Financial Contracting with Optimistic Entrepreneurs: Theory and Evidence*

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February 8, 2005

Abstract

Optimistic beliefs are a source of non pecuniary benefits for entrepreneurs that can explain the "Private Equity Puzzle". This paper looks at the effects of entrepreneurial optimism on financial contracting. When the contract space is restricted to debt, we show the existence of a separating equilibrium where optimists self-select into short-term debt and realists into long-term debt. Long-term debt is appropriate for a realist entrepreneur as it smooths payoffs across states. Short-term debt is appropriate for optimists for two reasons: (1) "bridging the gap in beliefs" by letting the entrepreneur take a bet on his project's success, and (2) letting the investor impose adaptation decisions in bad states.

We test our theory on a large dataset of French entrepreneurs. First, in agreement with the psychology literature, we find that differences in beliefs may be (partly) explained by individual characteristics. Second, as predicted by our model, we find that short-term debt is robustly correlated with "optimistic" expectation errors. Finally, to partially alleviate endogeneity concerns, we use instruments suggested by evidence from clinical psychology. They reinforce our initial conclusion that optimistic entrepreneurial beliefs lead to a preference for short-term debt.

*We thank, for insightful discussions, Nicholas Barberis, Marianne Bertrand, Gilles Chemla, Bengt Holmstrom, Steve Kaplan, Ulrike Malmendier, Sendhil Mullainathan, Bernard Salanié, Per Strömberg, Tano Santos, Antoinette Schoar, Enrico Perotti, Raghuram Rajan, Jeremy Stein and Luigi Zingales. This paper also benefited from comments of seminar participants at the University of Chicago, Wharton, Gerzensee, Pompeu Fabra, INSEAD, the NBER summer institute, the NBER entrepreneurship meeting, the AFA meeting in San Diego, the SIFR conference in Stockholm, and the RICAFE conference at LSE.

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1 Introduction

Starting a business is not a profitable activity: Hamilton [2000] documents that median entrepreneurial earnings after ten years of business are 35% less than the predicted alternative wage on a paid-job of the same duration. In addition, because the bulk of their wealth is invested in their own business, entrepreneurs bear a substantial amount of risk that only large private benefits can explain: Moskowitz and Vissing-Jorgensen [2003] estimate that entrepreneurs must enjoy non pecuniary benefits as high as 5 to 20% of their investment every year. These "private benefits of control", as the literature calls them, may correspond to pure hedonic flows: social status, the fun of running a firm or the independence that comes with it. However, in this case, one would be left with the puzzling fact that these benefits amount on average to some 150% of the entrepreneur's annual income.[1]

An alternative interpretation of these findings is that private benefits are pies in the sky: Entrepreneurs do not start new businesses because it is profitable, but because they wrongly believe it is. Many studies show that entrepreneurs typically overestimate the chances that their project will be successful. In their survey, Cooper, Woo and Dunkelberg [1988] find that 68% of entrepreneurs thought their own business would do better than their others' (see also Pinfold [2000]). Experimental evidence suggests that people's optimism about their own ability relative to their competitors' leads to excess entry in a game of entrepreneurship (Camerer and Lovallo [1999]).[2]

This paper examines and documents implications of the fact that entrepreneurial private benefits take the form of optimistic expectations. In a financial contracting framework, we find that differences in opinions between the (optimistic) entrepreneur and the (realistic) investor affect the optimal contract in a fashion similar to differences in objectives (agency conflict): in particular, optimistic entrepreneurs make more use of short term debt. Our results therefore stress the role of differences in opinions as a key determinant of capital structure[3], which has so far mostly been explained through agency consid-

[1] Moskowitz and Vissing-Jorgensen's estimates.

[2] Optimistic expectations about performance can result from the "above average effect", a bias in perception abundantly documented in psychology and particularly strong when uncertainty is high and motivation at stake (Armor and Taylor [2000]). In the case of entrepreneuship, a powerful driver of optimism is also *selection*: Individuals who leave other opportunities to start a new venture tend to be those who, on average, overestimate the prospects of their project. This selection effect creates a natural upward bias in expectations, much like the winner's curse effect set forth in the auction literature (Thaler [1988], Roll [1986]).

[3] We focus here on the maturity of debt because debt is the only means of external finance for most entrepreneurs. Similar insights can, however, be derived within more general contractual environment. When we allow for contingent control transfers for instance, we

erations only. We then go to the data, document the large heterogeneity of entrepreneurial beliefs and find robust, convincing, evidence that short term debt is related to optimism, controlling for its usual determinants.

Our theoretical analysis shows that optimal contracts for optimists are contingent on events that the entrepreneur *does not control* (external risk), but holds overoptimistic expectations about. Two effects are at work: First, optimistic entrepreneurs inefficiently persist in implementing the initially ambitious project even if new information calls for a safer strategy. Hence, optimal contracts for optimists (short-term debt) transfer control to the investor in those states of nature where a realistic decision maker is needed.[4] Secondly, an optimistic entrepreneur is willing to exchange cash flow rights in the low state (that he believes to be unlikely) against claims on the good state (that the investor knows to be unlikely). These differences in valuation across states of nature call for a contract that provides more upsides to the entrepreneur when he/she is optimistic.

Hence, modelling private benefits as optimism allows to reconcile some recent, apparently paradoxical, empirical findings with financial contracting theory. Common agency theory predicts that optimal contracts should *insure* the agent against risks he/she does not control. However, Kaplan and Stromberg [2002] have shown that VC backed entrepreneurs bear much more external risk than should be optimal. Along similar lines, one of the main lessons of CEO compensation literature is the surprising rarity of relative performance evaluation schemes (Murphy [2000], Bertrand and Mullainathan [2001]). These pieces of evidence conflict with common agency theory, but receive a natural interpretation in our framework: entrepreneurs or CEOs overestimate their chances of success. As a result, they have a strong preference for control and cash flow rights contingent on good states of nature.[5]

We then empirically document entrepreneurial optimism and test the major prediction of our model: Entrepreneurial optimism is one of the factors

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can prove that difference in opinions give rise to venture capital - like contracts where the entrepreneur loses control when they firm performs poorly.

