which work (empl)	120	114	118	141	85
Tenure at job at which currently work (yrs)	1.2	1.3	1.3	1.0	1.1

Table 2: Probability of Entering Entrepreneurship, by Percentile of Assets

Coefficients on Logit Regressions where dependent variable takes a value of 1 if individual who is employed in year t becomes an entrepreneur in year t+1

Variable	*Full Sample*	*Only those <= 45 Yrs old*	*Only those starting new jobs in t+1*	*Only those w/ university degree*
	(1)	(2)	(3)	(4)
40- 80th pctile in assets $_{1980\text{-}1982}$	0.180**	0.195**	0.229**	0.147
	(0.065)	(0.068)	(0.065)	(0.172)
80 - 95th pctile in assets$_{1980\text{-}1982}$	0.452**	0.460**	0.562**	0.239
	(0.085)	(0.089)	(0.085)	(0.227)
95 - 100th pctile in assets$_{1980\text{-}1982}$	1.025**	1.001**	1.302**	0.954**
	(0.093)	(0.101)	(0.092)	(0.243)
Individual and Firm-level controls	Yes	Yes	Yes	Yes
Industry, County, Year and Occupation Code Fixed Effects	Yes	Yes	Yes	Yes
Number of Observations	1,468,504	1,167,780	305,112	171,386

robust standard errors in brackets, clustered at the firm-level * p<.05 ** p<.01

Table 3: Probability of Entering Entrepreneurship, by Percentile of Assets and Starting Capital of firms in Industry

Coefficients on Logit Regressions where dependent variable takes a value of 1 if individual who is employed in year t becomes an entrepreneur in year t+1

Variable	*Full Sample*	*Only those <= 45 Yrs old*	*Only those starting new jobs in t+1*	*Only those w/ university degree*
	(1)	(2)	(3)	(4)
40- 80th pctile in assets $_{1980\text{-}1982}$	0.506**	0.473**	0.551**	0.443**
	(0.054)	(0.056)	(0.054)	(0.142)
80 - 95th pctile in assets$_{1980\text{-}1982}$	0.959**	0.922**	1.053**	0.655**
	(0.065)	(0.069)	(0.064)	(0.168)
95 - 100th pctile in assets$_{1980\text{-}1982}$	1.647**	1.557**	1.909**	1.435**
	(0.070)	(0.079)	(0.070)	(0.167)
40- 80th pctile x High Starting Capital$_{t+1}$	-0.080	-0.082	-0.071	-0.039
	(0.073)	(0.076)	(0.073)	(0.243)
80-95th pctile x High Starting Capital$_{t+1}$	-0.285**	-0.331**	-0.266**	-0.079
	(0.081)	(0.087)	(0.080)	(0.257)
95-100th pctile x High Starting Capital$_{t+1}$	-0.505**	-0.520**	-0.486**	-0.325
	(0.093)	(0.109)	(0.095)	(0.257)
Individual and Firm-level controls	Yes	Yes	Yes	Yes
Industry, County, Year and Occupation Code Fixed Effects	Yes	Yes	Yes	Yes
Number of Observations	1,468,504	1,167,780	305,112	171,386

robust standard errors in brackets, clustered at the firm-level * p<.05 ** p<.01

Table 4: Quality of Entrepreneurs - Proxied by Pre-Entry Salary

Dependent Variable is the Log of salary Income in year t

	Full Sample	*0-40 pctile of assets*	*40-80 pctile of assets*	*80-95 pctile of assets*	*95-100 pctile of assets*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
Become an Employer in t+2	0.051**	0.109**	0.053**	-0.017	-0.062**
	(0.007)	(0.015)	(0.009)	(0.011)	(0.021)
Log size of firm where employed	0.012**	0.013**	0.010**	0.009**	0.026**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Tenure at Firm	0.014**	0.029**	0.017**	0.001	-0.006**
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Tenure at Firm squared	-0.001**	-0.003**	-0.002**	0.000	0.001**
	0.000	0.000	0.000	0.000	0.000
Weeks of unemployment in past year	-0.064**	-0.058**	-0.066**	-0.061**	-0.071**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Individual-level Controls	Yes	Yes	Yes	Yes	Yes
Industry, County, Year and Occupation Code Fixed Effects	Yes	Yes	Yes	Yes	Yes
R-Squared	0.45	0.31	0.37	0.39	0.35
Number of Observations	1,468,504	482,566	619,034	274,588	92,316

robust standard errors in brackets, clustered at the firm-level * p<.05 ** p<.01

Table 5: Difference in Pre-Entry Salary between those becoming entrepreneurs and those remaining in paid employment

