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Lean and Hungry or Fat and Content? Entrepreneurs' Wealth and Start-up Performance

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Abstract: If entrepreneurs are liquidity constrained and not able to borrow to operate on an efficient scale, economic theory predicts that entrepreneurs with more personal wealth should do better than those with less wealth. We test this hypothesis using a novel dataset covering a large panel of start-ups from Norway. Consistent with liquidity constraints, we find a positive relationship between founder prior wealth and start-up size. The relationship between prior wealth and start-up performance, as measured by profitability on assets, increases in the first three wealth quartiles. In the top wealth quartile, however, profitability drops sharply in wealth. Our findings are consistent with a luxury good interpretation of entrepreneurship and that higher wealth may induce a less alert or a less dedicated management. We conclude that an abundance of resources might do more harm than good for start-ups.

Keywords: Entrepreneurial motivation, Entrepreneurship, Financial constraints, Independence, Liquidity, Organizational slack, Start-ups, Survival, Profitability.

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Let me have men about me that are fat, sleek-headed men, and such as sleep o'nights. Yond Cassius has a lean and hungry look; He thinks too much: such men are dangerous. William Shakespeare (Julius Caesar Act 1, scene 2).

1 Introduction

One of the oldest ideas in the study of entrepreneurship is that entrepreneurs may be liquidity-constrained and therefore unable to establish a venture at the right scale. To illustrate this point, Adam Smith used the example of the owner of a small grocery store, who must

> "be able to read, write, and account, and must be a tolerable judge too of, perhaps, fifty or sixty different sorts of goods, their prices, qualities, and the markets where they are to be had cheapest. He must have all the knowledge, in short, that is necessary for a great merchant, which nothing hinders him from becoming but the want of sufficient capital." (Wealth of Nations, bk. 1, ch. 10).

While Adam Smith held a favorable view of the effects of more liquidity, business people and venture capitalists caution that excess liquidity can facilitate overinvestment or adversely affect the entrepreneur's motivation and alertness. The idea that more liquidity can have a negative effect on outcomes can be traced back to Plato, who in the Republic wrote that "wealth is the parent of luxury and indolence". Who should we place our bets on, Adam Smith or Plato?

Using a newly collected dataset from Norway on a large representative sample of start-ups, our research investigates the effect of liquidity, as measured by founder's prior wealth, on start-up size and start-up profitability. To avoid capturing effects that go via more wealthy founders being more able, we control for human capital via age, education, and prior wage variables. We also control for business cycle and industry effects. The strength of the relationship between founder wealth and start-up performance, as measured by profitability on assets, increases over the bottom three quartiles of the wealth distribution, and decreases sharply in the upper wealth quartile. These findings suggest that a moderate amount of liquidity may propel entrepreneurial performance, consistent with Adam Smith's view, but that an abundance of liquidity may do more harm than good, consistent with Plato's view.

The theory of liquidity constraints of Evans & Jovanovic (1989) provides a useful reference point for the empirical analysis. Evans & Jovanovic (1989) classify entrepreneurs as constrained or unconstrained based on the relative magnitude of the start-up size and the founder's wealth. An entrepreneur that starts up a company that is small relative to his wealth is defined as unconstrained. Evans-Jovanovic predicts a negative relation between wealth and profitability for the constrained entrepreneurs, and a zero relation between wealth and profitability for the unconstrained entrepreneurs. The first prediction relies on the Evans-Jovanovic assumption of decreasing returns to scale. The second prediction is very general and will hold in any theory of liquidity constraints based on profit maximization.

We estimate that profitability on assets increases by about 8 percentage points from the 10th to the 75th wealth percentile. This result suggests that liquidity constraints could stop entrepreneurs from being able to exploit a "hump" in marginal productivity due to a region of increasing returns to scale. At the top of the wealth distribution, our estimates suggest that the profitability on assets *drops* by about 11 percentage points from the 75th to the 100th percentile. That profitability decreases for some range of entrepreneurial wealth is what one would expect if marginal profitability decreases as start-ups reach their optimum scale. It is, however, puzzling that profitability on assets falls sharply in the wealth range where entrepreneurs are least likely to be liquidity constrained.

One explanation for why the relation between liquidity and profitability is negative in the upper wealth quartile could be that liquidity constraints bind for some of these founders, and that such constraints – combined with suitable assumptions about the returns to scale inside the firm – are sufficiently strong to create a downward slope in profitability. Although we do not observe the scale returns of individual start-ups, we do observe start-up size. Based on the methodology of Evans & Jovanovic (1989), we find that the drop in profitability in the upper wealth quartile is driven by entrepreneurs that are unconstrained. Thus, quite strikingly, the drop in profitability in the upper wealth quartile is due to the lack rather than the presence of liquidity constraints. This finding stands in contrast to theories of liquidity constraints based on profit maximization, where there should be a zero relation between liquidity and profitability for unconstrained entrepreneurs.

Data limitations make us unable to pin down exactly which mechanism drives the puzzling inverse U-shaped relationship between founder wealth and start-up performance. Two types of mechanisms, not mutually exclusive, seem useful for understanding the finding; organizational slack and private benefits.

Although there is no universally accepted definition of organizational slack, financial freedom is one important aspect (Bourgeois, 1981, Tan & Peng, 2003). Since the financial situation of the founder and of the firm are tightly related for start-ups (see e.g., Aldrich, 1999), the financial freedom of the founder and of the firm are likely to be closely correlated. Management theorists generally tend to argue that slack is beneficial through creating a buffer from environmental shocks (Cyert and March, 1963, Pfeffer and Salancik, 1978) or allowing for experimentation (Thompson, 1967), and thus enhances performance. Cyert & March (1963, p. 116), however, caution that slack might induce a lowering of the threshold of acceptable outcomes in the search for alternative actions. This argument suggests a curvilinear relationship between slack and performance, where "there is an optimal level of slack for any given firm. If the firm exceeds that level, performance will go down" (Sharfman et al., 1988, p. 603). Our findings are consistent with the idea that some slack is beneficial to start-up performance, but that an abundance of slack is harmful.[1]

We believe that the negative effects of slack can be understood by considering entrepreneurial motivation, in particular the notion that entrepreneurship is a luxury good (Hamilton, 2000, Moskowitz & Vissing-Jorgensen, 2002, and Hurst & Lusardi, 2004). If entrepreneurship is a luxury good, wealthy individuals are willing to forgo income in order to enjoy its private benefits. Several non-pecuniary motivations for entrepreneurship have been analyzed by the entrepreneurship literature, typically by comparing answers to survey questions for entrepreneurs and non-entrepreneurs.[2] Although we have no direct way of finding out which non-pecuniary

[1] In the context of mature firms, the empirical literature on the relationship between slack and performance has been inconclusive (see Tan & Peng, 2003, Table 1, for an overview). Several studies fail to find evidence of a curvilinear relationship (e.g., Bromiley, 1991, Miller & Leiblein, 1996). Nohria & Gulati (1996) use innovation as a dependent variable, and find a curvilinear relationship between slack and innovation, while Tan & Peng (2003) find a curvilinear relationship between slack and profitability for a sample of Chinese state-owned enterprises.

[2] Shane et al. (2003) provide an excellent review of the literature on entrepreneurial motivation.

motivations are more important in our sample, our results are consistent with the notion that entrepreneurship gives social esteem or independence (Hisrich, 1985, Hornaday & Aboud, 1973, and Aldridge, 1997), and that more wealthy individuals have a greater demand for this. Our findings thus complement the existing entrepreneurship literature by suggesting that non-pecuniary motivations can have a large quantitative impact on start-ups, and by pointing out which types of entrepreneurs are most likely to act upon non-monetary motivations.

Most earlier studies on entrepreneurial performance have had limited access to sociodemographic information about the founders, and have analyzed the relation between start-up performance and variables such as firm size (e.g., Brüderl et al., 1992, Audretsch & Mahmood, 1995) rather than the relation between start-up performance and founder variables. The previous research with access to entrepreneurial wealth measures has analyzed the relation between liquidity and entrepreneurial wages (Evans & Jovanovic, 1989), and the relation between liquidity and start-up survival (Holtz-Eakin et al., 1994a).[3] Evans & Jovanovic (1989) find that a doubling of founder wealth is associated with a 14 percent increase in self-employed earnings (Table 3, p. 820). This result is hard to interpret, however, since the authors are unable to control for the possibility that investment levels (and hence earnings) tend to increase with founder wealth. Nor do Evans & Jovanovic (1989) control for wealthier founders having higher effective human capital. In contrast, our detailed data allow us to control both for investment levels and for human founder capital. Holtz-Eakin et. al. (1994) use data on the tax receipts of a sample of entrepreneurs that had received inheritances from large estates, and find that a $150,000 inheritance increases the survival probability by 1.3 percentage points (1994a, p. 53). Because this sample of entrepreneurs tend to have very high pre-inheritance incomes, the authors cannot conclude that liquidity enhances the survival of the typical new venture. In contrast to Holtz-Eakin et al. (1994), the dataset we use covers a representative sample of start-ups.

The rest of this paper is organized as follows: The next section describes the data. Section 3 derives formally the hypotheses from the Evans-Jovanovic (1989) model. Section 4 discusses our empirical strategy. Section 5 contains the empirical analysis, Section 6 provides further

[3] See Kerr and Nanda (2009) for a recent and excellent review of the litterature on entrepreneurship and financial constraints.

analysis and discusses limitations, and Section 7 concludes and discusses research implications. Two appendixes are available as e-companions to the paper. Appendix A contains a theoretical analysis of the relationship between wealth and start-up size in the Evans-Jovanovic model, and some additional discussion on the empirical relationship between wealth and start-up size in our data. Finally, to analyze the dynamics of liquidity constraints, we use the approach of Cabral & Mata (2003) to analyze the development of the firm size distribution in our data. In Appendix B, we analyze the relation between liquidity and, respectively, entrepreneurial wage and business survival.

2 Data

The data come from Norway, and consist of a random sample of limited liability firms that were incorporated between 1994 and 2002. The data are organized as a yearly panel ranging from 1992 to 2006, and contain incorporation and accounting information on the start-ups in addition to detailed sociodemographic information about all founders with at least 10 percent ownership share. Since the data are novel, we start out with a brief description of the Norwegian economy and of the data collection.[4]

Norway is an industrialized nation with a population of about 4.5 million. The GDP per capita in 2002 was about $40,000 when currencies are converted at PPP; this is higher than the EU average of $26,000. Norway is characterized by a large middle class, and a lower inequality in disposable income than most other industrialized nations. Norwegian households are subject to both a capital income tax and a wealth tax every year throughout their lives (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, as described in Campbell, 2006). Because of the existence of the wealth tax, 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 a variety of sources, including the Norwegian Tax Agency, welfare agencies, and the private sector. Financial institutions supply information to the tax agency on their customers'

[4] The description of the Norwegian economy is based on the 2002 and 2003 editions of the Statistical Yearbook of Norway. The yearbooks are available at www.ssb.no/english/yearbook/.

deposits, interest paid or received, security investments, and dividends. Employers similarly supply statements of wages paid to their employees.

The dataset is compiled from three different sources:

1. *Yearly accounting information from Dun & Bradstreet's database of accounting figures based on the annual financial statements reported by the companies.* This data include variables such as sales, assets, profits and 5-digit industry codes for the years 1994-2005. It is important to note that the D&B data contain all Norwegian incorporated companies, not a sample as in the US equivalent.