[4]This effect arises solely from differences in opinion, not from agency problem as in Aghion and Bolton [1992]. These contingent transfers in control are a feature typical of venture-capital contracts (Kaplan and Stromberg [2003]), but they are, in our paper, implemented through debt maturity.

[5]We stress that in equilibrium, investors do not *exploit* optimistic beliefs: They make zero profit on both realistic and optimistic entrepreneurs. The equilibrium is a separating one where, even though entrepreneurial beliefs are not observable, both revelation constraints – for optimists and realists – are non-binding: Optimists prefer short-term debt because it leaves large payments and control to the investor in states that (they believe) are never going to occur. For realists, these financing contracts simply look too risky, and they strictly prefer insurance provided by long term debt.

explaining capital structure, aside from well documented agency considerations. Our dataset comes from two waves of a survey conducted by the French statistical office on a population of entrepreneurs the very year their business was started. This survey contains direct information on (1) entrepreneur *initial expectations* on future business growth, (2) entrepreneurial socio-demographic characteristics and (3) project characteristics. This dataset is then matched with accounting data collected from tax files, which allow us to draw a relationship between the entrepreneur's characteristics, his expectations and the actual venture performance up to seven years after birth.

We draw several conclusions from this empirical analysis. First, we find that some observable characteristics are strongly associated with systematic upward expectation biases on the venture's performance. Notably, entrepreneurs with higher education and those who are developing their "own idea" tend to be more optimistic, whereas entrepreneurs who take the business over from someone else tend to be less optimistic. These differences may be understood in the context of a model of "choice-driven" optimism, a la Van den Steen's [2004]. Provided that some agents form beliefs about their entrepreneurial ideas that differ (positively or negatively) from the unbiased expectation, entrepreneurs are optimistic on average about their project, as the "pessimists" don't become entrepreneurs. Interestingly, this simple selection theory of has strong comparative statics implications that we find validated in the data: Those with higher non-entrepreneurial outside options (e.g. higher education) exhibit more optimism, while those receiving more accurate signals on projects have smaller biases (expertise in industry, idea less "novel").

Secondly, we find a fairly robust, positive, correlation between optimistic expectation errors and the use of short term debt. In a first stage, we simply correlate expectation errors with capital structure, using two different measures of both. These correlation are strong, and remain once we control for obvious determinants of expectations that may be correlated with capital structure. We have to acknowledge, however, that these estimates may be biased. This is why we then use instruments for expectations suggested by evidence gathered from clinical psychology: regional sunlight exposure, regional propensity to depression, and the regional propensity to hold religious beliefs. While these instruments are not perfect, they are likely to capture some of the endogeneity bias. With this methodology, the effect of expectation on capital structure shows up both statistically significant and large.

This paper is part of a growing literature, pioneered by Roll's [1986] analysis of takeovers, that explores the impact of managerial behavioral biases on decision-making. Heaton [2002] shows that managerial optimism offers a unifying view on overinvestment in the presence of free cash-flows (the manager overestimates their NPV) and underinvestment when funds have to be raised by issuing risky securities (the manager believes external finance is too costly).

Malmendier and Tate [2002,2003] empirically document, for large, listed firms, the link between CEOs overconfidence and overinvestment using the personal investments of these CEOs in their companies as a measure of overconfidence. Directly related to our topic, De Meza and Southey[1996] show in a model that heterogeneity of beliefs among potential entrepreneurs can explain high failure rates, credit rationing and a preference for debt rather than equity. Coval and Thakor (2003) develop a model where rational agents become financial intermediaries to act as a "beliefs bridge" between the optimists –who become entrepreneurs– and the pessimists –who choose to become investors in the intermediary.

The paper has four more sections. Section 2 documents in the light of the psychology literature what the most likely sources of differences in beliefs between entrepreneurs and investors are and relates them to observable characteristics. Section 3 outlines a credit-market equilibrium where both realistic and optimistic entrepreneurs coexist. Section 4 is devoted to the empirical analysis: We describe the empirical heterogeneity in beliefs and test for a link between beliefs and debt-contract choice. Section 5, the last one, concludes.

2 Differences in Beliefs and Entrepreneurial Optimism

At the core of our analysis is the assumption that entrepreneurs deviate from rational expectations about the odds of their project succeeding. What are the origins of such deviations? Entrepreneurial projects typically are highy uncertain; because of their novelty, there is very little evidence on which to base future expectations. Under these circumstances, experimental psychologists have shown that agents tend to rely on crude heuristics and that these heuristics may give rise to biased beliefs. At least three psychological mechanisms may be mentionned. The first one is the "above average" effect: the psychology literature documents the fact that, when odds are very difficult to assess, people tend to hold high beliefs on their chances of performing at a given task (Taylor and Brown [1988]). The circumstances under which such self-serving beliefs arise are, however, not well understood, as agents may also display excessively pessimistic beliefs in some settings (Ross and Anderson [1977]). In the case of entrepreneurship, however, the above average effect may be reinforced by strong motivational factors as positive beliefs help the entrepreneur to commit to a high effort (Armor and Taylor [2000]).