	(1)	(2)	(3)	(4)
	0-40 pctile of assets	*40-80 pctile of assets*	*80-95 pctile of assets*	*95-100 pctile of assets*
PANEL A: High Starting Capital Industries $_{t+2}$				
OLS Regression of Salary Income$_t$	0.129**	0.080**	0.024*	-0.017
	(0.020)	(0.013)	(0.012)	(0.032)
Quantile Regression at 25th Percentile of Salary	0.139**	0.054**	0.031**	-0.051*
	(0.021)	(0.009)	(0.011)	(0.022)
Quantile Regression at Median Salary	0.113**	0.068**	0.051**	0.039
	(0.014)	(0.008)	(0.010)	(0.023)
Quantile Regression at 75th Percentile of Salary	0.109**	0.093**	0.052**	0.033
	(0.013)	(0.009)	(0.013)	(0.024)
PANEL B: Low Starting Capital Industries $_{t+2}$				
OLS Regression of Salary Income$_t$	0.092**	0.039**	-0.041*	-0.084**
	(0.023)	(0.013)	(0.017)	(0.028)
Quantile Regression at 25th Percentile of Salary	0.047**	0.012	-0.021*	-0.074**
	(0.023)	(0.008)	(0.009)	(0.014)
Quantile Regression at Median Salary	0.058**	0.026**	-0.002	-0.028*
	(0.016)	(0.007)	(0.009)	(0.014)
Quantile Regression at 75th Percentile of Salary	0.051**	0.059**	0.015	0.008
	(0.014)	(0.008)	(0.011)	(0.016)

Notes: Each cell represents coefficients from separate regressions, where the dependent variable is the log of salary income and includes the full set of covariates and fixed effects outlined in Table 5

Table 6: Share of "Successful" Founders, by Percentile of Assets

Coefficients on Logit Regressions where dependent variable takes a value of 1 if total income in last year as entrepreneur > starting income

Variable	*Full Sample*	*Founders with an observed exit*	*Continuing founders (beyond sample)*	*Founded in Industry w/ high starting capital*	*Founded in Industry w/ low starting capital*
	(1)	(2)	(3)	(4)	(5)
40- 80th pctile in assets $_{1980\text{-}1982}$	0.004	0.031	-0.206	0.032	-0.046
	(0.081)	(0.091)	(0.202)	(0.116)	(0.117)
80 - 95th pctile in assets$_{1980\text{-}1982}$	-0.084	-0.030	-0.380	-0.125	-0.098
	(0.106)	(0.119)	(0.246)	(0.156)	(0.148)
95 - 100th pctile in assets$_{1980\text{-}1982}$	-0.270*	-0.159	-0.752**	-0.181	-0.386*
	(0.122)	(0.136)	(0.281)	(0.185)	(0.169)
Individual level controls	Yes	Yes	Yes	Yes	Yes
Industry, and Founding-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Number of Observations	5,948	4,470	1,478	2,751	3,194

robust standard errors in brackets * p<.05 ** p<.01

Appendix A1: Comparison of Self-Employment Rates across Select OCED Countries

	Self Employment as a % of non-agricultural employment		Self Employment as a % of all employment	
	1986	1996	1986	1996
Denmark	7.7	7.2	11.6	9.6
Germany	7.7	8.3	11.6	10.6
UK	9.6	11.3	11,5	13.6
USA	9.1	6.8	8.9	8.4

Source: OECD Labor Force Statistics as reported in Blanchflower (2000)