The Roles of Nature and Nurture in Entrepreneurial Success*

Hans K. Hvide† Paul Oyer‡

July 11, 2016

Abstract

What drives success of new ventures? We hypothesize that, in some industries, success is driven by innovation while, in other industries, it is driven by institutional knowledge, industry experience, and relationships. We argue that "nature human capital" (for example, IQ) will play a relatively large role in innovation while "nurture human capital" (knowledge of a parent's industry) will have a comparative advantage in more mature areas. We model the decision to become an entrepreneur and what type of venture to start as a function of gifts that affect nature human capital and those that affect nurture human capital. We then examine the implication of the model using data from all new ventures in Norway from 1999-2007. We show that, as the model predicts, nurture human capital is more valuable to entrepreneurs with less nature human capital and is also more prevalent in less innovative industries.

PRELIMINARY AND INCOMPLETE

PLEASE DO NOT DISTRIBUTE

Keywords: entrepreneurship, IQ

---

*We are grateful to seminar participants at Harvard Business School. Oyer thanks Michael Mazzeo and Scott Schaefer for earlier collaboration that inspired this paper.

†University of Bergen. Email: hans.hvide@econ.uib.no. Hvide is also affiliated with CEPR and the University of Aberdeen.

‡Stanford University, Graduate School of Business, and NBER. Email: pauloyer@stanford.edu.

1 Introduction

What leads a person to become an entrepreneur and what makes new ventures succeed? We consider two possible types of entrepreneurial human capital: “nature human capital”, which captures raw intelligence, and “nurture human capital”, which includes valuable knowledge of an industry learned through one’s parents’ occupation. We expect both of these types of human capital to be valuable, but that their relative value will vary across different types of entrepreneurial ventures. Consider, for example, a person who opens a funeral home. The funeral home industry has historically been dominated by family businesses. New generations of undertakers learn the trade from their parents so, when a new funeral home is opened, an entrepreneur who learned the business as part of growing up will have an advantage over someone who did not acquire the relevant institutional knowledge from family members. Google and Facebook (and technology-based startups in general) have been successful because the founders had an innovative idea for a new product concept. The founders of these companies could not have learned the trade from their parents – search engines and social networks did not exist. Their natural intelligence and education allowed them to create companies based on innovative ideas.[1] In this paper, we look at the role of nature and nurture human capital for entrepreneurs more broadly.

Figure 1 shows that this funeral home vs. high-tech anecdote holds in the broad sample of Norwegian entrepreneurs we will use in the formal analysis. The graph shows the propensity for new entrepreneurs to start businesses in the industry where their fathers worked (the y-axis in the graph) by the Norwegian measure of IQ (the x-axis). An entrepreneur with relatively low IQ (”3” on the scale – we exclude 1 and 2, as they each contain a very small fraction of the sample) is more than twice as likely to become an entrepreneur in his father’s industry than an entrepreneur at the top of the IQ scale. The rest of this paper explores this and related phenomena theoretically and empirically.

We first build a model that links the acquisition of nurture human capital (parental labor market experience), nurture human capital (IQ), and entrepreneurial entry, sector choice, and performance. The underlying intuition of the model is simple: starting a business in the same

[1] These two anecdotes highlight that nurture human capital is valuable, if not as valuable, in innovative industries given one of the three founders of Google and Facebook – Larry Page – was the son of two computer scientists. The other founders’ parents include two mathematicians, a dentist, and a psychiatrist.

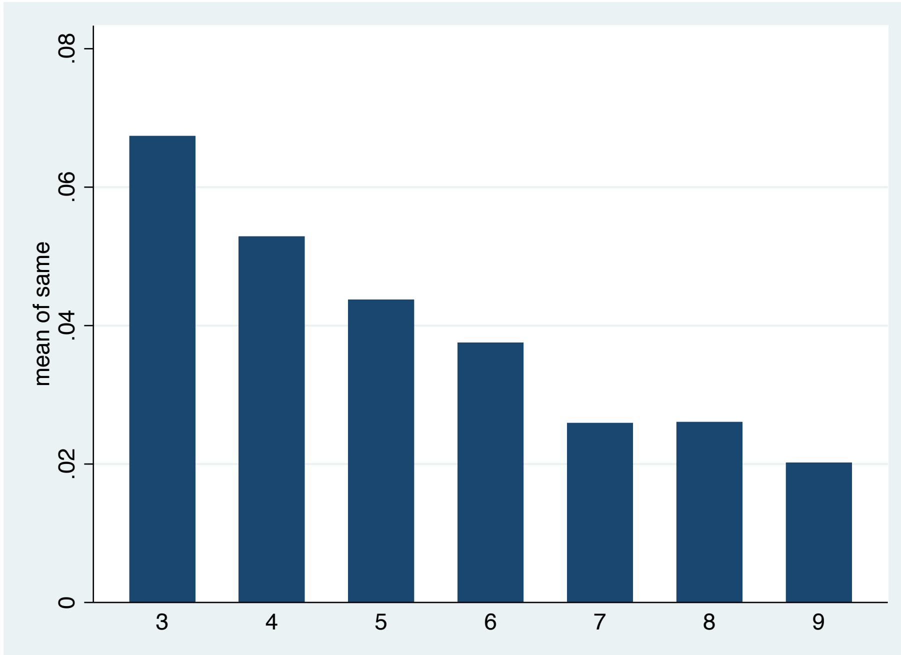

Figure 1: Entrepreneurial Entry into Father's Industry by IQ

industry as one's parents gives a head start through the acquired knowledge, but for high-IQ entrepreneurs the value of the opportunity may be greater in a sector that has higher returns to intelligence.

Empirically, we add to the literature that finds large heterogeneity in what type of firms entrepreneurs start. The gap between self-employed and VC-backed entrepreneurs is so great that they almost seem like distinct experiences. Here we attempt to explain what goes into the entrepreneurship black-box and leads to the chasm between low and high potential entrepreneurship by relating entrepreneurial choices to innate ability and parental human capital.

We use data from Norway that covers all new firms incorporated between 1999 and 2007 (though we limit the data to men who were 22-to-45 years old in 1996 and for whom we have an IQ measure) and we match this to a comparable set of workers in the labor market (that is, non-entrepreneurs). We construct a nurture human capital proxy based on parental occupation. We use IQ as our main proxy of nature human capital but also consider education as another source of intelligence-based human capital (though education is a bit more complicated given it is endogenous).