A probably more convincing explanation for entrepreneurial optimism is the *planning fallacy* (Kahneman and Lovallo [1993], Kahneman and Tversky [1979]). A common heuristic used to assess the chances of suceeding is to simulate the environment with chains of events linked together by probabilities. Experiments document the fact that agents have great difficulty in estimating compound probabilities and stick to a simple rule of thumb like taking the average probability of success across nodes, or the probability of success in the first node (Gettys, Kelly and Peterson [1973]). In many experiments, this inference process naturally leads to overoptimism about the probability and the time of completion of a task

In our viewpoint, the strongest source of entrepreneurial optimism is likely to be *selection*: people don't become entrepreneurs by accident but because they perceive that they have a project that dominates their other career choices. If they have noisy assessments of their projects, those who become entrepreneurs hold on average optimistic beliefs. This "choice-driven" theory of over-optimism is developped in Van-den-Steen [2004] and allows to make precise predictions about what observable characteristics we can expect to be correlated with optimism.

To see how, consider a population of potential entrepreneurs. Each agent i has an idea, whose value can be either high (V_H) or low ($V_L = 0$). The *objective* probability that the project is good is α_i, but agents have a prior belief $\widetilde{\alpha}_i$ drawn from a distribution G_i. Let's assume agents are right on average, i.e. $\int \widetilde{\alpha} dG_i = \alpha_i$. Agents become entrepreneurs if their subjective assesment of the project's value, $\widetilde{\alpha}_i V_H$ exceeds the value V_i they get by staying in paid employment. Conditional on becoming an entrepreneur, an agent has a belief which is on average higher than the objective one (α_i) by a factor:

$$\int_{V_i/V_H} \frac{\widetilde{\alpha}}{\alpha_i} \frac{dG_i(\widetilde{\alpha})}{1 - G(V_i/V_H)} > 1$$

If all agents were entering entrepreneurship, their average expectations would still be unbiased. But since only those who feel their idea has a value exceeding V_i actually choose to be entrepreneurs, occupational choice leads to an *average overoptimism* of entrepreneurs (the most pessimistic agents remain employed).

This simple model of entrepreneurial optimism generates two comparative statics that will guide us later in our empirical strategy. First, entrepreneurs who have larger outside options in employment (V_i) are on average more overoptimistic about their project's chances of success (because the selection effect described above is stronger). We thus expect that more educated and more experienced agents who select into entrepreneurship should be more optimistic, because they could claim a higher wage on the labor market. Second, agents with less precise information (e.g. in the sense of a mean-preserving spread in G) have a larger over-optimism bias. We thus expect agents with more expertise in the industry to be less optimistic. On the contrary, agents whose motivation is to implement a “novel idea” have a noisier signal and are expected to be more optimistic, provided they choose to become entrepreneurs.

3 Model

We now take this heterogeneity of beliefs as given among entrepreneurs and ask how it affects the credit-market equilibrium, in a model where both realistic and optimistic entrepreneurs coexist, are not distinguishable, and can raise funds for their projects.

3.1 Set-Up

There are three dates, $t = 0, 1, 2$. A cohort of wealthless entrepreneurs, protected by limited liability, raise I at $t = 0$ to finance a project. The returns of the project at time 2 depend on a strategy decision at time $t = 1$ (say, *growth* or *safe*) and on the project's fitness to the market - its type. Projects can be of two types: good or bad. When the entrepreneur chooses the *growth* strategy at time 1, a good project yields R , and a bad one yields zero. If the strategy chosen is *safe*, both types of projects yield L. When the project is a good one, the *growth* strategy is better than the *safe* strategy: $R > L$. When it is a bad one, the *safe* strategy is the better one: $L > 0$.

At time 1, the entrepreneur receives a noncontractible signal about the project's fitness and bases his choice of a strategy on this information. This signal takes the form of an intermediate cash flow generated by the firm at $t = 1$. This cash flow is R with probability 1 if the project is good. If the project is bad, this cash-flow is R with probability p and 0 otherwise. Hence, a zero cash flow is a sure sign that the project is bad, and that the optimal strategy is the safe one (which yields L instead of 0).

The sequence of events is summarized in figure 1. First, investment I is sunk. At date $t = 1$, the interim cash flow is observed. The strategy is chosen by whoever (entrepreneur or investor) holds control of the firm. Last, in $t = 2$, the project generates the final cash flows, depending on its type and the strategy chosen.

A priori, there are as many good as bad projects to pick up. Hence, a given project is good with probability 1/2 and bad with probability 1/2. All entrepreneurs are risk averse with concave VNM utility $u(.)$.

In order to pinpoint the effects of differences in beliefs on financial contracting, we choose here to simply posit that some entrepreneurs are more optimistic than others. In order to make things even clearer, we will make an extreme assumption about differences in beliefs. First, *realists* have correct priors about the project's type. Hence, they ex ante believe that the project is Good with probability 1/2. Once he observes interim cash flows, the realistic entrepreneur incorporates the additional information following Bayes' Rule. His new beliefs at date $t = 1$ are thus given by:

$$
\begin{aligned}
\mathrm{P}(\text{type} &= \text{good}|\text{interim CF } = R) = 1/(1+p) \\
\mathrm{P}(\text{type} &= \text{good}|\text{interim CF } = 0) = 0.
\end{aligned}
$$

Optimists don't have realistic a priori beliefs on the project's type. Ex ante, they believe the project is good with probability 1. Even though the optimistic entrepreneur also uses Bayes' law to update his beliefs at date $t = 1$, he interprets the interim cash flow information differently. Indeed, for an optimist:

$$
\begin{aligned}
\mathrm{P}(\text{type} &= \text{good}|\text{interim CF } = R) = 1 \\
\mathrm{P}(\text{type} &= \text{good}|\text{interim CF } = 0) = 1.
\end{aligned}
$$

In our extreme case, where optimists are *sure* that the project is a good one, they discard all interim information they get about it. Hence, optimists do not update when they see no interim cash flow: this is a limit case, but perfectly consistent with bayesian updating.[6] More precisely, optimists make two kinds of mistakes ex ante: first, they overestimate the probability of a good signal. They think good signals occur with probability 1 (good projects never fail), while realists think good signals occur with probability $(1 + p)/2 < 1$ (bad projects may fail). The second mistake optimists make is that they overestimate the probability of success of the growth strategy (1 versus 1/2). The business plan, as seen by an optimistic entrepreneur, is given in figure 2.