2. *Yearly data on individuals from 1986 to 2002 prepared by Statistics Norway.* These records include the anonymized personal identification number and yearly sociodemographic variables such as gender, age, education, wealth, interest payments and earnings split into labour income and capital income. Earnings and wealth figures are public information in Norway. This transparency is generally believed to make tax evasion more difficult and hence our data more reliable. We use these data to construct measures of founder background and founder wage income after starting up a venture. The Statistics Norway data contain all Norwegian individuals, not a sample as in e.g., the Panel Study of Income Dynamics or the Survey of Consumer Finance.[5]

3. *Founding documents submitted by new firms to the government agency 'Brønnysundregisteret'.* These data include the personal identification number of the founders, total capitalization of the company, and each founder's respective ownership share.

Using the founding documents we define an entrepreneur as a male with more than 50 percent of the total shares, in a newly established incorporated company (the average ownership share is 83 percent). Restricting the sample to majority owners makes us avoid the problem of defining liquidity when dealing with multiple founders with different levels of wealth. Other advantages include avoiding the problem of how to deal with nominal founders such as "sleeping

[5]Even if the names of the founders in some cases might be discerned, obtaining and using data based on mailings, telephoning, or internet-searches would be a breach of the confidentiality agreement with Statistics Norway, and would violate Norwegian law.

spouses". Restricting attention to males avoids measurement problems with female labor market participation. 7 percent of the founders are females and are excluded.

For each start-up selected in Dun & Bradstreet's database we compile a list of founders based on the founding documents. Next, we match in the founders' associated sociodemographic information from the public registers supplied by Statistics Norway. Due to alterations in the reporting requirement in 1998, and the transition from paper-based to digitally based archiving, we were able to match around 80 percent of the founders in companies founded after 1998 and around 20 percent before. Based on communication with Brønnøysund, we have no reason to believe that the low frequency in which we are able to match for companies started before 1998 creates a bias in any particular direction. This impression is confirmed by comparison of e.g., the size distribution of the companies founded before and after 1998. Altogether we have a sample of about 1500 unique founders and 10 700 founder-year observations. In the analysis we lose about 200 founders due to missing variables.

Like in 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-employed status except for the smallest projects. The formal capital requirement for registering an incorporated company was NOK 50,000 in equity until 1998 and NOK 100,000 thereafter. NOK 50,000 is equivalent to about 6,300 Euro. Incorporated companies are required to have an external auditor certifying the accounting statements in the annual reports.

An adverse consequence of the low barriers to starting up an incorporated company and its favorable tax treatment, is that many start-ups, particularly within real estate, are tax-shelters or have minimal activity. This problem was dealt with in two ways. First, by over-sampling manufacturing and IT since tax shelters are less likely to occur in these industries. We selected all start-ups within the high tech sectors NACE 23-35 and 72 from 1994-1998, and all start-ups within manufacturing and IT, NACE 15-37 and 72 from 1999-2002. We added a random 25 percent sample of other non-financial private sector start-ups from 1999-2002. We expanded the sample after 1998 because the cost of collecting data for the more recent period is lower. Second, to further reduce the share of “empty shells”, firms are included only if they have at least NOK 500,000 (about 63,000 Euro) in sales and at least two persons employed during one of the first two years of operation. Avoiding sampling empty companies is important as the incorporation documents had to be hand-collected by research assistants located in Brønnøysund.

We can note several advantages of our data compared to earlier datasets on entrepreneurship. A large literature within the entrepreneurship domain has limited generalizability because it is based on non-representative samples (Delmar & Shane, 2006). In contrast, our sample is representative of the population of newly founded incorporations in Norway. Second, relative to other representative data on entrepreneurs such as the Panel Study of Income Dynamics, the Survey of Consumer Finance, and the Surveys of Small Business Finances, our data have several strengths. Since our data are collected from government archives, we do not suffer from survey design biases due to non-response or imperfect recall of subjects. Also, our data have access to a long panel with yearly and multiple measures of entrepreneurial performance. This enables us to perform a time-series analysis and a variety of robustness tests. Finally, we have detailed data on the wealth and wage history of the founders. This enables us to control for founder human capital and liquidity much more comprehensively than in previous studies.

3 Hypothesis building

The theory of liquidity constraints of Evans & Jovanovic (1989) provides a useful reference point for the empirical analysis. In Evans-Jovanovic, individuals may have insufficient wealth to self-finance their venture, and can supplement their personal stake in the start-up by borrowing. Personal wealth plays the role of collateral. Entrepreneurs whose financing need exceeds the total available funds are defined as constrained, and entrepreneurs whose financing need is less than the available funds, and hence can establish a company at an efficient scale, are defined as unconstrained. We now analyze the Evans-Jovanovic model and derive its predictions on the relationship between founder wealth and start-up profitability.

Setup

The Evans & Jovanovic (1989) model attempts to explain entry into entrepreneurship by a risk-neutral individual using three key variables; opportunity cost (wage work), quality of idea/human capital, and liquidity constraints. The model is static where the individual makes two decisions simultaneously; whether to start up a business and the level of assets to put into the business.

Net profits conditional on entry equal,

$$y = \theta k^{\alpha}\epsilon - rk \tag{1}$$

where θ is entrepreneurial ability, a non-negative random variable known to the individual at the decision stage, k is the chosen level of assets, $\alpha \in (0,1)$ is a technological constant, ϵ is a noise term with non-negative support and mean equal to one, not known at the decision stage, r is the interest rate, and rk is the opportunity cost of assets deployed. It is straightforward to extend the analysis to the case where α and r are random variables. We assume, however, that α and r are deterministic.

The individual becomes an entrepreneur if net profits exceed foregone wage income w,

$$y > w \tag{2}$$

where w is stochastic and depends upon the individual's age, education level, and so forth. Conditional on entry, the individual solves

$$\max_{\{k\}} y \tag{3}$$

Without liquidity constraints, the optimal level of investments is defined by the first order condition $\theta\alpha k^{\alpha-1} - r = 0$ with solution

$$k^{*} = (\theta\alpha/r)^{\frac{1}{1-\alpha}} \tag{4}$$

The individual has non-negative random wealth z and can borrow up to $(\lambda - 1)z$ at interest rate r. We say that an individual is capital constrained (liquidity constrained) if $\lambda z < k^*$ and not capital constrained if $\lambda z \geq k^*$. The optimal investment level conditional on entry must therefore equal,

$$k = \min(k^*, \lambda z) \tag{5}$$

Remark 1 *For given $(\theta, r, \lambda, \alpha)$, there exist constants z_L and z_H such that (i) individuals with $z < z_L$ will not enter, (ii) individuals with $z_L < z < z_H$ will enter and be constrained (i.e., $k < k^*$) and (iii) individuals with $z > z_H$ will enter and be unconstrained (i.e., $k = k^*$)*

Proof. Define $z_H = \{z : \lambda z = k^*\} = (\theta\alpha/r)^{\frac{1}{1-\alpha}}/\lambda$, i.e., the wealth level just sufficient to be unconstrained. Throughout we assume that θ is sufficiently high for $y(z_H) > w$ to hold (the reverse case is not interesting as nobody will enter).

We now define z_L. First note that for $z < z_H$ then $\dfrac{\partial y}{\partial z} = \alpha\theta\lambda(z\lambda)^{\alpha-1} - r\lambda$ and $\dfrac{\partial^2 y}{\partial z^2} = (\alpha - 1)\alpha\theta\lambda^2(z\lambda)^{\alpha-2} < 0$. By the concavity of $y(z)$, and since $\dfrac{\partial y}{\partial z} = 0$ for $z > z_H$, it must be the case that $\dfrac{\partial y}{\partial z} > 0$ for $z < z_H$. On the other hand, $y(z = 0) = 0$. It follows that there must exist a unique cutoff $z_L \in (0, z_H)$ such that $y(z_L) = w$. Thus (i) for $z < z_L$ the agent will not enter, (ii) for $z_L < z < z_H$ the agent will enter but be constrained, and for $z \geq z_H$ the agent will enter and be unconstrained. ■

Wealth and profitability

We now analyze the model's predictions on the relation between wealth and profitability conditional upon the individual becoming entrepreneur, i.e., conditional upon $z > z_L$.

Let us first define realized profitability R as,

$$R = \theta k^{\alpha}\epsilon/k = \theta\epsilon k^{\alpha-1} \tag{6}$$

R equals profits gross of financing costs divided by the level of assets. R corresponds to OROA in the empirical analysis. For unconstrained entrepreneurs we can substitute in for $k = k^*$.

Taking logs we obtain,

$$\begin{aligned} \ln(R) &= \ln(\theta) + (\alpha - 1)\ln(k^*) + \ln(\epsilon) \\ &= \ln(\theta) + (\alpha - 1)\ln((\theta\alpha/r)^{\frac{1}{1-\alpha}}) + \ln(\epsilon) \\ &= \ln(r) - \ln(\alpha) + \ln(\epsilon) \end{aligned} \tag{7}$$

The prediction we obtain from (7) is straightforward. Running the following regression on a sample of unconstrained entrepreneurs,

$$\ln(R) = c_0 + c_z \ln(z) + c_\theta \ln(\theta) + \ln(\epsilon) + v \tag{8}$$

the predicted slope of both coefficients c_z and c_θ is zero. The constants $\ln(r)$ and $\ln(\alpha)$ will enter the constant term, c_0. The term ν is added to capture random noise.

Let us now consider constrained entrepreneurs. For these we can substitute in for $k = z$ in (6) and take logs (λ plays no role in the analysis and is normalized to 1). We then obtain,

$$\ln(R) = \ln(\theta) + (\alpha - 1)\ln(z) + \ln(\epsilon) \tag{9}$$

The prediction we obtain from (9) is the following. If we run the regression model (8) on a sample of constrained entrepreneurs, the predicted slope coefficient c_z equals $\alpha - 1 < 0$. Note that as long as θ is an observable variable, standard regression methods will yield consistent estimates of c_z even if θ and z are correlated. In the empirical application we proxy $\ln(\theta)$ with a set of human capital variables (age, education, and the pre start-up earnings history). This will give a consistent estimate for c_z to the extent that $\ln\theta$ has zero correlation with $\ln z$ once our set of observed human capital variables is partialled out.

Pooling the samples of unconstrained and constrained entrepreneurs, we have

$$\ln(R) = \begin{cases} \ln(r) - \ln(\alpha) + \ln(\epsilon) & \text{if } z \geqslant z_H \\ \ln(\theta) + (\alpha - 1)\ln(z) + \ln(\epsilon) & \text{if } z_L < z < z_H \end{cases} \tag{10}$$

In the empirical application, we are not able to identify exactly whether an entrepreneur is constrained or not since we do not know the cut-off value, z_H. We can still determine the shape of the graph in the $z - R$ plane since, for a given θ, all unconstrained individuals are located to the right of the constrained individual in the z-dimension. The partial derivative $\dfrac{\partial \ln(R)}{\partial \ln(z)} = (\alpha - 1)$ is negative, hence, $\ln(R)$ is falling in $\ln(z)$ up to $z = z_H = (\theta\alpha/r)^{\frac{1}{1-\alpha}}$ and flat thereafter at $\ln(r) - \ln(\alpha)$. In a regression this convex curvature is easily captured by a higher order polynomial in z. From this we conclude with the following remark:

Remark 2 *The EJ model predicts that estimating (8) should give a negative and convex relation between* $\ln(z)$ *and* $\ln(R)$ *conditional on* $\ln(\theta)$*.*

In the model, R is always positive since ε is assumed to be lognormal. In the data, however, OROA is sometimes negative and hence $\ln(R)$ is undefined. One common way to solve such problems in empirical applications is to replace $\ln(R)$ with $\ln(R+1)$. Note that this does not alter the main prediction since $\dfrac{\partial \ln(R+1)}{\partial \ln(k)} = \alpha - 1 < 0$ by (8).