Our main empirical findings include:

- Men who have higher skill as measured by higher IQs, more assets, and greater labor market earnings are relatively likely to become entrepreneurs.

- A man is much more likely to start a business in an industry in which his father worked than in other industries. This association is substantially decreasing in entrepreneur IQ (as we showed in Figure 1), decreasing in entrepreneur education, and decreasing in entrepreneur age at time of venture founding. Entrepreneurs are more likely to follow their fathers if they have more assets before starting their venture, if their parents are entrepreneurs themselves, and if they found their new business near where their parents live.

- New ventures are more likely to be technology-based if the entrepreneur has more education or higher IQ. Relative to other entrepreneurs, technology entrepreneurs are less likely to follow a father's industry and less likely to be the children of entrepreneurs.

- A venture founded by an entrepreneur who enters an industry where his father worked is noticeably different from other ventures both at founding and after four years of operation: They invest substantially more initial capital, are much more likely to survive four years, and have more employees. They are also much more likely to be positive outliers in the sense of having a large number of employees or high assets.

Our work contributes to several areas of research on business formation and family firms. First, we provide insight into the heterogeneity of entrepreneurs noted by Levine and Rubinstein (2015), Hurst and Pugsley (2011), and others, by showing some of the sources of variation in the type of business started up by entrepreneurs. We show that individuals with relatively low nature human capital, as measured by IQ, tend to start up companies in the same industry as their fathers have worked in, while individuals with high nature human capital are more likely to start up technology ventures. Thus our paper provides a better understanding of factors driving sector choice by entrepreneurs.

Second, it is well-known that entrepreneurship run in families, partly due to genetic and partly due to social effects (see Lindquist, Sol, and Praag (2015)). Little is known, however, about how human capital transmission within families affects entrepreneurship decisions. Our results suggest that entrepreneurs often start up companies based on industry knowledge acquired from their fathers. Moreover, our results suggest that such knowledge transmission improves startup performance.

Third, while it is known that higher IQ is associated with higher stock market participation rates (Grinblatt, Keloharju, and Linnainmaa (2011) and references therein), the relation between IQ and entrepreneurship has been less investigated. We find a strong relation between IQ and the decision to become an entrepreneur, and moreover that IQ predicts a stronger propensity to become a technology entrepreneur.

The paper proceeds as follows. The next section outlines a simple model of entrepreneurial entry and performance. Section 3 presents the data and Section 4 contains the empirical results. We conclude in Section 5.

2 Model of entrepreneurial entry and content

To guide the empirical analysis, we construct a stylized model of entrepreneurial choice in the spirit of Evans and Jovanovic (1989).[2] The model considers two decisions; whether to become an entrepreneur or stay on as a wage worker and, if becoming an entrepreneur, which sector to start up a firm in. We first outline the individual's decision problem, and then discuss the empirical implementation of the model.

2.1 Wage work versus entrepreneurship

Individuals are risk neutral and maximize expected payoff. The payoff from being an employee is known and determined by,

$$w = a + h_0 * IQ \tag{1}$$

where w is log wages and $a > 0$ is an individual-specific term that captures match quality, random factors, and education level. We will refer to a as "job match". We abstract from other variables that affect wages such as age and gender.

The payoff from being an entrepreneur depends on the industry. If the firm is started in the

[2] Unlike Evans and Jovanovic (1989), we do not focus on credit constraints.

same sector as a parent worked, which we denote sector 1, the payoff is

$$e_1 = K + h_1 * IQ + \epsilon_1 \tag{2}$$

where $K > 0$ is the institutional industry knowledge transferred from parents, and ϵ_1 is an idiosyncratic term unknown to the individual at the point of entry.[3]

If the firm is started in an industry different from where the entrepreneur's parents worked, the payoff depends only on IQ. Denote by Sector 2 the industry in which the returns to IQ is highest. The payoff in Sector 2 equals,

$$e_2 = h_2 * IQ + \epsilon_2 \tag{3}$$

where ϵ_2 is an idiosyncratic term unknown to the individual at the time of entry.

If $h_1 > h_2$ then the individual will always prefer sector 1, so the interesting case is $h_1 < h_2$. There are at least a couple of natural reasons why we might expect h_1 to be less than h_2. First, if the payoff from IQ is linear in each industry, industry 2, 3, 4, .., n, then the upper envelope of payoff will be convex in IQ. Second, we might expect that high intelligence people have a lower cost of general education and that general education has a higher return in Ssector 2. We return to this issue below.

There are two equilibrium conditions (assuming internal solutions). There will be a marginal individual who is indifferent between wage work and entrepreneurship and there will be a marginal entrepreneur who is indifferent between Sector 1 and Sector 2. Taking expectations in the equations above, the equilibrium equations are:

$$\begin{aligned} a + h_0 * IQ &= \max(e_1, e_2) \text{ (marginal worker)} \\ K &= (h_2 - h_1) * IQ \text{ (marginal entrepreneur)} \end{aligned} \tag{4}$$

Let us denote by *full separation* a state where wage work, Sector 1 entrepreneurship, and Sector 2 entrepreneurship all occur in equilibrium for different values of IQ. It follows directly from (4) that for full separation to occur then $h_1 > h_2$. We then have the following.

[3]It is very possible that K depends on IQ. We assume that this relationship is weak.

Remark 1 ***Selection***. *Full separation implies that*

(i)Low-IQ individuals become sector 1 entrepreneurs, intermediate IQ individuals become wage workers, and high-IQ individuals become sector 2 entrepreneurs.

(ii)$a < K$ *and* $h_2 < h_0 < h_1$.

Proof. (i)max(e_1, e_2) is convex and increasing in IQ , and w is linear and increasing in IQ. It is straightforward to see that the only way we can get full separation is that $h_2 < h_0 < h_1$. ■

The model explains both whether a person becomes an entrepreneur and what type of firm that person sets up. IQ is the key underlying variable. Conditional on entry, low IQ people will follow their parents (taking advantage of the nurture human capital gift they received). High IQ people will also be inclined to follow parents but less so. Note that, for full separation to occur, the returns to IQ in wage work (h_0) must lie between the returns to sector 1 entrepreneurship and sector 2 entrepreneurship.

One obvious shortcoming of the model is that we do not accommodate wage work in the parents' sector, in which case it is reasonable that there will also be some institutional knowledge that can enhance productivity (see Laband and Lentz (1983)). This can be accommodated in the empirical analysis.