To focus on the important effects, we make the following additional assumptions:

1. Financial markets are competitive and investors hold realistic beliefs.[7]

2. Conditional on the signal being good, growth is the efficient strategy:

$$\frac{1}{1+p}R > L;$$

   of course, this assumption ensures that $R > L$.

[6] We consider for its simplicity this limit case of optimism. Proofs available from the authors show how these results can be generalized to moderate optimism, as long as (1)optimism is sufficiently strong and (2) the signal is sufficiently informative about the project's choice.

[7] This assumption is consistent with Coval and Thakor (2003). They develop a theory of financial intermediation, where rational agents become financial intermediaries to act as a "beliefs bridge" between the optimists –who become entrepreneurs– and the pessimists –who choose to become investors in the intermediary. What matters for our model is that the marginal investor holds beliefs that are "more realistic" than an optimistic entrepreneur.

3. If the entrepreneur could commit to always choose the safe strategy (whether the signal is good or bad), the NPV of the project would be positive:
$$L > I.$$
4. The project cannot be fully financed by its payoff in the bad state, i.e.:
$$I > \frac{1-p}{2}L.$$
5. The signal is observable but not contractible.

In our data, an overwhelming majority of new ventures are financed by simple debt contracts of either short or long maturity. Venture capital contracts, which specify both contingent repayments *and* control transfers are used by only a very small fraction of new companies. This is not a surprise as the French private equity market is less developed and more late-stage oriented than the US one. For this reason, we analyze the credit-market equilibrium with debt contracting. The debt contract can take two forms: first, a short-term debt contract, that specifies a repayment at date 1. If cash-flow is 0, the entrepreneur has to default and the investor gets control and ownership of the firm. The other type of contract is long term debt, specifying a repayment at $t = 2$. Recall that the signal is observable, so renegotiation may occur in date 1 in order for the investor to induce the entrepreneur to choose the *safe* strategy if he is tempted to play *growth*.

3.2 Results

Our main result is that there is a unique competitive separating equilibrium. In this equilibrium, the optimists choose short-term debt contracts whereas the realists choose long-term debt.

Proposition 1 *When only debt contracts are available, the equilibrium is separating with optimists choosing a short-term debt contract and realists choosing a long-term debt contract.*

- *The short-term debt contract has a repayment level:*
$$D = \frac{2I - (1-p)L}{1+p}.$$
- *The long-term debt contract has a repayment level:*
$$D = I.$$

- *Investors make zero profit with either type of entrepreneur.*

To prove this result, we proceed in two steps: we first assume that the entrepreneur's beliefs are observable and solve for the optimal contracts. We then show that this pair of contracts is self-selecting.

To understand the logic behind the optimality of short-term debt, it is useful to ask oneself what the optimal contract would be with an optimistic entrepreneur in a frictionless world. Assume that the investor could observe that an entrepreneur is optimistic and that the signal were contractible. First, contrary to the investor, the entrepreneur believes the signal S will be positive for sure. The optimal contract will therefore give him a positive payoff only if $S > 0$ and zero otherwise. Second, the investor knows that in case of a bad signal, value can be created by taking the safe strategy rather than the growth one. A second feature of the optimal contract is therefore to allocate control to the investor in case of a bad signal. Ex ante, the optimistic entrepreneur believes this will not happen, therefore, such a provision in the contract has no cost from his perspective. The benefit is that it increases the project NPV from the investor perspective and therefore the payoff that can be left to the entrepreneur in the good state.

It turns out that short-term debt can implement this first-best contract: indeed, with short-term debt, the investor gets full control and ownership in the bad state. What is the promised repayment D the investor asks for? It is simply given by the zero-profit condition,

$$I = \frac{1+p}{2}D + \frac{1-p}{2}L$$

Note that the short-term debt contract that a realist could get would be exactly the same, as beliefs do not distort strategy choice for this type of contract. But is it the contract a realist would prefer? Consider an entrepreneur who is able to make the case that he is a realist. He is therefore able to commit to choose the safe strategy if $S = 0$ (he knows that not doing so would yield a zero cash-flow). Given that $L < I$, this makes long-term debt risk-free with a realist. The investor can therefore offer a long-term debt contract with repayment $D = I$. Our realist entrepreneur strictly prefers this contract to the short-term debt contract as it smooths cash-flows across states of nature:

$$\frac{1}{2}[u(2R-D)+pu(R-D)+(1-p)u(0)] < \frac{1}{2}[u(2R-I)+pu(R-I)+(1-p)u(L-I)].$$

To finally establish that these contracts are self-selecting, it remains to be shown that an optimist does not want to pretend to be a realist and get a long-term contract.

The revelation contraint for optimists is:

$$u\left(2R - \frac{2I - (1-p)L}{1+p}\right) > u\left(2R - I\right).$$

To see why it always holds, let us write the difference in expected payoffs:

$$\begin{aligned}\Delta &= \left(2R - \frac{2I - (1-p)L}{1+p}\right) - (2R - I) \\ &= -\frac{1-p}{1+p}(L - I) < 0.\end{aligned}$$

From an optimistic's viewpoint, investors lose money with the short-term contract. Short-term debt looks cheaper to them as they get more of the upside of the project.

4 Tests

This section is devoted to testing one premise and one prediction of our model. The premise is that beliefs are heterogenous across entrepreneurs. Using a large dataset on French entrepreneurs, we show that their expectation error (i.e. the difference between performance expectation and realization) can to some extent be predicted by observable entrepreneur and project characteristics.