To summarize, the Evans-Jovanovic model predicts a negative relation between wealth and profitability for the constrained entrepreneurs, and a zero relation between wealth and profitability for the unconstrained entrepreneurs. The first prediction relies on the Evans-Jovanovic assumption of decreasing returns to scale. The second prediction is very general and will hold in any theory of liquidity constraints that is based on profit maximization. We should finally point out that Evans-Jovanovic is not the only economic model that predicts a negative (and convex) relationship between liquidity and wealth. For example, Bernhardt (2000) and de Meza (2002) contain theoretical frameworks that can also produce these predictions.

4 Empirical strategy

Our regression models have start-up performance as the dependent variable, liquidity of the founder as the main explanatory variable, and a number of controls for founder and firm characteristics. We now describe the operationalization of the variables.

4.1 Measuring liquidity

Following previous work by e.g., Evans & Jovanovic (1989) and Hurst & Lusardi (2004), we measure liquidity as founder taxable wealth prior to start-up. The main components of taxable wealth are cash and inventory, publicly listed stock, non-listed stock, real estate, cars and boats. Therefore, wealth is correlated with greater inventory of liquid assets such as cash or publicly traded stocks and it is also correlated with the inventory of assets that can easily be put up as a collateral, such as real estate.

Taxable wealth is a noisy measure of true wealth since the value of property investments and investments in non-listed stocks has an artificially low tax value (the tax value of real estate is maximum 30 percent of market value, and non-listed stock is valued at book value). Debt, on the other hand, is fully deductible. Financing property and non-listed stocks by debt, therefore, is a common way to avoid the taxation of wealth. For this reason gross taxable wealth is likely to be at least as good a proxy for true wealth as net taxable wealth. To reduce measurement errors in gross wealth we construct the variable as an average over the three years preceding the start-up year. Since any measure of wealth in empirical studies is likely to be imperfect, we assess the robustness of our results by alternatively using net wealth and net capital income as measures for liquidity. The results are the same.

4.2 Measuring entrepreneurial performance

We use profitability as our benchmark performance measure. We believe that profitability as opposed to survival (e.g., Levinthal, 1991, Brüderl et al., 1992, Aldrich, 1999), is important in the current context for two reasons. First, while survival focuses on business risk, profitability focuses on what is arguably more important to the entrepreneur: Return on assets put in. Of course, one project can have vastly higher expected returns than another project, but still a higher risk of failure – consider the difference between a hi-tech start-up and a mom and pop business. Second, a positive relationship between liquidity and survival will result if high-wealth entrepreneurs are keeping low-quality ventures afloat by infusing capital (Gimeno et al., 1997). In contrast, focusing on profitability on assets will to a greater extent control for capital infusion.

To measure profitability, we use operating return on assets (OROA). OROA is defined as the ratio of earnings before interest and taxes (EBIT) to the total asset base used to generate them, and is the standard performance measure in a large accounting and financial economics literature (see e.g. Bennedsen et al., 2007, and the references therein). Unlike returns to equity or returns to capital employed, OROA compares firm profitability relative to total assets. In contrast to net income-based measures such as return on assets, OROA is not affected by capital structure or dividend policy differences across firms. The asset base we use to compute yearly OROA is the average of assets at the beginning and the end of the calendar year. To avoid that outliers drive our results, we have winsorized the yearly OROA values at the five percent level and replaced values of gross wealth less than NOK 10 000 with the value 10 000. Mean OROA in the sample is 0.16 and the standard deviation is .34. Median OROA is .13. For more mature firms mean OROA is about .10 with a standard deviation of about .16 (authors' calculations).

In addition to analyzing the relation between liquidity and profitability, we also analyze the relation between liquidity and, respectively, entrepreneurial wage and business survival. The interesting results, however, are captured by the profitability analysis; we find no relation between liquidity and entrepreneurial wages, once human capital is controlled for, and our results on survival are consistent with the results on profitability. These analyses are therefore reported in Appendix B.

4.3 Control variables

Using wealth as a proxy for liquidity is problematic if traits that make a person more likely to accumulate wealth also make him a better entrepreneur, either due to an ability to generate better opportunities (Cressy, 2000, Shane et al., 2003), a higher opportunity cost of time, or by being a better manager. We reduce omitted variable bias by extensively controlling for potential underlying traits correlated with wealth, such as wage-making ability, expertise and experience. To this end, we use standard human capital variables such as age and education.[6] In addition we use the detailed information on the entrepreneur's wage earnings before starting up the company.

[6] Age and education may act as controls for more than just human capital. Age can be correlated with risk attitudes, attitudes toward non-pecuniary aspects of entrepreneurship, and cost of labour supply. Years of education may affect which type of firm an individual starts up.

We also include dummy variables for the age of the start-up, and for year and 2-digit NACE industry in order to capture business cycle and industry effects.

5 Main empirical analysis

5.1 Descriptive statistics

Table 1 presents descriptive statistics of the firms and founders in the sample. The figures are close to those reported by previous studies using US data (Hamilton, 2000, Hurst & Lusardi, 2004, or Campbell, 2006). Founders tend to be experienced workers, on average 41 years old, and are relatively wealthy. Start-ups are small, on average they have NOK 2 million (about Euro 250 000) in assets at the end of the first year, with the median being considerably lower. The average start-up size is similar to the 2003 Survey of Small Business Finance from the US.[7] It therefore seems reasonable to assume that the sample may be representative for nascent firms also outside the Norwegian context.

[7] The unweighted mean assets value in the Survey of Small Business Finance (2003) is about NOK 9 million for first-year (C-corporations and limited liability) firms. Since SSBF oversamples businesses with more than 20 employees, one needs to calculate the weighted mean. Using the weights provided by Mach (2007) gives an SSBF mean of about NOK 2.2 million. The SSBF data are available at http://www.federalreserve.gov/Pubs/Oss/Oss3/ssbf03/ssbf03home.html#ssbf03dat.

TABLE 1: Descriptive statistics

N=1307	Mean	Median
Start-up year	1999	1999
	(2.4)	
Start-up equity at start-up date	173	101
	(981)	
Start-up assets at the end of first year	2071	772
	(6676)	
Start-up sales in the first year	2695	1143
	(7031)	
Age at start-up date	41	40
	(9)	
Education in years at start-up date	12.8	12
	(2.6)	
Taxable wealth, 3-year average before start-up date	1550	542
	(7614)	
Net capital income, 3-year average before start-up date	-9	-33
	(121)	
Wage income, 3-year average before start-up date	515	437
	(555)	
Founder net capital income, 3-year average after start-up date	57	-6
	(188)	
Founder wage income, 3-year average after start-up date	460	394
	(310)	
Start-up operating return on assets, OROA, all years	.16	.13
	(.34)	
Share of start-ups in non-IT manufacturing	.47	
Share of start-ups in IT	.49	
Share of start-ups in non-IT services	.05	

Krone values are inflation-adjusted and expressed in 1000 2002 values. Standard deviations in parenthesis. OROA is winsorized at the 5 percent level.

5.2 Founder wealth, start-up size and debt

If liquidity constraints are not present we would expect there to be no relation between wealth and business size, controlling for other characteristics of the entrepreneur such as age, education and wage history. If liquidity constraints are binding, on the other hand, it follows from Evans & Jovanovic (1989) that wealthy entrepreneurs should on average start larger companies (see Appendix A where we derive this prediction formally). We now investigate whether wealth is correlated with larger start-up size, controlling for founder human capital and industry.

TABLE 2: The effect of gross taxable wealth on start-up size and debt

Dependent variable	ln(equity) at start-up	ln(assets) at end of 1st year	ln(employees) at end of 1st year	ln(debt+10000) at end of 1st year
ln(wealth)	.105***	.288***	.170***	.040***
	(.020)	(.037)	(.029)	(.008)
ln($wage_{t-1}$)	-.014	.118***	.005	.016**
	(.026)	(.045)	(.033)	(.008)
ln($wage_{t-2}$)	.055*	.071	.017	.016**
	(.029)	(.044)	(.029)	(.008)
age	-.029*	-.046*	-.066***	-.009**
	(.015)	(.025)	(.022)	(.004)
age^2	.0003*	.0005	.001***	.0001*
	(.0002)	(.0003)	(.0003)	(.0001)
education in years	.003	.022	.003	.006**
	(.008)	(.014)	(.012)	(.003)
R^2	.15	.22	.19	.23
N	1307	1307	1132	1307

The estimation method is ordinary least squares. t is the start-up year. Two digit industry dummies and dummies for the year of the start-up are included, but not reported. Robust standard errors in parenthesis. *** Significant at the 1 % level ** Significant at the 5 % level * Significant at the 10 % level.

We see from Table 2 that the estimated effect of wealth on start-up size is highly significant. The elasticity of equity with respect to wealth is 0.105 at the start-up date, and the elasticity of assets at the end of the first year with respect to wealth is 0.288. Evaluated at the means this implies that NOK 100 000 higher wealth gives NOK 1200 more in equity at the start-up date and NOK 38 500 more in assets at the end of the first year. At the medians, the numbers are slightly larger, 2000 and 41 000 respectively. The effect of wealth is substantially larger on total assets than on equity. This is reasonable as a higher founder wealth is likely to ease access to both short-term credit and long-term debt.

In column 3 we report the relation between wealth and start-up size, taking employees at the end of the first year as our size measure. Again, the relation between wealth and start-up size is highly significant, with the estimated elasticity lying in between the elasticities reported in the equity and the assets regressions.

Our estimates fit reasonably well with previous studies from the US. Using survey evidence from US Small businesses, Ando (1985) finds that the elasticity of start-up size with respect to founder wealth is around .4. Holtz-Eakin et al. (1994) study small business owners who receive a large inheritance and find that each dollar of inheritance induces about 18 cents of extra investments.

In column 4 we explore the relationship between wealth and the level of debt. The Evans-Jovanovic model predicts that constrained entrepreneurs should borrow more the higher the level of wealth, while unconstrained entrepreneurs should borrow less the higher the level of wealth. This follows from (5). Hence, if the relationship between wealth and debt in the data is increasing this suggests that liquidity constraints are binding. We find that debt at the end of the first year is significantly increasing in wealth with an elasticity of .04. A robustness analysis shows that a strong positive relation between the level of debt and the level of wealth holds for all wealth groups. The positive and significant coefficients on wealth in Table 2 are clearly consistent with liquidity constraints being present.[8]

In Appendix A we discuss other mechanisms than liquidity constraints that could drive the positive relationships reported in Table 2. The conclusion of this analysis is that liquidity constraints are the most likely explanation for our findings.

5.3 Founder wealth and profitability

We now analyze the relationship between founder wealth and start-up profitability on assets. Building on Evans-Jovanovic, our regression models will have start-up profitability as the dependent variable, wealth of the founder as the main explanatory variable, and a number of controls for founder and firm characteristics. Since less wealthy founders are more likely to be constrained, Evans & Jovanovic (1989) suggest that the relation between wealth and profitability should be initially negative and then fade out as founders become wealthier and less likely to be constrained. We accommodate this convexity using a forth order polynomial in log gross wealth in our main specification.