Figure 2 illustrates the separation implied by the model. Individuals who match the wage sector particularly well (high job match or a) do not choose entrepreneurship. For a lower job match, individuals with a low IQ will choose Sector 1 entrepreneurship and individuals with a high IQ will choose Sector 2 entrepreneurship. Note that the separation in this figure does not depend on assuming $cov(a, IQ) = 0$. Note also that an increase in K will shift the solid line above "Sector 1" upwards and hence shift IQ^* to the right. An increase in h_1 will rotate the same line counter-clockwise, and an increase in h_2 will rotate the solid line above "Sector 2" counter-clockwise. Finally, an increased h_0 will rotate both solid lines clockwise.

2.2 Empirical Implications

The model generates the following testable implications.

Remark 2 ***(i)Entry****: Holding* a *fixed, the propensity to become an entrepreneur is increasing in IQ.*

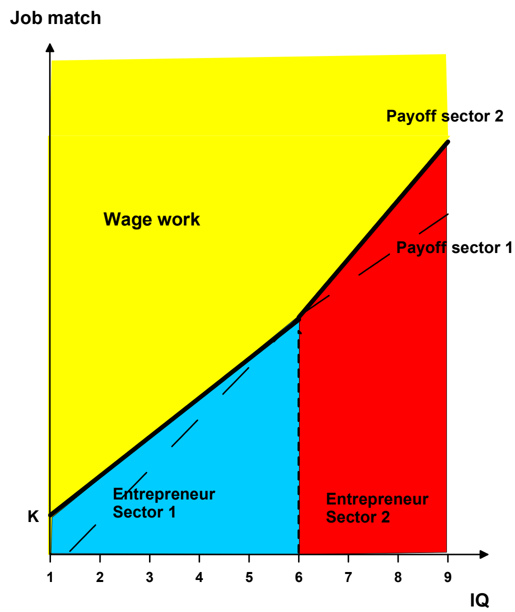

Figure 2: Sector Choice

(ii)Startup type*: Holding* a *fixed, higher IQ individuals are more likely to become Sector 2 entrepreneurs.*

(iii)Entrepreneur performance*: Venture performance is increasing in IQ of the founder.*

(iv)Entrepreneur performance: *Low-IQ individuals that become entrepreneurs will do, on average, better than in wage work.*

(v)Entrepreneur performance: *Entrepreneurs who follow their parents (enter Sector 1) will perform better, on average, than other entrepreneurs.*

(vi)Nurture human capital: *Low-IQ entrepreneurs are more likely to follow their parents (enter Sector 1) than high-IQ entrepreneurs.*

2.3 Education

We can extend the model by investigating the choice of education. We think of education as something that gives general human capital that is cheaper to acquire for high-IQ individuals. We modify the model in the following way

$$w = a + h_0 * IQ + b * s \tag{5}$$

where b is the return to education and s is the years of schooling. We assume that the cost of education is convex and decreasing in IQ,

$$c(s) = \frac{s^2}{IQ}$$

(we need to depart from linearity here in order to get interior solution for education choice).

[Still under development...]

3 Data

3.1 Norway

We start with a brief description of the Norwegian economy, the tax code, and the basis for the data collection.[4] Norway is an industrialized nation with a population of about 4.7 million. The GDP per capita in 2008 was about \$58,717 when currencies are converted at purchasing power parity; this is higher than the EU average of \$30,651. Norway is characterized by a large middle class and an unusually equitable distribution of disposable income. For labor income, the maximum marginal tax rate (for incomes above \$75,000) is about 50%, which is fairly typical by European standards. The capital income tax is a flat 28% on net capital gains.

Similar to other industrialized countries, setting up an incorporated company in Norway carries tax benefits relative to being self-employed (e.g., more beneficial write-offs for expenses such as home office, company car, and computer equipment), and incorporation status will therefore be more tax-efficient than self-employment status except for the smallest projects.

[4]The material is taken from the OECD Statistical Profile for Norway: 2010, available at OECD.org, and from Statistics Norway webpages.

The formal capital requirement for registering an incorporated limited liability company was NOK 50,000 in equity until 1998 and NOK 100,000 thereafter (in 2008, \$1 was equal to about 7 NOK).

In contrast to most OECD countries, Norwegian households are subject to a wealth tax every year throughout their lives.[5] The government's statistical agency, Statistics Norway (also known by its Norwegian acronym SSB) collects yearly data on wealth and income at the individual level from the Norwegian Tax Agency, and we obtain our data from SSB. Earnings and wealth figures for individuals are public information in Norway. This transparency is generally believed to make tax evasion more difficult and hence data more reliable.

The tax value of a firm, which is included in its owners' wealth statements, is calculated as sixty percent of assets subtracted debt, where debt is evaluated at face value while assets are at book value (typically lower than market value). Selling off a non-listed company therefore produces a tax liability if, which one can expect to commonly be the case, the transaction price exceeds the tax value of the company. This liability can be evaded by transferring the company to a holding company before selling off. We therefore do not expect the capital gains tax to bias the individuals that inherit a non-listed company towards keeping it or selling it off. In Norway there is also tax on inheritance. The inheritance tax on a non-listed company is based on the tax value of the firm on January 1 in the year of death. This means that the inheritance tax is effectively sunk once inheritance has taken place. We have therefore no reason to believe that the inheritance tax will bias our results in any particular direction.[6]

[5]In contrast, the U.S. tax system requires wealth reporting only in connection with estate tax, which is imposed only on the very rich at the time of death. The wealth tax in Norway is 0% up to about \$120,000 in net wealth, and about 1% for net wealth above \$120,000.

[6]If a spouse inherits, no inheritance tax will be paid until the spouse dies or remarries. If children of the entrepreneur inherit, in the period we study there was a 20% inheritance tax on inheritances whose tax value exceeded NOK 550.000, 8% rate on inheritances between 250.000 and 550.000 and 0% below 250.000 (for unrelated beneficiaries, the rates were slightly higher). For example, if the firm has NOK 2.1 million in assets and NOK 1 million in debt, the tax value is NOK 1.1 million. If two children inherit, they receive NOK 550.000 each, and are taxed 8% on NOK 300.000, i.e., they pay NOK 24.000 in inheritance tax each. (NOK 24,000 is equivalent to about 3,200 Euro.) This is unlikely to be a challenge for most Norwegian households, so we do not expect liquidity constraints to be important, in contrast to Tsoutsoura (2015). The approximate median tax value of the firms in our sample is NOK 324.000, the 75 percentile is NOK 1.2 million, and the 90 percentile is NOK 4.5 million. In 2008, \$1 was equal to about NOK 7.