Then this section tests the main conclusion of the model: other things equal, optimistic entrepreneurs self select into short term debt contracts. We first look at the controlled correlation between expectation errors and initial capital structure and find it positive and significant. Although we attempt, in this analysis, to control for industry and year effect, as well as project characteristics, this estimate remains potentially plagued by endogeneity and measurement error biases. We then propose an identification strategy based on regional, noneconomic, determinants of beliefs suggested by clinical psychology. It confirms our initial results.

4.1 A Short Description of the Data

Our dataset consists of the merging of two sources (see data appendix for more details). The first dataset comes from a survey conducted by the French statistical institute (INSEE) on a sizeable portion of businesses started/taken over in 1994 and 1998. This survey (SINE) provides us with the entrepreneurs' main sociodemographic characteristics (age, education, social background), and their *growth expectations* as they start/take over/inherit the business. Other qualitative questions relate to (1) the reasons for which the firm was started and (2) the conditions under which it was started (financing, initial research, customer prospection).

This survey does not, however, provide much detail on subsequent corporate performance and finance. We thus match this information with accounting data compiled from tax reports (Bénéfices Industriels et Commerciaux). For all years from 1994 to 2000, accounting data provide fairly detailed information on the firm's balance sheet, profit account and employment. The problem is that the tax system collects this information only for firms with sales above 110,000 euros. Thus, we lose approximately one third of the sample, in particular because we are interested only in firms that start reporting their accounts in their *first* year of existence.

We thus end up with a basic sample of some 39,000 firms: a little more than half of them (23,000) are newly created, the rest are existing firms taken over by new entrepreneurs. The upper panel of table 1 displays some accounting variables of firms the year they were started or taken over (that is, either 1994 or 1998). In their first year of existence, newly created ventures are small: they typically employ 1.5 workers, and use 35,000 euros of fixed assets, to make up no more than 200,000 euros of total sales. Breaking down the sample into corporations and noncorporations highlights the considerable skewness of firm-size distribution. In contrast, firms that merely changed hands are on average twice as large as newly created firms, consistent with a simple age effect.

Our theory has predictions on the share of short-term loans in outside finance. For a subset of our firms[8], the accounting data allow to break down total debt into (1) short-term debt (all loans with maturity of less than two years), (2) long-term bank debt and (3) "other financial debt". For our small firms, this last item mostly consists of loans made to the firm by the owners and their relatives. Given that these loans are likely to be junior to any bank loan, we treat them as equity. In addition, the data provide us with the share of short-term bank debt that takes the form of bank overdrafts.

Unfortunately, the share of bank debt with less than 2 years of maturity includes longer-term loans that will end in less than two years. It is thus a noisy measure of short-term debt, especially for firms taken over: being older, these firms are likely to have accumulated long-term debt in the past. Hence, to measure the level of short-term indebtness, we will use the ratio of credit lines to total bank loans *in the year when the firm is created/taken over*.[9] We

[8] Basically, all firms with turnover above 250,000 euros (see appendix).

[9] We ran - but do not report - separate regressions using bank loans with less than two years of maturity; they delivered results similar to – albeit sometimes weaker than – the

divide bank overdrafts by total bank loans because, as mentionned above, they are the almost exclusive source of outside finance.[10] The lower panels of table 1 provide descriptive statistics on short term debt, depending on whether the firm is a startup and/or a corporation. As it appears, credit lines constitute the bulk of short-maturity debt.

4.2 Heterogeneity of Beliefs

This section documents the heterogeneity of beliefs prevailing among entrepreneurs. Our information on beliefs comes from two questions asked of entrepreneurs at the end of the year the firm was created/taken over. These expectational variables are discrete: we know whether the entrepreneur initially expects business sales to "develop" ($EXPGR = 1$) or not ($EXPGR = 0$) within the next years. We also know whether the entrepreneur initially expects to hire additional employee(s) ($EXPEM = 1$) or not ($EXPEM = 0$).[11]

We also know from the accounting data by how much firm sales and employment actually grew over the first two years. We then construct expectation error as the difference between expectations and realizations. Since expectation variables are discrete, we also discretize realizations of sales and employment growth such that:

$$\begin{aligned} \Delta_S &= EXPGR - 1_{(\Delta \ln(\text{SALES})>3\% \text{ and firm survives})} \\ \Delta_E &= EXPEM - 1_{(\Delta(\text{Employment})>0 \text{ and firm survives})}. \end{aligned}$$

These measures are clearly noisy, first of all because the accounting data may not be that reliable. This, however, should weaken, not strengthen, our estimates. Second, because expectations are not quantified, the 3% threshold is arbitrary – what do entrepreneurs mean by growing instead of stagnating ? Our choice matches the average consumer price increase of the French economy over the period, and is therefore very conservative: an entrepreneur with a positive expectation error did not overestimate growth if his business's growth was more than zero in real terms. We therefore underestimate the magnitude of optimism in the sample, if "reasonable growth" is above zero. Provided all entrepreneurs understand the term "growth" in the same way (above X%), this is not going to affect our results very much – and indeed, changing the threshold does not really affect our regression results, as long as there remain enough observations per category. If, however, different entrepreneurs were to interpret the question differently – as is certainly the case – this could bias our results. We try to control for this issue by incorporating industry dummies

ones with credit lines we provide in the following analysis.

[10] Only a negligible fraction of our firms are financed through venture capital.

[11] See the data appendix and table A1 for further description of these variables.

as explanatory variables, as “growth” standards are most likely to vary across industries. Given the cross sectional nature of our dataset, however, we saw no other way of dealing with this problem.

The sample distribution of the expectation errors Δ_S and Δ_E is shown in table 2. Distributions are given separately for 1994 and 1998, both for real startups and firms that are taken over. As one can see, the distribution of employment-based expectation errors is more spread out than the development expectation error. Aside from this, both measures deliver the same message. The first lesson from table 2 is related to the interaction between beliefs and the business cycle. In 1994, growth was very weak in France, while 1998 was a strong recovery year. As it turns out, more entrepreneurs were “disappointed” – had upbeat, but unmet, expectations – in 1998 than in 1994. This is true for both measures of expectation errors and both for firms created and taken over. This is particularly surprising since the French economy did not do very well in 1995-1996, while growth was very strong in 1999-2000. So the evolution of the overall economy cannot explain this disappointment.