In the empirical implementation of (8) we use $OROA$ as our profitability measure rather

[8] In contrast, Paulson et al. (2006) find in their data from Thailand that the probability of being a borrower is inversely U-shaped in wealth (figure 5a), with the most wealthy being less likely to borrow than those with median wealth. The reason for the discrepancy between Norway and Thailand could be that the Thai start-ups are very small. In the Thai data, the median initial investment is about one sixth of the average annual income in Thailand (Paulson & Townsend, 2004, p. 235). The median initial investment in the Norwegian data is more than one third of average annual income in Norway.

than $\ln(OROA+1)$. The fourth order polynomial in wealth on the right hand side in our main specification is sufficiently flexible to make the transformation of the dependent variable unimportant. All our results are robust to using $\ln(OROA+1)$ as left hand side variable rather than $OROA$. $OROA$ is winsorized at the 5 percent level.

TABLE 3: Effects of log gross taxable wealth on OROA

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln(wealth)	.016**	.007	.206***	-6.36**			.135
	(.007)	(.007)	(.071)	(3.12)			(.111)
ln(wealth)^2			-.008***	.702**			-.005
			(.003)	(.350)			(.004)
ln(wealth)^3				-.033*			
				(.017)			
ln(wealth)^4				.0006*			
				(.0003)			
Dummy2					-.001	.079***	
					(.033)	(.019)	
Dummy3					.082***	-.020	
					(.031)	(.033)	
Dummy4					.076**		
					(.033)		
Dummy5					.169***		
					(.045)		
Dummy6					.047		
					(.046)		
Dummy7					-.016		
					(.051)		
Dummy8					-.017		
					(.049)		
ln(wage$_{t-1}$)		.023**	.023**	.022**	.020*	.021**	.041
		(.011)	(.011)	(.011)	(.010)	(.010)	(.018)
ln(wage$_{t-2}$)		.032**	.031**	.032**	.032**	.033***	.028
		(.013)	(.013)	(.013)	(.013)	(.013)	(.018)
education in years	.014***	.012***	.012***	.012***	.013***	.013***	.012
	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.005)
age	.001	-.005	-.008	-.010*	-.011**	-.011**	-.015
	(.005)	(.005)	(.005)	(.005)	(.005)	(.005)	(.008)
age^2	-.00004	.00003	.00006	.00008	.00009	.00009	.0001
	(.0005)	(.00005)	(.00006)	(.00006)	(.00006)	(.00006)	(.0001)
R^2	.05	.07	.07	.07	.08	.08	.11
N	5832	5832	5832	5832	5832	5832	2776

The estimation method is ordinary least squares. The dependent variable is the yearly OROA, and t is the start-up year. In column 5, dummy 2-8 represent the 10-30, 30-60, 60-90, 90-92.5, 92.5-95, 95-97.5, 97.5-

100 percentiles of the wealth distribution, respectively. In column 6, dummy 2 represents percentiles 30-95 and dummy 3 represents percentiles 95-100. Low wealth individuals are the reference category in both columns. Two digit industry dummies, time dummies and dummies for the age of the start-up are included, but not reported. Huber-White robust standard errors allowing for clustering of errors by firms are reported in parenthesis.

*** Significant at the 1 % level   ** Significant at the 5 % level   * Significant at the 10 % level.

In column (1) we regress profitability on log wealth controlling only for age and education. We find a significant positive relation between prior gross taxable wealth and profitability. As discussed in previous sections, however, wealth is likely to be correlated with unobserved human capital (ability), and this may create a positive bias in the wealth coefficient. Looking at column (2) where we include prior wage as a control for ability, we see that this concern is highly relevant. The effect of wealth on profitability falls sharply, and now we find no or a slightly positive log-linear relation between gross taxable wealth and profitability on assets. It could be that the effect of wealth varies with human capital, but extending the specification by including an interaction term between wealth and prior wage does not give significant results.[9]

The result that there is no or a slightly positive relation between log wealth and profitability, once controlling for human capital, is not immediately consistent with the Evans & Jovanovic (1989) model, which predicts a negative and convex relationship in logs. The log-linear specification we use in columns (1) and (2) may be too restrictive, however, and we explore more flexible functional forms for how wealth can affect profitability in columns (3)-(6).

In column (3) we continue to control for human capital and add a quadratic term in log wealth. The quadratic term in wealth turns out significant and negative, indicating a *concave* relationship between log wealth and profitability. Since a second-order formulation imposes a symmetry that might or might not be present in the data, we investigate the relationship between wealth and profitability further in column (4) by estimating a fourth-order polynomial in log wealth (we also tried using a third- and a fifth-order polynomial specification and the results were very similar). All coefficients are significant, and in Figure 1 we plot the predicted

[9] We note from column (2) that previous wage is important for entrepreneurial performance. This relationship may have several explanations. First, higher wage is likely to be correlated with greater ability to produce business ideas. Second, high wage workers have a higher opportunity cost of starting up a company, and hence demand more from their project before going ahead. Third, high wage workers are likely to be better at running their company, once they get started.

OROA.

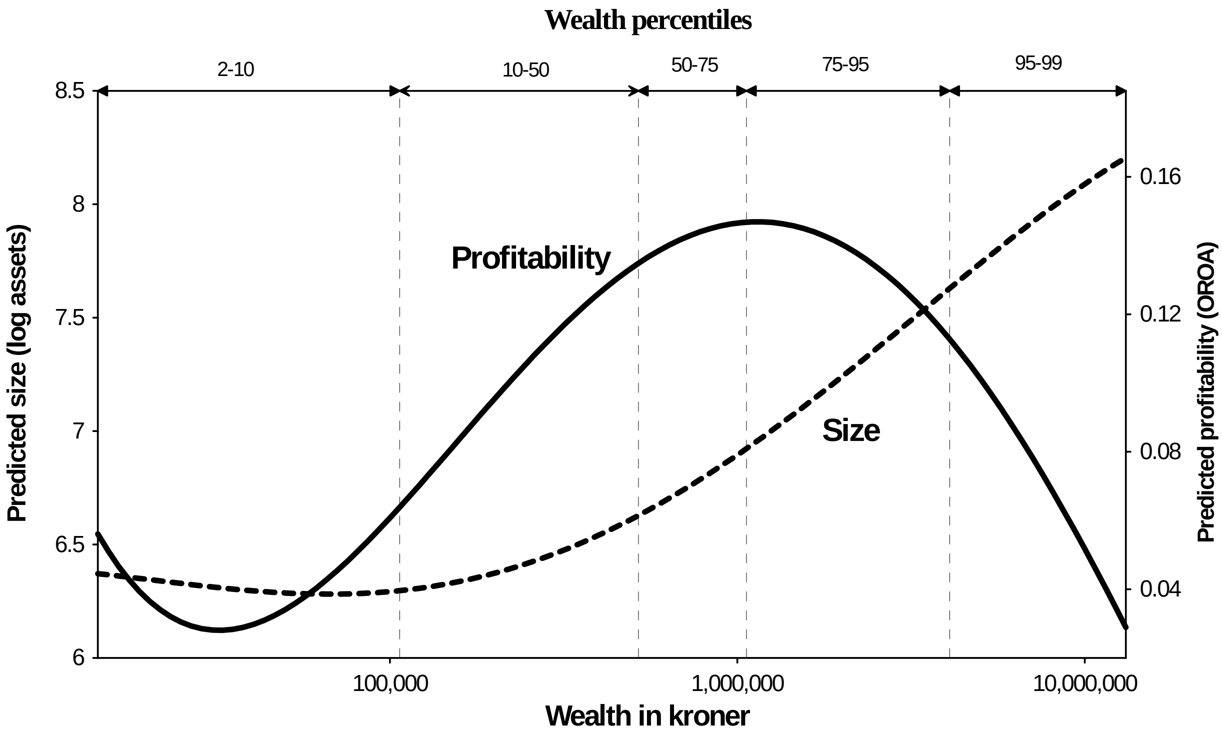

Figure 1: Wealth, Profitability and Size

The horizontal axis (log scale) runs from NOK 15 000 to NOK 13 million in gross wealth, and covers the 2nd to 99th percentiles as shown in the upper part of the figure. The unit on the vertical axis to the right is operating returns on assets (OROA). The unit on the vertical axis to the left is log assets at the end of the first year. The effect of wealth on profitability is depicted by the full line, where the constant term is calibrated to fit the second-year performance of a start-up operating in the median return 2-digit NACE industry and with founder characteristics at mean values. The relation is fairly flat up until about NOK 100 000 (the 10th percentile), then upward-sloping, and reaches a maximum at about NOK 1 million (the 75th percentile), before it falls quite sharply.[10] The stapled line depicts the predicted relation between wealth

[10]We do not believe that the estimated "dip" in performance at the very bottom of the wealth distribution represents an interesting economic phenomenon. The difference in wealth when measured in levels rather than logs is very modest. However, to be certain that the estimated shape in this region is not significant, we have run an extra regression where we expand the specification in table 3, column 5, by introducing a separate dummy for percentiles 5-10. The coefficient on this dummy is near identical to the coefficient on the 10-30 interval (both are -.003) and none of them are significantly different from the constant term identified by percentiles 0-5.

and start-up size, measured in log assets at the end of the first year, also using a fourth-order polynomial in wealth.

The upward-sloping part of the full line in Figure 1 is consistent with a production function with a region of increasing returns: For liquidity constrained entrepreneurs, access to more capital increases marginal returns and thus average profitability. An entrepreneurial production function with a region of increasing returns stands in contrast to the Evans & Jovanovic (1989) model. It suggests a welfare loss since liquidity constraints could stop entrepreneurs with little wealth from being able to exploit a "hump" in marginal productivity. A simple calculation can give an indication of the magnitude of this problem. Individuals in the 0-30 percentiles of the wealth distribution represent, at the end of the first year of operations, about 15 percent of the total assets in the sample. Using this fraction as a weight, we find that an increase in OROA for the 0-30 percentiles up to the same level as that of the 30-60 percentiles, would increase overall OROA in the sample by about 1.2 percentage points. Since the smallest start-ups tend to grow faster than the larger start-ups, this figure will be larger if we use asset-weights based on later years.

As an alternative explanation for increasing returns, the upward-sloping part of the curve in Figure 1 could be due to more wealthy entrepreneurs being less exposed to moral hazard. In Aghion & Bolton (1997) wealthier entrepreneurs borrow less and have stronger incentives to supply effort because a smaller fraction of the marginal return will have to be shared with the lender. However, in contrast to the prediction of Aghion & Bolton (1997), we established in Table 2 that the relationship between founder prior wealth and the level of debt of the start-up at the end of the first year is positive. The role of moral hazard in explaining the upward-sloping part of the curve in Figure 1, therefore, seems limited.