3.2 Data

We consider all Norwegian men who were between the ages of 22 and 45 in 1996 and for whom we have a measure of intelligence from their armed forces entry test. For the sample of entrepreneurs, we only consider the first venture a person starts between 1999 and 2007 and we drop entrepreneurs if we cannot identify the industry of employment for either parent.

For entrepreneurs, we use a database that consists of the universe of newly incorporated, limited liability firms in Norway between 1999 and 2007.[7] The data include yearly accounting and employment measures for each firm until the end of 2011. Covering the population of new firms means that the majority of firms in the database are small. The advantage of this approach is that it will not be subject to selection biases commonly encountered in the literature that uses ”tip-of-the-iceberg” datasets (e.g., Hall and Woodward (2010)).[8] While many of these firms are small, a substantial fraction are not, even in the first year: the 75th percentile for book value of assets and number of employees in the first year of operations is about $400,000 and four, respectively.

The data are compiled from three different registers:

1. *Accounting information from Dun & Bradstreet's database of accounting figures based on the annual financial statements submitted to the tax authorities.* This data include variables such as 5-digit industry code, sales, assets, number of employees, and profits for the years 1999-2010. Note that the D&B data contain yearly information on *all* Norwegian incorporated limited liability companies, and not a sample as in the U.S. equivalent. Incorporated companies are required to have an external auditor certifying the accounting statements in the annual reports.

2. *Data on individuals from 1993 to 2009 prepared by Statistics Norway.* These records are based on government register data and tax statements, and include the anonymized personal identification number and yearly socio-demographic variables such as gender, age, education in years, taxable wealth, and income. The data identify the year of death, if applicable, and also identifies family relationships between individuals, which allows

[7] For 1999, the data contain only a sample of the firms started. Diagnostic tests do not suggest any selection bias.

[8] Relative to datasets covering the self-employed, as in Hamilton (2000), the advantage is that we can measure firm performance at a much more detailed level.

us to identify family firms. The data contain *all* Norwegian individuals, not a sample as in the Panel Study of Income Dynamics or the Survey of Consumer Finance. As with the PSID and the SCF, the data are anonymized (contains no names of individuals).

3. *Founding documents submitted by new firms to the government agency 'Brønnøysund-registeret'.* This register data include the start-up year, total capitalization, and the personal identification number and ownership share of all initial owners with at least 10 percent ownership stake.

For each new firm identified in 1), we create a list of owners identified through 3) and compile their associated socio-demographic information from 2). We define an entrepreneur as a person with more than 33% percent ownership of the total shares in a newly established limited liability firm. We interchangeably refer to this person as "the entrepreneur" or "the founder". For a small fraction of firms, the first year of financial reporting, defined through 1), is different than the year of incorporation defined by 3). For these firms, we define the first year as the first year of reporting. To avoid counting wealth management vehicles as start-ups, we omit finance and real estate firms (NACE 65-70).

3.3 Summary Statistics

Table 1 displays summary statistics for our sample. Of the roughly 650,000 men who meet our criteria, 2.7% are entrepreneurs (that is, they start a business of which they own more than 33% between 1999 and 2007).[9] Entrepreneurs are slightly more educated than the rest of the sample (an education level of four corresponds to a high school diploma). For both groups, we looked at earnings (in thousands of Norwegian Kroner) in their highest earning year between 1996 and 1998 (that is, while the entrepreneurs are still working in the labor market). Earnings for the entrepreneurs were 38% higher than non-entrepreneurs, which reflects their slightly higher education, slightly higher IQ, and the fact that their much higher asset levels suggest the entrepreneurs come from wealthier backgrounds.

The entrepreneurs own, on average, 63% of the companies they start. Four percent of the entrepreneurs started a business in the same industry that employed their father. Non-

[9] This share is somewhat of an underestimate of the population given we limit the entrepreneur sample to those people for whom we know what industry employed their fathers.

entrepreneurs work in the same industry as their fathers at a noticeably higher rate but this is because a substantial number of non-entrepreneurs work in the same establishment as at least one parent (see Kramarz and Skans (2014)).

Panel B shows the basic features and performance metrics for the ventures founded by the entrepreneur sample. There are 17,539 such ventures started, though the sample is smaller after four years due to businesses failing or becoming part of another company. The average new venture in our sample starts with 175,000 Norwegian Kroner (approximately $20,600 at the current exchange rate) in invested equity. However, there is a great deal of variation in the size of these ventures, as evidenced by the standard deviation in the table. The median equity at founding is 100,000 Kroner and the 90th percentile is about 300,000 Kroner. 8.6% of new companies are technology-related.

Four years after founding, 62% of ventures are still operating. Size and profitability are highly variable at this stage. For example, while the average firm has just over three employees, a large share have none beyond the founders while 8% of firms have at least ten employees. Total employment at the firms in our sample is about 60,000 people, which represents between two and three percent of the Norwegian labor force.

4 Results

Before looking at entrepreneurial decisions, we show the determinants of paid work for our sample before they become entrepreneurs. Panel A of Table 2 shows regressions where the dependent variable is log of wages in the person's highest earning year between 1996 and 1998. The entrepreneurs in this group start businesses beginning in 1999, so these regressions capture them while they are still working for other firms (though they are only a very small part of the sample).

We want to see how education and IQ, which are important for our analysis of entrepreneurship, affect worker's reservation wages in the paid work sector. In some specifications we use linear measures of education, age, and IQ as explanatory variables while we use a full set of dummies in other specifications.

The armed forces IQ coefficient in the column 1 regression suggests that a one-unit increase in this measure (which is just under a one standard deviation increase) is associated with about a seven percent higher wage (about a tenth of a standard deviation). Column 2 shows that most of this IQ effect goes away when education is included in the regression, but that an additional IQ point increases pay by a little under two percent and the coefficient remains highly significant. That is, people who have higher IQs get more education and some of the pay/IQ relationship is due to this education. Our measure of education is by levels (nine years of compulsory education, high school, bachelors, etc.). The coefficient in column 2 shows that pay goes up by about 9% with each of these steps. When we use years of education (which in these data is measured with some noise), we get a coefficient of around 6% which, given we control for IQ, is in line with typical estimates. Each additional year of job market experience (using age as a proxy) is associated with approximately two-and-a-half percent higher pay. In unreported regressions, we found that finer controls for education and labor market experience (that is, including a full set of dummy variables for all values of these variables) does not affect our estimate of IQ on pay.