A second message is that entrepreneurs starting new firms tend to be more “disappointed” than entrepreneurs who took their firm over. This difference is true for both measures of expectation errors and for both years. This fact is consistent with the fact that “real” entrepreneurs tend to be more optimistic than those who took their firm over from an existing owner.[12] As we argued in section 2, this fact is consistent with many results from experimental psychology. “Real” entrepreneurs face more “novel” situations and therefore have very little information to base their expectations on, which is likely to bias their expectations upwards.

Finally, we see from table 2 that expectation errors are not always zero, far from it. Almost 50% of all entrepreneurs made mistakes about their forecasts of employment, while some 30% make mistakes about their future development.[13] Of course, expectation errors have no reason always to be equal to zero: entrepreneurs need not be prescient to be rational. Δ_S and Δ_E are indeed the sums of two components: first, the true expectation error, that is the difference between realization and the unbiased expectation. The second component is the difference between the actual expectation and the unbiased expectation: this is what we called the bias in the model. In mathematical

[12] This will be confirmed by our multivariate analysis, as shown in tables 5-6.

[13] Furthermore, these distributions have some degree of asymmetry. In three cases out of four, there are more people expecting a bad outcome and ending up with a good one than the contrary. Given the discretized nature of our variables, we do not feel confident in discussing the *absolute value* of our expectation errors: it depends too much on how we discretized the continuous employment/sales variable realizations. We feel much more comfortable actually *comparing* the distributions across categories, thereby assuming that the threshold chosen on employment/sales remains fairly constant among categories.

terms, for entrepreneur i:

$$
\begin{aligned}
\Delta_{S,i} &= b_{S,i} + u_{S,i} \quad (1)\\
\Delta_{E,i} &= b_{E,i} + u_{E,i} \quad (2)
\end{aligned}
$$

where b_i is the bias of individual i (difference between objective and subjective expectations) and u_i is the true expectation error (difference between realization and objective expectation). As we said above, there is a priori no reason to believe that b_i and u_i should always be zero, since agents may be biased ($b_i \neq 0$) and, even if rational, they may make mistakes ($u_i \neq 0$). But even on *average*, there is still no reason for $\Delta_{S,i}$ and $\Delta_{E,i}$ to be zero. First, all agents might have the same bias ($\Sigma b_i \neq 0$), as we have argued in the case of entrepreneurs. Second, even when rational, all agents may be affected by a similar shock – like for instance a macro shock – that they did not expect to occur with probability 100%. In this case, there turns out to be an average difference between objective expectations and realizations ($\Sigma u_i \neq 0$).

Our goal in this section is to study the heterogeneity of beliefs in our population of entrepreneurs. Since our model hypothesizes that the b_i's are positive for some entrepreneurs, we are thus interested in knowing more about the distribution of b_i's. The problem is that we only observe the expectation errors Δ_i's from the data. We thus need to make an additional, identifying, assumption. To see more precisely where this additional assumption should enter, let us first rewrite the problem. Let us call X_i the entrepreneurial characteristics that explain part of b_i, such that:

$$b_i = E(b_i|X_i) + \eta_i,$$

where, by definition, $E(\eta_i|X_i) = 0$. To make things simpler, assume that $E(b|X_i) = X_i\beta$ is linear in X_i. In this case, rewriting $\Delta_{E,i}$ and $\Delta_{S,i}$ yields:

$$
\begin{aligned}
\Delta_{S,i} &= X_i\beta_S + \eta_{S,i} + u_{S,i}\\
\Delta_{E,i} &= X_i\beta_E + \eta_{E,i} + u_{E,i}\ .
\end{aligned}
$$

In this framework, naïvely regressing Δ_i on X_i is tempting, but unbiased estimates of β_E and β_S can be obtained only if $E(u_i|X_i) = 0$. In other words, expectations errors must be occurring independently of the entrepreneur's characteristics. Assume for instance that skilled entrepreneurs are purely rational – $b_i = 0$ – but that they tend to cluster in the software industry. Assume further that the software industry is hit by a negative shock, which was not expected to occur with probability 1. In this case, all skilled entrepreneurs are going to have a large, positive, expectation error and the naïve procedure is going to attribute it to skilled entrepreneurs' biases.

We thus need to filter out shocks. To do this, we make the identifying assumption that we can find variables Z_i that allow us to control for industry shocks for a given X:

$$E[(u_i - E(u_i|Z_i))|X_i] = E[\varepsilon_i|X_i] = 0$$

In this case, assuming for simplicity that $E(u_i|Z_i) = Z_i\gamma$, we need to estimate the following equations:

$$\Delta_{S,i} = X_i\beta_S + Z_i\gamma_S + \eta_{S,i} + \varepsilon_{S,i} \quad (3)$$
$$\Delta_{E,i} = X_i\beta_E + Z_i\gamma_E + \eta_{E,i} + \varepsilon_{E,i} \quad (4)$$

which can be easily done with OLS. The β's are going to represent the distribution of biases provided the attached characteristic X is not also part of the Z's. The η's represent the unobservable components of the bias and the ε's the expectation errors.

Following (3)-(4), we thus regress the two expectation errors Δ_E and Δ_S on a series of entrepreneur and project characteristics (the X's) and on industry and survey year dummies (the Z's). Arguably, industry dummies may also affect the distribution of biases. For example, new industry may elicit more optimism than low tech, well known industries. Given our identification strategy, it is, however, impossible to empirically disentangle both effects. In addition, *we assume here that the X's are not included in the Z's.* This looks like a strong assumption, but data constraints prevent us from making a weaker one at this point.