The downward-sloping part of the full line in Figure 1 is intriguing. A falling liquidity-performance relation on some interval of the wealth distribution is to be expected from models such as Evans & Jovanovic (1989) where marginal profitability decreases as start-ups tend towards their efficient scale. It is, however, puzzling that profitability falls sharply in the region of the wealth distribution where entrepreneurs are least likely to be liquidity constrained. Since the wealthiest founders tend to found the largest companies, their weaker performance has a quite strong impact on overall profitability: The individuals in the top 5 percent of the wealth distribution represent about 26 percent of the total assets in the sample at the end of the first year of operations. Thus if the profitability increased to the same level as that of the 30-95 percentiles, this would increase the first-year overall profitability in the sample by about 2.5 percentage points.[11] Possible interpretations of why wealth and profitability are negatively related at the top of the wealth distribution are discussed further in Section 6. We first discuss the robustness of our findings.

To ensure that the curvilinear wealth-profitability relationship depicted in Figure 1 is not driven by outliers, we construct a set of dummies which split the wealth distribution into fine intervals and put very little structure on the estimated relationship. In column (5) dummies 2-8 represent the 10-30, 30-60, 60-90, 90-92.5, 92.5-95, 95-97.5, 97.5-100 percentiles of the wealth distribution, respectively. There are about 35 founders behind each of the top four wealth dummies. Founders in the 0-10 percentiles are the reference category. We find that founders in percentiles 10-30 do equally well to the founders in percentiles 0-10. Founders in percentiles 30-60 and 60-90 do significantly better than those in 0-30. Percentiles 90-92.5 seems to be a positive outlier, and the concavity is associated with the three dummies representing the top 7.5 percent of the wealth distribution. The three top dummies are lower than any of the dummies 30-60, 60-90 or 90-92.5, and the two top dummies significantly so, suggesting that the concave relationship between wealth and OROA represents a systematic pattern in our data. In column (6) we accommodate the pattern revealed in column (5) and estimate average effects for founders in percentiles 30-95 and 95-100, relative to founders in percentiles 0-30. We find that founders in percentiles 30-95 have 8 percentage points higher profitability than founders in percentiles 0-30 while founders in percentiles 95-100 have 2 percentage points lower profitability. These differences are near identical to the differences in average raw returns for these three wealth classes. The average raw returns are 11 percent, 18 percent and 8 percent, respectively. The results in column (6) are similar to those depicted in Figure 1.

[11] One may ask whether the lower returns are of any consequence for the founders themselves. The median share of assets to gross wealth is 41 percent in the 95-100 percentile of the wealth distribution. This suggests that the answer to this question is affirmative.

To investigate the robustness of our results further, we have performed several exercises. First, we have re-run the regressions on the three industry classes non-IT manufacturing, IT, and other services. The estimated coefficients using a fourth-order polynomial in wealth suggest that the inverse U-shaped relation between wealth and performance is strongest for IT, but holds up within all three industry classes. The following figure plots the predicted OROA.

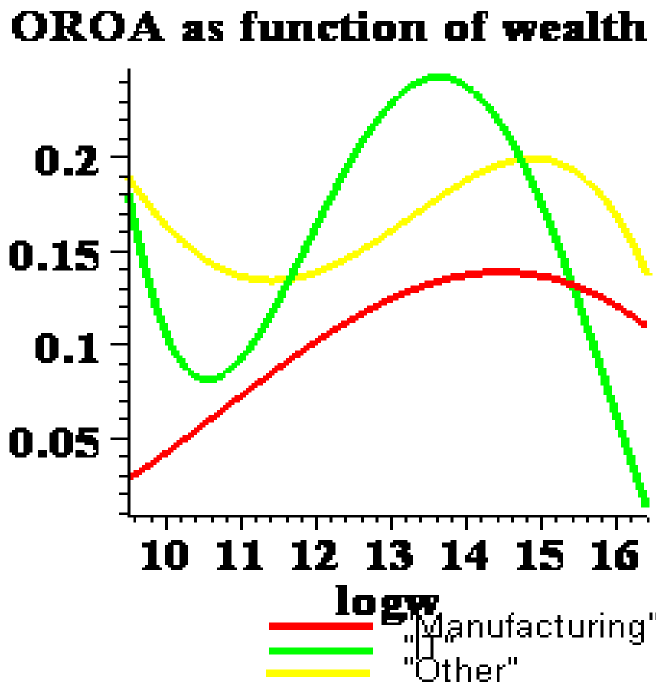

Figure 2

When splitting the sample in three, the precision of the estimates obviously decreases. This suggests caution when interpreting the difference between the curves. Taken at face value, however, the estimated relationships suggest that performance for start-ups in the IT-industry is more sensitive both to reaching optimal scale and to excessive entrepreneurial wealth.[12]

As a second robustness check we have experimented with alternative wealth measures. Instead of log gross wealth, we used net wealth (gross wealth deducted debt) and net capital income

[12] One possible explanation for why the upward sloping part of the figure is steeper in the IT-industry may be the rapid technological change and the fact that this industry is far more R&D intensive than the other two. A high rate of technical change increases business risk, and R&D being largely a fixed cost, creates strong returns to scale.

(gross capital income deducted interest payments), both calculated as three-year averages before the start-up year. The results were qualitatively speaking the same as in the main analysis, in that we obtained a clear inverse U-shaped relation between liquidity and profitability. As a third robustness check, we re-ran all regressions using median and robust regressions. The results were the same. As a fourth robustness check, we followed e.g., Frank & Goyal (2003) and tried using 3-year weighted average OROA (weighted by the yearly level of assets) as a performance measure rather than yearly OROA. The results of this cross-sectional regression were the same as in the main analysis. As a fifth robustness check, we used ln (OROA+1) as a dependent variable in order to follow the functional form suggested by the Evans-Jovanovic (1989) model more closely (see Section 3). The results of these regressions were the same as in the main analysis. Thus the curvilinear relationship between wealth and profitability holds across a large number of different specifications and seems very robust.

Finally, we investigated the distribution of performance for various levels of wealth. In order to do so, we tabulated the distribution of OROA for various percentiles of the wealth distribution (not reported). The pattern revealed in Figure 1 is clearly evident even without any conditioning on co-variates. The basic shape holds for both the 25th, the 50th and the 75th percentiles of the OROA-distribution. Hence, the underperformance of the wealthiest entrepreneurs is not driven by a few large underperformers. The median entrepreneur in terms of OROA underperforms slightly more than the mean, but the performance variance among the wealthy entrepreneurs is smaller than the performance variance among the less well off. The relationship we estimate in the regression, therefore, seems representative for the broader mass of wealthy entrepreneurs.

As two alternative performance measures, we have investigated the relation between wealth and entrepreneurial wages and the relation between wealth and business survival. Since this analysis does not yield significant new insights, it is relegated to Appendix B.

6 Profit maximization and the negative wealth-performance relationship in the upper wealth quartile

In the absence of liquidity constraints, profit maximization implies a zero relation between wealth and profitability, as conveyed by (8). Our empirical results are at odds with this hypothesis, in that there is a negative relation between wealth and profitability in the upper quartile of the wealth distribution. Before concluding that more founder wealth can have harmful effects on start-up performance we need to discuss alternative explanations consistent with the profit maximization hypothesis.

6.1 Technology

A possible explanation for the negative relation between founder wealth and start-up profitability could be that liquidity constraints bind for some of the wealthiest founders, and that such constraints – combined with suitable assumptions about production technology – are sufficiently strong to create a downward slope in profitability. Although we do not observe production technologies, we do observe start-up size, and can therefore construct a measure of liquidity constraints based on the discrepancy between the start-up size and founder wealth. We follow Evans & Jovanovic (1989) and define an unconstrained entrepreneur as one whose business is initially smaller than a multiple λ of net worth. Estimates of λ vary, but tend to be in the region of 1.5-2 (Evans & Jovanovic, 1989, Paulson et al., 2006). To err on the conservative side, we choose the lowest estimate in this region, 1.5, and compare the level of assets at the end of the first year with 1.5 times net worth. Entrepreneurs for which the level of assets is lower than 1.5 times net worth are labeled "EJ-unconstrained", and entrepreneurs for which the level of assets is higher than 1.5 times net worth are labeled "EJ-constrained" The fraction of EJ-unconstrained entrepreneurs in the four wealth quartiles is 1 percent, 3 percent, 30 percent, and 39 percent.

To examine whether the classification into EJ-constrained and EJ-unconstrained entrepreneurs captures liquidity constraints, we analyzed the relation between entrepreneurs' wealth and start-up size in the upper wealth quartile for both categories of entrepreneurs. If the classification captures liquidity constraints, we would expect a weak positive relation between start-up size and wealth for the EJ-unconstrained entrepreneurs and a stronger positive relation between wealth and start-up size for the EJ-constrained entrepreneurs. Running a regression between founder wealth and start-up equity with the same control variables as in Table 2 gave an estimated elasticity of start-up equity with respect to founder wealth of 0.752 for EJ-constrained entrepreneurs (significant at the 1% level). The estimated elasticity is 0.048 for the EJ-unconstrained entrepreneurs (and not statistically significant at conventional levels). The estimated relationship between wealth and start-up size is much stronger for the EJ-constrained than for the EJ-unconstrained entrepreneurs, which suggests that the classification captures true differences in liquidity constraints. It also suggests that omitted variable bias is less important than liquidity constraints when interpreting the positive relationship between wealth and start-up size found in Table 2.

In Table 4 we investigate the relation between wealth and profitability for EJ-unconstrained and EJ-constrained entrepreneurs, respectively, in the top wealth quartile.

TABLE 4: Wealth vs. OROA, top 75% of the wealth distribution

	Unconstrained		Constrained	
	(1)	(2)	(3)	(4)
ln(wealth)	-.072***	.484	-.009	.002
	(.027)	(.659)	(.019)	(.360)
ln(wealth)^2		-.018)		-.000
		(.021)		(.011)
R^2	.17	.18	.07	.07
N	519		980	

The estimation method is ordinary least squares. The same controls as in Table 3 are included, but not reported. Robust standard errors in parenthesis. *** Significant at the 1 % level ** Significant at the 5 % level * Significant at the 10 % level

In column (1) we find a strong negative relation between wealth and profitability for the EJ-unconstrained entrepreneurs. This coefficient suggests that predicted OROA drops by about 18 percentage points from the 75th wealth percentile to the 99th percentile. In column (2) we add a quadratic term in log wealth. Although the two coefficients in column (2) are not individually statistically significant, they are jointly significant at the 1% level, and predict a very similar relation between wealth and profitability to the estimate in column (1). In columns (3) and (4) we analyze the relation between wealth and profitability for EJ-constrained entrepreneurs. We find an essentially zero relation, in that the coefficients are close to zero and not statistically significant either individually or jointly. Thus, surprisingly, the drop in profitability in the upper wealth quantile seems to be due to a lack of, rather than the presence of, liquidity constraints.

Using all EJ-unconstrained entrepreneurs from the upper half of the wealth distribution, rather than from the upper quartile, gives almost identical predicted OROA as in Table 4. IT start-ups are on average smaller than start-ups in other industries. Hence, entrepreneurs from the IT industry tend to be over-represented among the EJ-unconstrained. Even excluding IT start-ups, we find a significantly negative relation between wealth and profitability for the unconstrained, and no relation for the constrained.