Column 3 repeats the wage regressions with father fixed effects. The coefficients in this specification are based on within-family variation. In this specification, the education and age relationships with pay are not noticeably affected. The IQ coefficient suggests that a man who has a one-point higher IQ than his brother will, on average, earn just under one percent more than his brother. Though this effect is small in magnitude, it remains quite precisely estimated.

Another way to interpret the IQ coefficients is to note that one IQ point on the Norwegian armed forces test is approximately eight points on a standard IQ scale. So column 1 suggests that a Norwegian who scores eight points higher on a standard IQ test (that is, a test with a mean of 100 and a standard deviation of 15) than another Norwegian will earn approximately seven percent more. Column 3 indicates that a man with a ten point higher IQ than his brother will earn about one percent more.

Overall, Panel A of Table 2 shows that wages in Norway respond in expected ways to education and job market experience. Also, IQ is a strong predictor of wages, though a good portion of that relationship is due to the fact that people with higher IQs attain higher levels of education.

4.1 Entrepreneurial entry

Having established (unsurprisingly) that education and IQ both have important positive effects on salaries in the paid employment sector, we now examine how these and other factors affect the decision of whether or not to become an entrepreneur. Note that our model (like many others) predicts that people of higher ability are more likely to become entrepreneurs. We will capture "ability" two ways – IQ and education – while controlling for having resources that facilitate entering the entrepreneurial sector (assets before becoming an entrepreneur) and for the person's reservation wage in the paid work sector (which we capture through the pay dependent variable we used in Panel A of the table).

Panel B of Table 2 shows results from linear probability models where the dependent variable is an indicator variable that equals one if the person starts a business between 1999 and 2007.[10] The dependent variable has a mean of 2.7%, so entrepreneurship is relatively rare in this sample.

Consistent across all specifications, we find that a one point increase in the Norwegian IQ measure (which is about an eight point increase in a standard IQ score) is associated with a 0.2 percentage point increase (which is more than a 7% increase) in likelihood of becoming an entrepreneur. This is not a huge effect but it is not trivial given the low probability of entrepreneurship for the sample as a whole. Delaying entrepreneurship makes it less likely to ever happen, as the probability of becoming an entrepreneur is declining in age. Each year that passes decreases the probability of becoming an entrepreneur 5-6%. Assets to fund a venture are an important predictor of becoming an entrepreneur. The propensity to become an entrepreneur increases by two percent with every ten percent increase in assets.

The relationship between entrepreneurship, education, and pre-entrepreneurship labor market earnings are harder to interpret. Education leads to higher pay and higher pay in the non-entrepreneurial sector predicts a higher propensity to leave that sector and become an entrepreneur. However, controlling for labor market income, more educated workers are less likely to become entrepreneurs. Combined with the positive relationship between IQ and entrepreneurship, the evidence in Panel B of Table 2 is consistent with our model in that entrepreneurship is more likely for people of higher innate ability as measured by IQ. Some of

[10] We used linear probability specifications for ease of interpretation. The conclusions are unchanged if we use a logit or a probit.

that effect appears to be mitigated by the fact that higher IQ people get more education, on average, and this education has a higher payoff in the labor sector than the entrepreneurship sector. At the same time, greater earning power leads to higher entrepreneurship propensity, possibly because those who earn more have more resources to put towards a new venture and because they have a higher market value that they want to capture rather than split with an employer.

In Table 3, we analyze the role of "nurture" human capital in entrepreneurial entry. The table shows results of linear probability models (again, results are insensitive to the choice of specification) where the sample is entrepreneurs who start a business between 1999 and 2006 and the dependent variable equals one if the entrepreneur's father worked in the same industry.[11] We use very finely defined, five-digit industry codes. Examples of these industries include "Manufacture of other electronic and electric wires and cables", "Freight ocean transport", and "Tax consultancy activity". Using the distributions of entrepreneur and father industries if fathers and entrepreneurs were randomly mixed, we would find that 0.5% of entrepreneurs choose the same industry as their fathers.[12] In the actual data, the fraction following a father is 4%. So following one's father happens much more often (more than eight times as often, to be precise) as we would expect if it only occurred by chance.

Panel A shows regressions that do not control for industry-fixed effects and we find evidence very much in line with what we would expect from our model. The IQ coefficient suggests that each additional IQ point (or each additional eight IQ points using a standard IQ scale) lowers the probability of following one's father by about one fifth (0.008 compared to 0.04 unconditional probability) with no controls (column 1). With controls added, the IQ coefficient is always highly significant and indicates more than a 10% increase for each IQ point. So, as our model predicts, "nurture" human capital is more important in determining sector for entrepreneurs with less natural intelligence. These results are consistent with the idea that the gift people get, in terms of industry knowledge from their parents' labor market experience, is relatively more valuable for those who have less natural intellectual skill.

The education result is similar – those with more general human capital gained from the

[11] All our results are qualitatively similar if we define nurture human capital as following the industry of either parent. We focus on fathers given our entrepreneur data is limited to men and that, when our sample was growing up, fathers were more likely to be attached to the labor force and to be the primary breadwinner in a household.

[12] The 0.5% estimate is based on simulations where we randomly assigned the same overall distribution of industries to fathers as we see in the data and then see how many sons (using their actual industry codes) match these random father industries.

education system are less likely to follow their parents. A one unit increase in our education measure (for example, changing from a high school graduate to someone with a bachelor's degree) decreases the likelihood of an entrepreneur's venture being in his father's industry by a bit less than half of one percentage point (about 10%).

We interpret this as a reflection of the match between the entrepreneur's ability and the sector(s) his parents worked in. If the budding entrepreneur got a "nurture" human capital gift in an industry where his stellar intelligence would not be rewarded, it is in his best interests to forsake the gift from his parents and seek his fortune in an industry where his talents will be better compensated. But if the industry is relatively simple, so that his "nurture" human capital makes him likely to succeed and his natural talents are not great, then he follows his father. This difference-in-industries interpretation is supported by the fact that, when we include industry fixed effects in Panel B of Table 3, the IQ effect is much smaller and, in some specifications, insignificant and the education coefficient is trivial economically and insignificant statistically. That is, different industries have different likelihoods of attracting entrepreneurs with nurture human capital but, within an industry, innate ability does not affect the decision of whether or not to employ nurture human capital in a new business.