The precise way the X variables are constructed, as well as the accurate phrasing to the questions they are extracted from, is given in the appendix of this paper (population statistics are given in table A2). Here is a short description of the X's, as well as an explanation for why we might think they can affect biases:

- **Entrepreneur education**: broken down into four levels (high school dropout, high school graduate, college graduate, post graduate/*grande école* level). Educated entrepreneurs enjoy a larger outside option on the labor market: hence, those who choose to start a firm must have received a better private signal, other things equal; Hence, as outlined in our model in section 2, they are more likely to be optimistic. On the other hand, more educated entrepreneurs may simply be more "rational". In general, psychology theory is ambiguous about possible biases arising from education. First, general education gives entrepreneurs a view on the "big picture" which according to Kahneman and Lovallo [1993] leads to more unbiased expectations. More specific to France and interesting to us, is the highly selective "grande école" system. Provided these successful students suffer from *base rate neglect*, they might overattribute their academic success to their own ability, and end up for this reason overestimating their odds of success as entrepreneurs.

- **Entrepreneur age**: as a proxy for general experience. Experience is likely to increase entrepreneurs' outside options on the labor market. Thus, like education, age may have a positive impact on optimism (see again our model section 2). But it could also be argued that experienced entrepreneurs are likely to observe more precise signals. In this case, optimism should be less prevalent among older entrepreneurs. The expertise variable - described below - is however more likely to capture this effect.

- **Entrepreneur gender**: using a dataset on positions and trading records for some 35,000 investors, Barber and Odean [2001] show that the turnover rate of common stocks for men is one and half times larger than that of women. They rely on evidence from psychological literature to interpret this difference as evidence that men are more overconfident (i.e. overestimate the precision of their information) than women. Combined with selection (into entrepreneurship), the overweighting of private information translates into greater optimism. Hence, if they are overconfident, male entrepreneurs should also be more optimistic.

- **Serial entrepreneur**: a dummy equal to one when the entrepreneur has already started a business before this one. Serial entrepreneurs might have been successful or not in the past. Psychology documents the fact that agents tend to attribute success to their own ability and failures to bad luck (Zuckerman [1979]). The pool of repeat entrepreneurs is therefore likely to exhibit higher optimism than new entrants. Moreover only the most optimistic among entrepreneurs are likely to "try again", a selection effect that reinforces the previous one.

- **Expertise in the industry**: a dummy equal to one when the entrepreneur was previously working in the same industry. In the management literature, Russo and Shoemaker [1992] provide statistical evidence that expertise allows one to "know what one does not know", i.e. to exhibit less optimism in the field of expertise. Many psychologists do, however, argue otherwise. Self declared areas of expertise are those areas where the agent is personally commited the most, and personal commitment is likely to foster optimism (Weinstein [1980]). Slovic, Fischhoff and Lichtenstein [1980] argue that experts tend to be *overconfident*, i.e. they always overestimate the precision of their knownledge, which leads them to underweight outside information (Kahneman and Tversky [1979] recall that experts are also subject to the *planning fallacy*).

- **Desire to implement a new idea:** A dummy equal to one when the entrepreneur's motivation was the implementation of a new idea. Evidence from experimental psychology gives a concordant and ambiguous insight. As we argued above, when faced with a high level of uncertainty, entrepreneurs are more likely to use heuristics that are biased toward optimism. First, the desire to implement one's own, new, idea is a sign of high self commitment in the project. Commitment is, in general, a source of optimism. Second, novelty prevents entrepreneurs from keeping their eyes on the "big" picture; Kahneman and Lovallo [1993] argue that it forces them to do "scenario thinking". As we said above, scenario thinking is subject to the planning fallacy, which yields optimism. Last, the use of the representativeness heuristic is more likely to generate optimism in our self-selected population of entrepreneurs, as seen in section 2.

- **Desire for autonomy**: A dummy equal to one when the entrepreneur's motivation was to achieve independance. A priori, this can affect optimism in both directions. A desire for independance is likely to magnify the "inside view effect" (the underweighting of external information) and therefore to be correlated with higher optimism. However entrepreneurs who value independance might have a lower subjective outside option in paid employment, which could mitigate the optimism of this category.
- **Real Start-Up:** A dummy variable equal to one whenever the firm is really started in the year of survey. Indeed, a little less than half of the sample consists of entrepreneurs taking their firm over from an already existing owner (in the family or not). These entrepreneurs are likely to face less uncertainty, because the firm – its customers or at least its assets – already exists. Moreover their selection into entrepreneurship might be more exogenous (e.g. inheriting the business). The psychological evidence discussed in section 2 suggests that they should be less optimistic than "real entrepreneurs". Note that psychological evidence is complemented by sizeable evidence from the economics and management literature (see e.g. Busenitz and Barney [1997], Kahneman and Lovallo [1999]). Hence, we expect a positive coefficient on this variable.

Regression results are reported in table 3 (columns 1-3 use the employment expectation error as the dependant variable, while columns 4-6 use the development expectation error). For each of the two measures of expectation errors, we performed three types of estimations. We use a linear probability model to make results easier to read, though a logit model does not deliver different results. All estimates assume a broad form of correlation across firms of the same industry and some 350 4-digit industry dummies. Columns 1 and 4 simply estimate regressions on the whole sample of start-ups. To check robustness and account for the potential effects of macroeconomic fluctuations on the formation of expectations, the other columns provide separated estimates for years 1994 and 1998.

Before we turn to the effect of each explanatory variable, two general remarks are in order. First, our observables have a low explanatory power. This is particularly true for the development expectation error ($R^2 = 0.05$ in the pooled regression), while the employment error seems slightly better predicted ($R^2 = 0.09$). Notice however that there is no reason for us to expect a high R^2. Even if we had the best possible explanatory model for the bias, regressions could still have a low R^2 because the degree of ex ante uncertainty faced by agents is large. Going back to equations (3) and (4), the ε's are going to have a large variance, and this will mechanistically decrease the regression's R^2.