6.2 Overconfidence and excess scale

One possible explanation for the negative wealth-profitability relationship for the unconstrained entrepreneurs in the top quarter of the wealth distribution is entrepreneurial overconfidence. Survey evidence (e.g. Arabsheibani et al., 2000, Landier & Thesmar, 2003) and experimental evidence (Camerer & Lovallo, 1999) suggest that entrepreneurs are subject to excess optimism about their start-up prospects. Since more liquid founders are less disciplined by outside investors when setting up a company, one would expect this tendency to be more pronounced for wealthier founders, who may then set up companies that are excessively large (de Meza & Southey, 1996). Under the excess scale hypothesis, the relation between wealth and start-up size should be positive for founders that are not constrained. In our (unreported) analysis, we find this relation to be close to zero and statistically insignificant. As a further check that the negative relation between performance and wealth is not driven by overinvestment, we have experimented with specifications where we include a polynomial in assets to the regressions in Table 4, columns (1) and (2). We find that the effect of wealth is negative and significant also when we control for scale directly in this manner. This finding is robust across a number of specifications. Thus we do not find support for the excess scale hypothesis.

6.3 Omitted variables

It is well-known that omitted variables can cause bias in coefficient estimates, through making the explanatory variables correlated with the residual. In the current context, the most relevant concern is that even after including several human capital variables as controls, wealth might still capture unobserved ability in addition to liquidity (Cressy, 2000, Shane et al., 2003). For example, our data do not contain information about prior entrepreneurial success, a variable that is likely to be correlated both with higher wealth and with a higher entrepreneurial ability (Blanchflower & Oswald, 1998, Shane, 2000). Importantly, to the extent to which wealth captures unobserved ability, it is likely to be a positive correlation. We would therefore expect our estimates of the effect of wealth on start-up performance to be, if anything, upward biased. Our main result is that the effect of liquidity is negative in the top quartile of the wealth. If wealth captures more than liquidity, it is likely to understate, rather than overstate, the negative relation. If there is a bias, we are therefore likely to underestimate the negative effect of liquidity for wealthy individuals.

6.4 Selection

The general selection bias problem in estimation of entrepreneurial performance is that attrition at various stages in the entrepreneurial process can bias the estimated coefficients (Delmar & Shane, 2006). For example, if only wealthy individuals started up their own businesses, estimates of the relation between wealth and performance would capture the effect of wealth conditional on entry, but would not capture the effect of more liquidity of the individuals that did not start-up a businesses (but would if they were more wealthy). This mechanism makes it important to emphasize that our estimates are only valid for the subset of individuals that start-up a business at their current wealth level but our estimates are mute on the effect of increased wealth on the entry and performance of non-entrants.

A related selection problem is that since wealth affects business survival, our estimates of the effect of wealth on performance will capture the effect on the firms that survive, but will not capture the effect of providing more liquidity to those that do not survive, but might have done so with more liquidity. This mechanism is likely to have an effect for low and medium wealth entrepreneurs, in that these require a higher level of profitability to continue operations of business (Levinthal, 1991, Gimeno et al., 1997), but is unlikely to have a large effect on the wealthy entrepreneurs. Thus this mechanism does not seem very important for our main result.

In terms of policy-making, the distinctions discussed above are relevant. However, initiatives that increase entrepreneurial liquidity, such as government subsidies, will affect the composition of entrants and the composition of businesses that survive. It is therefore of interest to evaluate the direction of the bias introduced by the attrition effects that we are not able to estimate. A priori it is more likely that both selection effects, entry and survival, are likely to affect low-wealth individuals more than high-wealth individuals, as the former are more likely to be liquidity constrained. If the non-entrants and non-survivors are marginal in terms of profitability, then an estimate of the relation between wealth and profitability that includes selection effects is likely to have a stronger upward slope than the estimates we obtain.[13]

7 Wealth, underperformance and non-pecuniary benefits

Our findings provide evidence that a higher founder wealth can hurt the performance of start-ups. This result holds for start-ups whose entrepreneurs are in the upper quartile of the wealth distribution. In this section we analyze the underlying mechanisms for this relationship. One possible explanation is that a higher wealth induces the entrepreneur to become less alert or less dedicated to the management of the company. This would be consistent with the notion of entrepreneurship being a luxury good, giving such benefits as social esteem or independence (Hamilton, 2000, Moskowitz & Vissing-Jorgensen, 2002, and Hurst & Lusardi, 2004). Although we do not have direct measures of the quality of management, an entrepreneur dedicated to profitability of the new venture seems more likely to spend time inside the venture. We analyzed the probability that the entrepreneur has the start-up as his main employer (i.e., the job with most hours put in per week). While 85 percent of the entrepreneurs in the bottom 95

[13] The standard approach to solve these selection problems is to use a Heckman two-step procedure. This method relies on the availability of variables that are likely to be correlated with entry (or survival) but not with profitability. It is very hard to think of variables with these properties that can act as instruments.

percent of the wealth distribution have the start-up as their main employer at the end of the second year of operations, the corresponding figure for entrepreneurs in the top 5 percent of the wealth distribution is 68 percent. The difference in presence across these two groups, which is statistically significant at the 1 percent level, is consistent with more wealth implying less dedication or attention.

That wealthy entrepreneurs spend less time with their start-ups could be due to the fact that they have many business engagements or that they enjoy a relaxed life style. While we do not observe the number of business engagements of the entrepreneurs in our sample, we are able to construct proxies for their total work loads. We have analyzed (i) The number of hours per week that the entrepreneurs work with their main employer (ii) The number of employment relationships outside the main employer and (iii) Whether or not entrepreneurs that are not employed in their start-up are employed full time elsewhere. These exercises do not suggest that wealthy entrepreneurs withdraw from the labor market to enjoy a relaxed life-style.[14]

The differences in the propensity to be involved with the firm across the wealth distribution creates a concern: are we just observing different sub-samples? For example, do those who are more wealthy run a portfolio of companies, one as a tax shelter and the other as a real business? Or are these just "angel investors" who are investing in pet projects, financing friends' projects etc and not really running their own businesses? Do our results continue to hold if we only include those who continue to work in their businesses untill they exit? With respect to angel investors, we should recall that we focus on majority owners. It seems very unlikely that a person who is merely helping out friends or family would hold a majority share. To elaborate on the role of founder presence, we run a regression where we only include years where the founder is employed by the company. The results are tabulated in Table 3, column (7). The estimated coefficients are not statistically significantly different from zero, but the estimated relationship between wealth and profitability is curvilinear and very similar to the relationship estimated in column (3). Thus our results do continue to hold if we only include entrepreneur-years where

[14] Wealthy entrepreneurs work slightly fewer hours than less wealthy entrepreneurs, but this relationship is far from significant. We find no relationship at all between wealth and the number of employment relationships outside the main employer. Among entrepreneurs that are not employed in their start-up, 95 percent of those with below median wealth are employed full time elsewhere. For workers with wealth in the 50-75 percentile and 75-100 percentile, 94 percent are employed full time elsewhere.

the entrepreneur has the start-up as his main employer. We next expand the regressions in Table 3 with a dummy variable that equals one if the owner is employed in the start-up. We find a strong, positive and significant effect of this dummy and the estimated negative wealth-performance relationship among the most wealthy becomes less steep. However, a clear, negative effect of wealth on performance is still present.[15]

It is possible that wealthy entrepreneurs view entrepreneurial activity as some form of "charity". One indication of such behavior would be that they pay their workers higher wages than strictly profit-maximizing firms. In order to investigate this, we have identified all workers employed by the new ventures in our sample and run a standard Mincer wage regression. We have added controls for the wealth of the entrepreneur prior to starting the new venture, controls for the profitability of the new venture and interactions between these variables. On a sample of 26 850 observations of 9 960 individual workers, we have tried altogether 14 different specifications including both polynomials and dummy-variable approaches.[16] We find no evidence suggesting that there is an interaction effect between OROA and wealth of the kind that one would expect to find if the underperformance of wealthy entrepreneurs was driven by their firms paying high wages.

If entrepreneurship is a luxury good, richer individuals are more likely to start-up companies and these companies will (at least at the margin) be of poor quality since their primary purpose is to satisfy the entrepreneur's non-pecuniary needs.[17] This mechanism would be consistent with Hurst & Lusardi (2004), who, using US data on the self-employed, find that the relation between wealth and entry is flat for the main bulk of the wealth distribution, and sharply increasing at the top. It would also be consistent with Nanda (2008), who structurally estimates the Evans-Jovanovic model using a tax reform in Denmark and finds that less liquidity deters high-wealth, low-human-capital, individuals from starting up a company. Since it is hard to think of variables that are correlated with entry but not with performance, we have not been

[15] Note that regressions of this type should be interpreted with causion since whether to work for the start-up or not is an endogenous choice. Hvide (2008) uses founder death as a quasi experiment that generates random variation in owner presence. His findings suggest that owner presence do not have a large impact on start-up performance.

[16] The data come from various administrative registers and are prepared for research by Statistics Norway.

[17] It could also be that richer entrepreneurs start up companies at an excess scale. However, our analysis in Section 6.2 does not give support for this conjecture.

able to make progress on this question using Heckman (1979) type techniques. We have, however, investigated whether the relationship between wealth and entry is similar to that in Hurst & Lusardi (2004). Our analysis of this question suggests that the relation between log wealth and the propensity to start-up a business is flat up to the 50th wealth quantile, and then increasing monotonically throughout the upper wealth quantile. This result seems equally consistent with liquidity constraints and with the luxury good interpretation of entrepreneurship.

In addition to excess entry, richer entrepreneurs could be more prone to keep failing companies afloat. If that were true, we would expect the negative cross-sectional relation between profitability and wealth to become stronger the older the population of firms. To investigate this hypothesis, we added an interaction term between firm age and founder wealth in the regressions in Table 3. Although the estimated coefficients were negative, they were close to zero and far from being statistically significant. Thus this does not seem to be a major mechanism behind our findings.

8 Concluding remarks

8.1 Discussion

We have analyzed the relation between liquidity, as measured by founder wealth, and performance, as measured by profitability, using data for a large and representative panel of start-ups in Norway. We find a positive relation between founder wealth and profitability in the lower 75 percent of the entrepreneurial wealth distribution, and a strong negative relation between founder wealth and profitability in the upper 25 percent of the wealth distribution. That start-up profitability decreases in wealth on some interval of the wealth distribution is what one would expect if marginal profitability decreases as start-ups reach their efficient scale. It is, however, quite striking that the profitability drops sharply in the high-wealth region, where entrepreneurs are least likely to be liquidity constrained. This finding stands in contrast to economic theories of liquidity constraints based on profit-maximization. These predict a zero relation between liquidity and profitability for unconstrained entrepreneurs.

Data limitations make us unable to pin down exactly which mechanism drives the puzzling inverse U-shaped relationship between founder wealth and start-up performance. Two types of mechanisms, not mutually exclusive, seem useful to understand the finding; organizational slack and private benefits.

Since the financial situation of the founder and for the firm are tightly related for start-ups, the financial freedom of the founder and of the firm are likely to be closely correlated. This could be through several mechanisms such as a wealthy founder providing more initial financial resources, accepting limited dividend payments, or providing easy credit. We therefore suggest that the negative relation between wealth and profitability at the top of the wealth distribution can be related to the notion of organizational slack, or "the difference between existing resources and activated demand" (March & Olsen, 1976, p. 87). Management theorists tend to argue that slack is beneficial through creating a buffer from environmental shocks. Cyert & March (1963, p. 116), however, caution that slack might induce a lowering of the threshold of acceptable outcomes in the search for alternative actions. This argument suggests a curvilinear relationship between slack and performance, where "there is an optimal level of slack for any given firm. If the firm exceeds that level, performance will go down" (Sharfman et al., 1988, p. 603). Our findings are consistent with the idea that some financial slack is beneficial to start-up performance, but that an abundance of slack is harmful.