Table 3 also shows that entrepreneurs with more assets before they start their venture are more likely to start businesses in industries where their parents worked. One possible explanation for this is that those whose parents were more successful (and, as a result, gave their sons more money directly or more opportunities to earn money in their fields) also gave their sons larger nurture human capital gifts. The table also shows that sons of entrepreneurs are more likely to follow their parents than sons of non-entrepreneurs. Combining our results with the fact that children of entrepreneurs are more likely to be entrepreneurs themselves (e.g., Lindquist, Sol, and Praag (2015)), it appears parents pass along general entrepreneurial skill and industry-specific entrepreneurial skill. Finally, note that entrepreneurs who start their new venture near where their parents live are substantially more likely (twice as likely, in fact) to be following the sector where their parents worked. This could be for any number of reasons including that they take direct advantage of their parents' contacts and/or consult with their parents as they develop their companies.

4.2 Type of business

We now turn our attention to the type of businesses entrepreneurs start and the initial investment. From our model, we expect to find that entrepreneurs with higher "ability" (either innate or learned in school) will be more likely to start more innovative firms and will attract (or make) larger investments in those firms. Our proxy for innovation of the firm is an indicator for whether the industry of the firm can be described as technology-based. For this, we define any firm that is not "low-technology", using the Eurostat definition, as technology-based. We have an accurate measure of scale of initial investment, as the Norwegian data include how much equity was invested in each venture at the time it was started.

Panel A of Table 4 shows linear probability models where the dependent variable equals one if the venture is technology-based. The mean for the sample as a whole is 8.6%.

First focus on columns 1 and 3, which look at the cross-section of our entrepreneur sample. As expected, higher IQ entrepreneurs are more likely to found technology companies. Each point increase in IQ (eight IQ points using a standard IQ test) increases the odds of the startup being technology-based by about a quarter (two percentage points). More education is also associated with more technology-based startups. Each unit of education is associated with about a 6% increase in the likelihood that a startup is technology-based.

Columns 1 and 3 of Panel A also show that a technology-based startup is much less likely to be in the same industry as the founder's father worked than other startups. Entrepreneurs who start technology companies are less likely to be children of entrepreneurs. These findings are consistent with our conjecture that "nurture" human capital has lower returns in industries where innovation is more valuable.

In column 2, we introduce father fixed effects so the coefficients are identified by differences in the explanatory variable of sons of the same fathers. The IQ coefficient continues to be positive and significant, indicating the smarter son within a family is much more likely to start a technology-based company than his less intelligent brother. The huge "same" coefficient indicates that sons who start technology companies are much less common than sons who start other ventures. Throughout the rest of the paper, we do not report other within-father regressions because they are generally too noisy. In most specifications, the coefficient on "same" is as large or larger than in cross-section regressions but these coefficients are not statistically significant.

Panel B of Table 4 examines the scale of initial investment. The dependent variable is the log of the amount invested at founding. In all specifications, more natural ability (as captured by IQ) leads to bigger investments in the new venture. The economic magnitude of the relationship is not huge – one more IQ point on the Norwegian scale increases startup investment by less than 1% – but it is highly significant once we control for the five-digit industry of the startup. Education is negatively associated with startup size when not controlling for industry but the estimated relationship is basically zero once we control for industry. More educated entrepreneurs are attracted to industries where initial investment is smaller (probably largely professional service firms).

The coefficient on the "Same" variable shows a very strong relationship between the founder following his father in terms of industry and the initial equity investment. Entrepreneur sons who enter industries where a father preceded them invest 7-8% more equity than those who do not follow a father (columns 3 and 4) and up to about 12% more when we don't control for the industry chosen. An interpretation of this that follows from the model is that nurture human capital makes expected returns greater because they have contacts within the industry or, due to their backgrounds, they are expected to be more successful. Similarly, their industry knowledge could reduce the risk to investors who are therefore willing to put up more money.

In addition, we find (not surprisingly) that entrepreneurs with more assets start larger ventures and that entrepreneurial children of entrepreneurs start larger ventures.

4.3 Startup performance

We look at longer-term performance in Table 5. Columns 1 and 2 show linear probability models where the dependent variable equals one if the business is still operating four years after founding. Education is not a significant predictor of survival. However, we see an interesting pattern with respect to IQ. Higher intelligence is associated with lower survival when not controlling for industry but the sign flips (and remains statistically significant) when industry controls are added. This suggests that higher intelligence entrepreneurs are choosing riskier industries where survival is less likely but, conditional on that industry choice, founder intelligence enhances survival chances. The magnitude of this relationship is small, however, with each IQ unit increasing survival probability by about half a percentage point (which is less than a 1% increase in probability).

While we do not want to read too much into this table, the results on education and IQ are consistent with education enhancing labor market and entrepreneurial productivity/opportunity equally while raw intelligence is more valuable in the entrepreneurial sector than in the employed labor market. Education could be making people more valuable in both sectors but, by raising an entrepreneur's outside option as much as his venture's value, may not tip the balance to one sector or the other.

Consistent with our model's prediction that nurture human capital enhances firm productivity, survival is noticeably higher for those with nurture human capital. Survival is eight percentage points, or about 12%, higher for those who follow their parents. Also, entrepreneurs with more assets before they start their venture are more likely to survive, though the amount initially invested in the business does not predict survival.

Columns 3-6 show results for two continuous measures of success – Return on Assets and Number of Employees. The ROA regressions are on a smaller sample because we cannot include businesses that are no longer operating or that have zero or negative assets. We set employees to zero if the venture is no longer operating four years after founding. Using either measure, we find inconsistent and economically small relationships between performance and either IQ or education. Education is a small positive predictor of ROA when we use industry fixed effects. The IQ relationship to these variables is negative when not controlling for industry but small and insignificant when controlling for industry, suggesting smarter entrepreneurs pick industries with slightly worse performance but perform at industry standard.

The relationship between these performance measures and having a parent who worked in the founder's industry, however, again has a strong and consistently positive association with performance. Nurture human capital increases ROA by three percentage points (which is large given a sample mean of eleven percent) when not controlling for industry. The effect is still economically large but becomes insignificant when we control for industry, which implies following a father is more likely in industries with relatively high ROA and that ROA may or may not be higher for followers conditional on industry. The relationship between following one's father and number of employees is statistically more consistent and quite large economically. When a venture is four years old, it is likely to have two-to-three more employees if the business is in the same industry as that in which the founder's father worked. This is a very large effect given the average surviving four-year-old firm has a little more than three employees.

In Table 6, we look at extreme outcomes rather than means. The dependent variables in the regressions in this table equal one if the firm is in the top five percent of all firms in the relevant category. Firms that do not survive are part of the sample, so there is no depletion of the sample (and, naturally, the dependent variable can only equal one for surviving firms).

The regressions (which are linear probability models) support the conclusion that nurture human capital is valuable. Founding a business in the same industry as a father predicts almost double the probability of being a positive outlier for total assets and sales and more than double for employees. The coefficient on ROA is, again, large economically but not significant – as is often the case, ROA is quite noisy.

The effects of the other explanatory variables are not as consistent but both IQ and education predict a greater probability of being a positive outlier. The economic significance of these relationships is not great but they are somewhat important predictors of success. As we might expect, entrepreneurs who have more assets before starting their venture or who invest more equity at the start of their ventures are more likely to be positive outliers. For example, a 10% increase in the amount of equity invested initially is associated with about 0.8% and 0.4% higher probability of being in the top 5 percent of ventures (within a given industry) as measured by assets or employees, respectively.

The conclusion from Tables 5 and 6 is clear – businesses started by sons that are in the same industry that employs their fathers are more successful, on average, than those that do not. This relationship is much stronger and more consistent than the relationship between performance and other features of the founder including age, intelligence, education, and financial background. We can only speculate on how nurture human capital is leading to better new venture performance. It could be as simple as parents in the industry who provide contacts or direct inputs to the firm or it could be that those who grow up learning a trade are simply better at it when they start a business. Understanding the mechanisms that lead to value from nurture human capital is difficult in such a large dataset, but is something we hope to explore as this project develops.

5 Conclusion

We speculated that, in some industries, raw entrepreneur ability is critical to success while, in others, success is more a function of industry-specific institutional knowledge. We developed a model of a labor market entrant choosing between paid employment, starting a business in an industry he already knows well through parental connections, or striking out in a new business in a new field. We developed implications of this model and then showed the implications are broadly consistent with data on business started in Norway between 1999 and 2007. Specifically, we showed that entrepreneurs who are more intelligent are less likely to their fathers and more likely to start technology-based companies. We go on to show that businesses started by people who follow the industry in which their fathers worked are noticeably more successful after four years of operation by several different measures. We interpret this as suggesting that "nurture human capital" is quite valuable and that many parents give their children a valuable gift of industry knowledge.

References

Evans, D. S., and B. Jovanovic (1989): "An Estimated Model of Entrepreneurial Choice under Liquidity Constraints," *Journal of Political Economy*, 97, 808–827.

Grinblatt, M., M. Keloharju, and J. Linnainmaa (2011): "IQ and Stock Market Participation," *Journal of Finance*, 66, 2121–2164.

Hall, R. E., and S. E. Woodward (2010): "The Burden of the Nondiversifiable Risk of Entrepreneurship," *American Economic Review*, 100, 1163–1194.

Hamilton, B. H. (2000): "Does Entrepreneurship Pay?: An Empirical Analysis of the Returns of Self-Employment," *Journal of Political Economy*, 108, 604–631.

Hurst, E., and B. Pugsley (2011): "What Do Small Businesses Do?," *Brookings Papers on Economics Activity, Microeconomics*, 43, 73–142.

Kramarz, F., and O. N. Skans (2014): "When Strong Ties are Strong: Networks and Youth Labour Market Entry," *Review of Economic Studies*, 81, 1164–1200.

Laband, D. N., and B. F. Lentz (1983): "The Burden of the Nondiversifiable Risk of Entrepreneurship," *Southern Economic Journal*, 50, 474–493.

Levine, R., and Y. Rubinstein (2015): "Smart and Illicit: Who Becomes an Entrepreneur and Do They Earn More?," Working Paper.

Lindquist, M. J., J. Sol, and M. V. Praag (2015): "Why Do Entrepreneurial Parents Have Entrepreneurial Children?," *Journal of Labor Economics*, 33, 269–296.

Tsoutsoura, M. (2015): "The Effect of Succession Taxes on Family Firm Investment: Evidence from a Natural Experiment," *Journal of Finance*, 70, 649–688.

Table 1: Summary Statistics

Panel A: Individuals		
	Entrepreneurs	Non-Entrepreneurs
Education "Level"	4.38	4.18
	(1.30)	(1.34)
Highest Earnings (000), 1996-1998	402.07	291.94
	(1,502.24)	(290.30)
Age in that year	32.49	34.38
	(5.81)	(6.76)
Assets in that year (000)	693.70	345.86
	(5,531.54)	(311.03)
IQ (1-9 scale)	5.65	5.41
	(1.74)	(1.86)
Entrepreneur in Fathers's Industry	4.05%	N/A
At Least One Entrepreneur Parent	25.79%	N/A
Share of Venture Owned	63.00%	N/A
	(25.88%)	
Number of Observations	17,610	627,834

Panel B: Entrepreneurial Ventures	
Equity at Founding (000s)	175.27
	(680.90)
Assets in Fourth Year (000s)	3.51
	(24.89)
Sales in Fourth Year (000s)	5.07
	(11.60)
Employees in Fourth Year	3.15
	(6.79)
Return on Assets in Fourth Year	10.63%
	(26.98%)
=1 if Technology-based	8.64%
=1 if Survived at least 4 Years	62.19%
Number of Observations	17,610

Table 2: Earnings and Entrepreneurial Entry

Panel A: Pay Regressions			
	(1)	(2)	(3)
IQ	0.0663	0.0166	0.0076
	(0.0005)	(0.0005)	(0.0016)
Education		0.0909	0.0884
		(0.0007)	(0.0022)
Age		0.0267	0.0308
		(0.0002)	(0.0004)
Father Fixed Effects	No	No	Yes
R-square	0.0318	0.1114	0.8905
Observations	633,240	633,240	633,240

Panel B: Entrepreneurial Entry			
	(1)	(2)	(3)
IQ	0.0018	0.0016	0.0022
	(0.0001)	(0.0001)	(0.0004)
Education		-0.0006	-0.0018
		(0.0002)	(0.0006)
Age		-0.0019	-0.0014
		(0.00004)	(0.0001)
Ln(Highest Pay, 1996-1998)		0.0122	0.0132
		(0.0003)	(0.0012)
Ln(Assets in same year)		0.0040	0.0048
		(0.0001)	(0.0004)
Father Fixed Effects	No	No	Yes
R-square	0.0004	0.0090	0.8748
Observations	633,240	633,240	633,240