Our research also suggests reasons for why slack can be harmful for start-ups. Let us first point out a prominent reason discussed in the literature on organizational slack that is not likely to underlie our results, namely agency problems (Jensen, 1986, Davis & Stout, 1992, and Tan & Peng, 2003). The reason is simple: The entrepreneurs we study are majority owners, and are therefore not weakly incentivized in any standard meaning of the term. Agency problems are therefore unlikely to be the underlying reason why slack is harmful in our sample.

We believe that our results can be understood through the notion of entrepreneurship yielding non-pecuniary private benefits. Several non-pecuniary benefits for entrepreneurship have been analyzed in the entrepreneurship literature (See Shane et al., 2003 for a review). Although we have no direct way of finding out which non-pecuniary motivations are more important in our sample, our results are consistent with the notion that entrepreneurship gives social esteem and independence to the entrepreneur (Hisrich, 1985, Hornaday & Aboud, 1973, and Aldridge, 1997), and that more wealthy individuals have a greater demand for this. In other words entrepreneurship is a luxury good. Our findings complement the existing entrepreneurship literature by arguing that non-pecuniary motivations can have a large quantitative impact on start-ups, and by pointing out that wealthy entrepreneurs may be most likely to act upon non-monetary motivations.

8.2 Research implications

Within the entrepreneurship area, a large literature studies how entrepreneurs craft strategies to assemble initial resources (e.g., Shane, 2003, ch. 8). An implicit assumption in this literature is that due to various liabilities of newness (Stinchcombe, 1965), and the limits to self-financing, the amount of resources assembled will be suboptimal, at least from the entrepreneur's perspective. Our findings indicate that a start-up can under certain conditions have *too much* resources, and that such slack could hurt profitability. This finding could explain, for example, why venture capitalists tend to provide financing to new firms in stages, with strict attention to whether benchmarks have been reached or not. It would also be interesting to know whether our finding extends to non-financial resources such as personnel.

Second, that the non-monetary aspects of entrepreneurship seem to have most bite for wealthy entrepreneurs could suggest that the mechanism we identify has greater relevance for entrepreneurship in wealthy countries than in developing countries. The recent surge in databases on entrepreneurship from several countries (Denmark, Sweden, Thailand, US) could enable replication of our study for other countries than Norway, and also cross-country comparisons. Third, a limitation of our study is that although we believe that the well-established notion of luxury good is useful in order to understand our results, we know less about the underlying causes that make entrepreneurship a luxury good; is it because higher wealth is associated with a lack of dedication to the venture, or is it because too much wealth is harmful due to a greater propensity to enter entrepreneurship with mediocre or bad ideas? Studies that combine data on start-up performance with survey evidence on entrepreneurial motivation could make progress on this question.

Our study also has implications for the study of mature firms. Since the negative effects of slack are unlikely to be due to agency problems, our study implies that the negative effects of slack for mature firms should be more closely examined, both from a theoretical and from an empirical perspective. Malmendier & Tate's (2008) study of overconfident managers finds support for the view that motivational effects are important in the context of mergers and acquisitions, but clearly there are many other corporate decisions that can be investigated in this light.

The most important managerial implication of our work is to highlight the fact that resources are beneficial for start-ups only up to a point. This can provide a consolation for budding entrepreneurs that lack resources, and can also be a useful insight for business people that consider investing their human or financial capital in young companies.

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Appendix A: Wealth versus start-up size (e-companion)

We argued in the text that the positive relationships between wealth and start-up size as reported in Table 2 were likely to be caused by liquidity constraints. In this appendix we discuss this statement further. We first show that the Evans-Jovanovic (1989) model predicts a positive relationship between wealth and start-up size. We then discuss some other mechanisms than liquidity constraints that could underlie the empirical relationship, and finally we report the results from an analysis of liquidity constraints along the lines of Cabral & Mata (2003).

Evans-Jovanovic (1989) on wealth versus start-up size

First recall from (5) that conditional upon the individual becoming entrepreneur, i.e., conditional upon $z > z_L$, the investment into the start-up equals,

$$k = \min(k^*, \lambda z) \tag{11}$$

where $k^* = (\theta\alpha/r)^{\frac{1}{1-\alpha}}$ from (4). Let us first consider unconstrained entrepreneurs. For these $k = k^*$. Taking logs we get,

$$\ln(k) = \frac{\ln(\theta) + \ln(\alpha) - \ln(r)}{1-\alpha} \tag{12}$$

The prediction we obtain from (12) is that the relation between $\ln(k)$ and $\ln(z)$ is zero for unconstrained entrepreneurs. Hence, if running the following regression on a sample of unconstrained entrepreneurs,

$$\ln(k) = c_0 + c_z \ln(z) + c_\theta \ln(\theta) + v \tag{13}$$

the predicted c_z is zero and c_θ should be positive. The constant term c_0 will be determined by the constants r and α. The term ν is added to capture random noise.

For constrained entrepreneurs, $k = \lambda z$. On log form, and again normalizing λ to 1, we get

$$\ln(k) = \ln(z) \tag{14}$$

Running the regression (13) on a sample of constrained entrepreneurs, therefore, the predicted

c_z is positive (unity with λ normalized to 1), and the predicted c_θ is zero.

Pooling the samples of unconstrained and constrained entrepreneurs, we have

$$\ln(k) = \begin{cases} \dfrac{\ln(\theta) + \ln(\alpha) - \ln(r)}{1-\alpha} & \text{if } z \geqslant z_H \\ \ln(z) & \text{if } z_L < z < z_H \end{cases} \tag{15}$$

As stated in Section 3, in the empirical application we are not able to identify exactly whether an entrepreneur is constrained or not, i.e. we do not know the value of z_H. Note again, however, that we can still determine the shape of the graph in the $z - k$ plane since, for a given θ, all unconstrained individuals have higher wealth than the constrained individuals. We see from (15) that $\ln(k)$ increases in $\ln(z)$ up to the breakpoint $z = z_H$ and is flat thereafter. Even though z_H is unknown in a regression, this concave curvature is easily captured by a higher order polynomial in z. We summarize with the following remark.

Remark 3 *The EJ model predicts that estimating (13) should give a positive and concave relation between* $\ln(z)$ *and ln(k).*

Discussion

The positive and significant relationships between wealth and start-up size in Table 2 are clearly consistent with liquidity constraints as in the Evans-Jovanovic (1989) model. Here we discuss other mechanisms than liquidity constraints that could drive the positive relationship. For brevity, we report a summary of our analysis without presenting tables.

Blanchflower & Oswald (1998, p. 28) suggest that a positive relation between wealth and start-up size could be due to the fact that "inherently acquisitive individuals [may] both start their own businesses and forego leisure to build up family assets". This could cause wealth and start-up size to be correlated even in the absence of liquidity constraints. We would expect such an acquisitive trait to be a rather permanent characteristic of the individual and hence independent of the start-up opportunity. As argued by Buera (2003) and Hurst & Lusardi (2004), liquidity constrained founders, on the other hand, would be expected to accumulate wealth in the run-up to the formation of the start-up. In order to investigate this selection issue, we have analyzed the timing of the wealth accumulation. In this analysis, we found that founders have a marked wealth accumulation in the run-up to the start-up date, a result that also holds when comparing the founders to a control group of non-founders (see Appendix B for how this control group was constructed).

It is possible, however, that even if founders are liquidity-constrained at the starting date, once the firm is established outside investors quickly realize which companies are worth investing in, and provide capital to those. Under such an hypothesis, companies that start out small, but perform well will receive capital from external investors, while companies that do not perform well will continue to be small or fail to survive. To investigate this question, we have analyzed whether the relation between wealth and size continues to hold also after the first year, the idea being that the relation between wealth and size should be vanishing if liquidity constraints are transient. We ran yearly regressions on the size of the venture, using current profitability as an additional control to those used in Table 2, and found that profitability is an important explanatory factor for size. The importance of profitability for size increases over time. We also found, however, that wealth has an approximately constant effect on the size of the company over the first five years, which suggests that liquidity constraints at the start-up date are binding well into the life of the venture. Thus it seems unlikely that liquidity constraints that are present initially vanish fast.

The positive relation between wealth and start-up size may be due to omitted variable bias, and reflects that individuals with higher entrepreneurial ability start up larger companies, rather than that they are liquidity constrained. In Section 6.1, we followed Evans & Jovanovic (1989) and divided entrepreneurs into "constrained" and "unconstrained" depending on the relative magnitude of founder wealth and start-up size. In unreported analyses, we find that the relation between wealth and start-up size is much stronger for entrepreneurs that are defined as constrained. This suggests that omitted variable bias is less important than liquidity constraints in driving the positive relationship between wealth and start-up size.

Liquidity constraints and the firm size distribution

In order to further substantiate our claim that liquidity constraints are present and binding, we use the approach of Cabral & Mata (2003). They develop a simple model showing that liquidity constraints will have implications for the firm size distribution over time. If a fraction of firms are below optimal size at birth due to liquidity constraints, and if these constraints become less binding over time, the firm size distribution of a given cohort of surviving firms should start out being right-skewed and over time become more symmetric. Cabral-Mata (2003) use a survey covering all Portuguese manufacturing firms that employ paid labor in the years 1983 to 1991. They show that the firm size distribution is significantly right-skewed initially and evolves over time towards a lognormal distribution. They conclude that a calibrated version of their model "does a god job at explaining the evolution of the firm size distribution", and reason that "financing constraints can to some extent explain the increased skewness in the size distribution that is typically observed in young cohorts of firms".

Inspired by Hoshi et al (1991) and Gusio et al (1999) we assume that new firms that are spin-outs from established firms are less constrained than new firms established by individual entrepreneurs.[18] In Figure 3, we compare the firm size distribution measured by the natural logarithm of the number of employees at firm age one and five for these two groups. We see that firms established by individual entrepreneurs are much smaller than comparable new firms that are spin-outs from established firms and – more importantly – that the firm size distribution for firms established by individual entrepreneurs is more skewed. This is true both in the first and fifth year of operations.

[18] Hoshi et al (1991) and Gusio et al (1999) both use group membership as a proxy for no financial constraints.

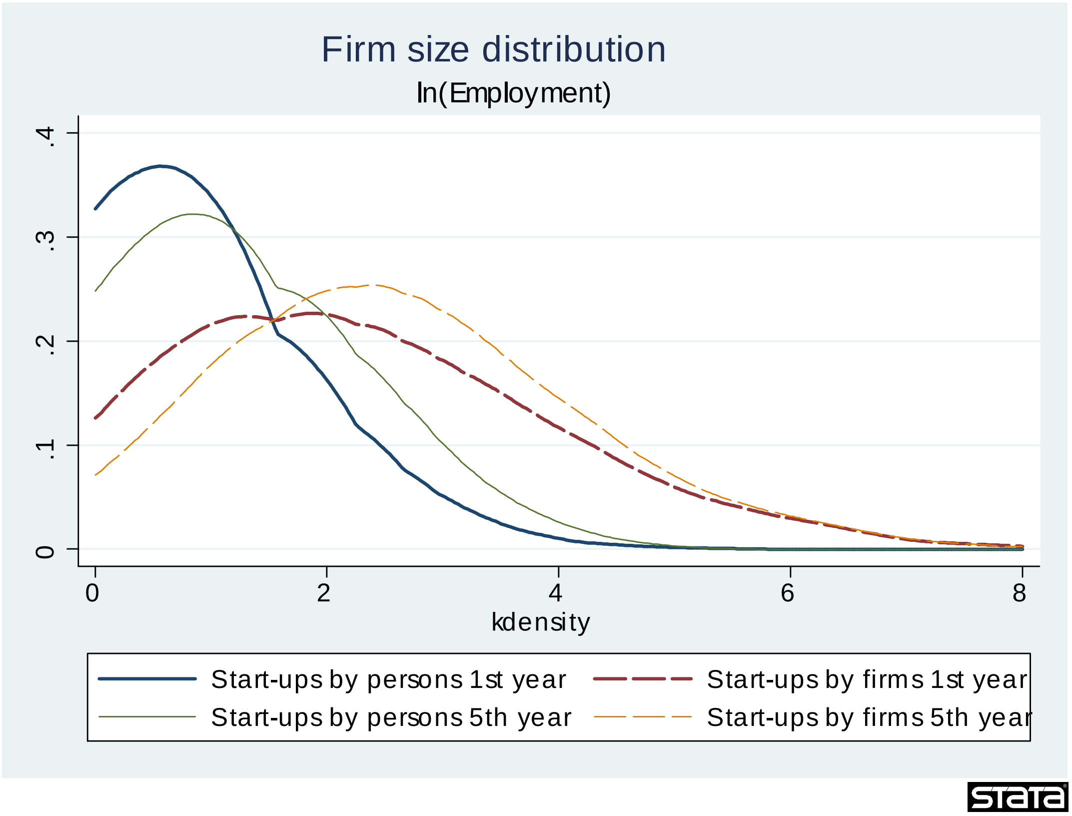

Figure 3: The firms established by individual entrepreneurs corresponds to the sample of start-ups that are described in the data section. The sample of spin-outs is constructed exactly the same way, i.e. as a random sample of limited liability firms that were incorporated between 1994 and 2002. Firms included are firms that survive for at least five years, and where we have information about the number of employees both in year one and five. The curves are obtained using a kernal density smoother with bandwith 0.7.

Table 3 gives more detailed information about the four distributions graphed in Figure 1. We note that the change in skewness over the first five years is larger for firms established by individual entrepreneurs than for spin-outs. We conclude that the approach of Cabral & Mata (2003) yields results on our data that are consistent with liquidity constraints being present.

Table 5: The firm size distribution of start-ups

	Mean	St.dev.	Skewness	# obs
Start-ups by persons, 1st year	.73	.85	1.13	812
Start-ups by persons, 5th year	1.09	1.00	.60	812
Start-ups by firms, 1st year	2.22	1.60	.66	709
Start-ups by firms, 5th year	2.57	1.46	.55	709

Firm size is measured by ln(employees).

Appendix B: Other performance measures (e-companion)

This appendix analyzes the relation between liquidity, founder wages and start-up survival.

Entrepreneurial wages

In addition to generating a stream of profits, the start-up generates a stream of wage income for the entrepreneur, that is traceable with the tax data. To evaluate the relation between prior wealth and entrepreneurial wage, we construct a control group of individuals that are similar to the founders in terms of gender, wage, wealth, age and education. The idea behind the control group is that although estimates of the wealth coefficient may be biased, the difference in wealth effects between entrepreneurs and observably similar workers that do not become entrepreneurs is less likely to be biased.

The control groups are constructed by sorting the entire population of individuals by gender, wage (rounded to the nearest 20 000), wealth (rounded to the nearest 20 000), age and education, year by year. For each founder, we have selected the two closest neighbors in the start-up year ranking, excluding neighbors that are founders. Table 6 presents descriptive statistics of the founders versus the control group.

TABLE 6: Descriptive statistics

	Founders		Control group	
	Mean	Median	Mean	Median
Age at start-up date	41	40	42	41
	(9)		(10)	
Education in years at start-up date	12.8	12	12.9	12
	(2.6)		(2.7)	
Taxable wealth, 3-year average	1550	542	1240	517
before start-up date	(7614)		(3670)	
Net capital income, 3-year average	-9	-33	-5	-23
before start-up date	(121)		(117)	
Wage income, 3-year average	515	437	494	415
before start-up date	(555)		(502)	
Founder net capital income, 3-year	57	-6	12	-21
average after start-up date	(188)		(138)	
Founder wage income, 3-year	460	394	533	444
average after start-up date	(310)		(452)	

Krone values are expressed in 1000 2002 kroner. Standard deviations in parenthesis.

We see from Table 6 that the two groups are quite similar. The control group has slightly lower gross taxable wealth and net capital income before the start-up date, suggesting that it has slightly less debt. With respect to wage before the start-up date, we see that the two groups are very similar. After the start-up date, however, the control group has a wage increase while the founders have a wage decrease. This decrease is partly compensated for through a stronger increase in net capital income.

We now study the relation between wealth and entrepreneurial wages.

TABLE 7: The effect of prior wealth on entrepreneur wage

	(1)	(2)	(3)	(4)	(5)	(6)
		Wage for entrepreneurs			Wage for control group	
ln(wealth)	.073***	.015	.081	.111***	.039***	-.094
	(.017)	(.017)	(.171)	(.012)	(.011)	(.102)
ln(wealth)^2			-.003			.005
			(.007))			(.004)
ln(wage$_{t-1}$)		.156***	.156***		.295***	.295***
		(.033)	(.033)		(.039)	(.039)
ln(wage$_{t-2}$)		.178***	.179		.223***	.221***
		(.034)	(.033)		(.042)	(.039)
age	.045***	.005	.004	059***	.012	.014*
	(.013)	(.013)	(.013)	(.008)	(.007)	(.008)
age^2	-.0005***	-.0001	-.0001	-.001***	-.0002*	-.0002***
	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.00008)
education in years	.039***	.025***	025***	.071***	.046***	.044***
	(.007)	(.007)	(.007)	(.005)	(.004)	(.004)
R^2	.07	.15	.15	.19	.39	.39
N	6760	6760	6760	12593	12593	12593

The estimation method is ordinary least squares. t is the start-up year. The dependent variable is yearly ln(wage) for the entrepreneur after start-up, excluding the start-up year. Two digit industry dummies, time dummies and dummies for the age of the start-up are included, but not reported. We report Huber-White robust standard errors allowing for clustering of errors by individuals. *** Significant at the 1 % level ** Significant at the 5 % level * Significant at the 10 % level

In column (1) of Table 7, we regress wealth on wage controlling only for age and education. We find a significant positive relation between prior gross taxable wealth and entrepreneurial wages. Note, however, from column (4) that the wage effect is even stronger in our matched control group of non-entrepreneurs. A likely explanation is that wealth is correlated with unobserved human capital (ability). Introducing prior wage as a control for ability in column (2) we see that the effect of wealth on wages falls sharply and becomes insignificant. Prior wealth still has a significant effect in the matched control group of non-entrepreneurs, see column (5). This is probably because the sample size is larger and the wage variance smaller. Measured human capital has more explanatory power, and R-square is far higher for non-entrepreneurs than for entrepreneurs. We see from columns (3) and (6) that the quadratic term in wealth enters with a small and non-significant coefficient in the wage regressions. Thus there is no evidence of a non-linear relationship between log wealth and entrepreneurial wage. We have also tried to include third and fourth order polynomials in wealth, reaching the same conclusion. To further assess robustness, we have used median and robust regressions, but the results were still the same. The analysis suggests overall that prior wealth has no causal effect on entrepreneurial wages.

Start-up survival

Defining start-up survival to occur if a start-up has submitted a tax report for the fifth year of operations, we have the following results.

TABLE 8: Effects of log gross taxable wealth on survival

	OLS				Probit			
	(1)	(2)	(3)	(4)	(5)	(7)	(8)	(9)
ln(wealth)	.066**	.287**	-.130		.202**	.749*	4.906	
	(.014)	(.130)	(7.614)		(.044)	(.404)	(22.039)	
ln(wealth)^2		-.009	-.008			-.022	-.674	
		(.005)	(.881)			(.016)	(2.558)	
ln(wealth)^3			.002				.042	
			(.045)				(.130)	
ln(wealth)^4			-.0001				-.001	
			(.008)				(.002)	
Dummy2				.145**				.147***
				(.038)				(.038)
Dummy3				.163**				.146**
				(.074)				(.058)
ln(wage$_{t-1}$)	.027	.029	030	.031	.083	.092	.102*	.031
	(.021)	(.020)	(.020)	(.021)	(.066)	(.062)	(.061)	(.021)
ln(wage$_{t-2}$)	-.004	-.006	-.008	.005	-.008	-.016	-.028	.006
	(.022)	(.021)	(.021)	(.022)	(.073)	(.071)	(.071)	(.023)
education in years	-.002	-.002	-.001	.000	-.004	-.005	-.003	.003
	(.007)	(.007)	(.007)	(.007)	(.020)	(.020)	(.020)	(.007)
age	-.024**	-.028**	-.028**	-.026**	-.089**	-.097**	-.098**	-.030**
	(.011)	(.011)	(.012)	(.012)	(.039)	(.040)	(.041)	(.013)
age^2	.0003**	.0003**	.0003**	.0003**	.001**	.001**	.001**	.0004**
	(.0001)	(.0001)	(.0001)	(.0001)	(.0005)	(.0005)	(.0005)	(.0002)
R^2	.08	.08	.09	.07	.06	.07	.07	.06
N	971	971	971		952	952	952	

The estimation method is OLS in (1)-(4) and probit in (5)-(8). The dependent variable is four-year survival. Two digit industry dummies, time dummies and dummies for the age of the start-up are included, but not reported. In column 6, dummy 2 represents percentiles 30-95 and dummy 3 represents percentiles 95-100. Low wealth individuals are the reference category in both columns. Huber-White robust standard errors allowing for clustering of errors by firms are reported in parenthesis. *** Significant at the 1 % level ** Significant at the 5 % level * Significant at the 10 % level

Table 8 provides estimates of the relation between founder wealth and business survival. Columns (1)-(4) use a linear probability model, and (5)-(8) a probit specification. (1) and (5) regress survival on log wealth, using the same controls as in Table 3. Columns (1) and (5) show that the log-linear relationship between wealth and survival is significantly positive. For example, (1) suggests that a one-log increase in founder wealth gives seven percentage points higher probability of five-year survival, which translates into a 1.4 percentage points higher yearly survival rate. As the average five-year survival rate is 73 percent across the sample, wealth does not seem to have a large effect on survival probability.[19] In columns (2) and (6) we use a quadratic specification, and in (3) and (7) we use a fourth-order polynomial specification. Across these specifications, we find a relationship between founder wealth and business survival that is initially increasing and then constant. In columns (4) and (8) we estimate average effects for founders in percentiles 30-95 and 95-100 respectively, relative to founders in percentiles 0-30. We find that founders in percentiles 30-95 have about 15 percentage points higher survival probability than founders in percentiles 0-30. The estimated survival probability for the founders in the 95-100 percentiles is very similar to the estimated survival probability in the 30-95 percentiles. Thus in spite of starting up larger companies and having access to more liquidity, the richest founders do not have a higher survival rate than the 30-95 percentiles. Overall, our results on survival are quite similar to our results on profitability in that wealth seems beneficial, but only up to a point.

[19] The estimated effect of wealth on survival is very similar to those reported by Holtz-Eakin et al. (1994a).