Table 3: Entrepreneurial Following Father

Panel A: No Industry Controls				
	(1)	(2)	(3)	(4)
IQ	-0.0079	-0.0062	-0.0059	-0.0053
	(0.0009)	(0.0010)	(0.0010)	(0.0012)
Education		-0.0046	-0.0046	-0.0035
		(0.0013)	(0.0013)	(0.0016)
Age		-0.0002	-0.0003	-0.0004
		(0.0003)	(0.0003)	(0.0003)
Ln(Assets pre-Entrepreneurship)			0.0051	0.0052
			(0.0009)	(0.0016)
Parent Entrepreneur			0.0505	0.0055
			(0.0034)	(0.0042)
Live in Same Town as Parent				0.0371
				(0.0037)
R-square	0.0048	0.0056	0.0202	0.0302
Observations	17,539	17,539	17,539	17,539

Panel B: Controls for 5-Digit Industry of Entrepreneurial Venture				
	(1)	(2)	(3)	(4)
IQ	-0.0025	-0.0023	-0.0023	-0.0018
	(0.0010)	(0.0010)	(0.0010)	(0.0013)
Education		0.0001	0.0000	0.0015
		(0.0014)	(0.0014)	(0.0017)
Age		-0.0003	-0.0003	-0.0004
		(0.0003)	(0.0003)	(0.0004)
Ln(Assets pre-Entrepreneurship)			0.0041	0.0045
			(0.0009)	(0.0012)
Parent Entrepreneur			0.0482	0.0520
			(0.0034)	(0.0042)
Live in Same Town as Parent				0.0312
				(0.0037)
R-square	0.0672	0.0673	0.0794	0.0947
Observations	17,539	17,539	17,539	17,539

Table 4: Initial Industry and Scale

Panel A

Dependent Variable:	Tech Dummy	Tech Dummy	Tech Dummy
IQ	0.0220	0.0313	0.0220
	(0.0014)	(0.0137)	(0.0014)
Education	0.0047	-0.0070	0.0048
	(0.0010)	(0.0095)	(0.0010)
Age	-0.0027	-0.0023	-0.0023
	(0.0004)	(0.0034)	(0.0004)
Same	-0.0596	-0.4265	-0.0558
	(0.0106)	(0.0906)	(0.0107)
Ln(Assets pre-Entrepreneurship)			-0.0043
			(0.0013)
Parent Entrepreneur			-0.0084
			(0.0049)
Family Fixed Effects	No	Yes	No
R-square	0.0304	0.9972	0.0312
Observations	17,539	17,539	17,539

All specifications include Year Dummies

Panel B

Dependent Variable:	Equity at Founding	Equity at Founding	Equity at Founding	Equity at Founding
IQ	0.0023	0.0020	0.0081	0.0074
	(0.0028)	(0.0028)	(0.0029)	(0.0029)
Education	-0.0067	-0.0081	0.0008	-0.0004
	(0.0020)	(0.0020)	(0.0021)	(0.0021)
Age	0.0049	0.0011	0.0045	0.0015
	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Same	0.1174	0.0981	0.0833	0.0692
	(0.0219)	(0.0220)	(0.0217)	(0.0217)
Ln(Assets pre-Entrepreneurship)		0.0360		0.0293
		(0.0027)		(0.0026)
Parent Entrepreneur		0.0215		0.0204
		(0.0100)		(0.0098)
5-digit industry dummies	No	No	Yes	Yes
R-square	0.0151	0.0259	0.1222	0.1291
Observations	17,539	17,539	17,539	17,539

All specifications include Year Dummies

Table 5: Year Four Performance

Dependent Variable:	4-Year Survival	4-Year Survival	Year 4 ROA	Year 4 ROA	Year 4 Employees	Year 4 Employees
IQ	-0.0057	0.0049	-0.0052	-0.0015	-0.1110	0.0391
	(0.0024)	(0.0024)	(0.0015)	(0.0016)	(0.0322)	(0.0321)
Education	-0.0002	0.0004	0.0049	0.0022	-0.0504	0.0157
	(0.0017)	(0.0018)	(0.0011)	(0.0011)	(0.0226)	(0.0232)
Age	-0.0004	-0.0010	-0.00001	-0.0003	-0.0141	-0.0054
	(0.0007)	(0.0007)	(0.0004)	(0.0004)	(0.0093)	(0.0090)
Same	0.0970	0.0394	0.0285	0.0083	2.8543	2.0912
	(0.0185)	(0.0184)	(0.0114)	(0.0116)	(0.2489)	(0.2412)
Ln(Assets pre-Entrepreneurship)	0.0142	0.0139	0.0061	0.0050	0.1190	0.1211
	(0.0022)	(0.0022)	(0.0015)	(0.0015)	(0.0305)	(0.0294)
Ln(Startup Equity)	-0.0190	-0.0029	-0.0126	-0.0061	1.4038	1.3681
	(0.0064)	(0.0065)	(0.0040)	(0.0041)	(0.0861)	(0.0855)
5-digit industry dummies	No	Yes	No	Yes	No	Yes
R-square	0.0169	0.1144	0.0120	0.0944	0.0326	0.1705
Observations	17,539	17,539	13,382	13,382	17,539	17,539

All specifications include Year Dummies

Unconditional Prob(survival) = 62%
Prob(survive|same) = 73%

Table 6: Year Four Extreme Performance

Dependent Variable = 1 if company is in top 5% of the relevant category in Year 4 after founding

Dependent Variable:	Assets	Employees	ROA	Sales
IQ	0.0022	0.0019	0.0003	0.0014
	(0.0011)	(0.0010)	(0.0011)	(0.0011)
Education	0.0025	0.0009	0.0023	0.0019
	(0.0008)	(0.0007)	(0.0008)	(0.0008)
Age	-0.0004	-0.0002	0.0002	-0.0004
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Same	0.0402	0.0682	0.0079	0.0488
	(0.0082)	(0.0077)	(0.0083)	(0.0079)
Ln(Assets pre-Entrepreneurship)	0.0096	0.0025	0.0010	0.0040
	(0.0010)	(0.0009)	(0.0010)	(0.0010)
Ln(Startup Equity)	0.0784	0.0416	-0.0140	0.0601
	(0.0029)	(0.0027)	(0.0029)	(0.0028)
R-square	0.1287	0.1590	0.0986	0.1836
Observations	17,539	17,539	17,539	17,539

All specifications include year and 5-digit industry dummies