Second, entrepreneur characteristics come out jointly and separately significant. We interpret this as evidence of different biases across individuals: beliefs indeed are heterogenous in our sample of entrepreneurs, *provided we assume realized shocks were homogenous across entrepreurial observables*, once we control for industry (the Z's in equations 3 and 4). Though this assumption is identifying, we have ways of checking its validity by looking at results across specifications.[14] Some of the variables we described above (education, the project implementing a new idea, the project being a real start-up) seem to predict a bias in expectation that is consistent across years and across expectation error measures. We interpret these two pieces of evidence as showing that these variables are not highly correlated with industry-wide shocks, and that they really describe the heterogeneity of beliefs. Some other variables may still be convincing candidates as explanatory variables of the bias. "Experience in the industry" is only significant to explain employment expectation in 1994, but *always* decreases optimism on employment expectations. In the opposite, entrepreneurs who have accumulated entrepreneurial experience seem, on average, more optimistic when it comes to their development expectations. Last, results on "drive for autonomy" raise a little more suspicion: they come out significant in both pooled regressions, but deliver different results in 1994 and 1998, so we may here control more for project specific shocks rather than explain the bias.

Let us now look closer at the coefficients. In all specifications, education seems to be positively correlated with high expectations when compared to realizations. It is always significant for "low" levels of education, and also significant for high levels of education when we look at "employment" expectation errors. Economically, the effect is not very large, but still worth considering: the *grande école* coefficient is approximately one sixth of the standard deviation for employment expectation errors, and one fifth for the development error. This effect is consistent with education giving self-confidence and endowing potential entrepreneurs with better outside options, thus compelling

[14] We also ran, in unreported results, separate regressions for small and large firms, corporations and sole proprietorships, and start-ups and nonstart-ups. Results were very consistent with the ones we present in table 3, so we chose not to present them to save space.

them to choose the project when their subjective evaluation is higher. The other robust result concerns the novelty of the project. Here, novelty props up expectations, consistent with what experimental psychology predicts. Entrepreneurs implementing their own new idea tend to systematically overestimate their growth prospects. Economically, the effect is smaller than that of education, roughly one tenth of the standard deviation in expectation errors. The coefficient on "real start-up" confirms these results by being positive and strongly significant. Quantitatively, its effect is slightly larger: the coefficient amounts to roughly one fifth of the expectation error standard deviation in both specifications.

Turning to the somewhat less robust findings, serial entrepreneurs are consistently more optimistic in terms of development expectations. This effect is consistent with self serving attribution of outcome, or insufficient updating, or structurally excessive base rate neglect from entrepreneurs who renew the experience. The size of the effect is again roughly one fifth of the standard deviation of development expectation error, but becomes tiny when we look at employment expectation errors. As far as development decisions are concerned, expertise seems to reduce optimism, but the effect is very small - one twentieth of the standard deviation.

We are now set to test the relation between optimism and the use of short term debt that is the main prediction of our model. We start with a nïve assessment of the correlation between the bias in expectation and the use of short term debt.

4.3 Optimism and Short Term Debt: Naïve Regressions

As can be seen from equations (1) and (2), expectation errors Δ_S and Δ_E are noisy measures of the biases b_S and b_E; in this setting, the difference between unbiased expectations and realizations can be considered as measurement error. A simple approach is therefore to regress our measures of short term debt on Δ_S and Δ_E:

$$STD_i = \alpha + \beta.\Delta_i + W_i\delta + \upsilon_i \tag{5}$$

where W_i include standard determinants of the use of short term debt. Before proceeding to the analyses of regression results, let us first discuss the various endogeneity problems that they will face. First, as we just said, expectation errors Δ_i are noisy measures of the expectation biases. Measurement error is likely to bias our results toward zero provided the measurement error u_i is uncorrelated with equation (5)'s residual υ_i.

This is, however, a priori unclear: assume for example, that for some exogenous reason, the banker demands that the entrepreneur borrows short term, and that, because the credit market does not function well, the entrepreneur has to accept. Assume further that short term debt enhances the risk of a liquidity crisis and/or debt overhang and hence of poor firm performance. In this case, firms borrowing short term will have, on average, lower performance. As a result, the entrepreneur will mechanistically have a larger expectation error. Hence, such firms will boost the correlation between expectation error u_i – as a proxy for bad performance – and short term debt ν_i – as a cause of bad performance. This (very) plausible mechanism will generate a positive correlation between capital structure and our measure of optimism, for reasons that have nothing to do with our theory.

A second reason for which the OLS bias could be positive would be a spurious correlation induced by industry or project-specific risks. Assume for example that educated entrepreneurs start internet related projects, which they rationally expect may fail in two years. These companies could be in all industries, but have a specific component that makes their destinies related – faith in the internet, say. Bankers expected this could happen and therefore signed short-term debt contracts. Imagine now that these projects were in fact mostly bad ideas. In this case, these entrepreneurs will appear optimistic (have a positive expectation error) and will have been financed through short term debt, although optimism has, per se, no effect on debt maturity.

Hence, plain OLS estimates of (5) may be biased toward underestimating or overestimating the effect we seek to identify. In a first step, we will content ourselves with controlling for observable characteristics - more on this below. In the next section, we will propose an identifying strategy to deal as much as possible with this problem.

Which controls W_i do we choose? Analyzing the determinants of debt maturity among listed US corporations, Barclay and Smith [1995] argue that firms with higher growth prospects should make more use of short-term debt. The reason is that these firms have smaller collateral and that short-term debt provides the necessary commitment to substitute for it. To control for growth opportunities and available collateral, we use in our sample of small private firms the date-zero share of fixed assets in total assets, as well as 2-digit industry fixed effects as controls. Barclay and Smith [1995] also include firm size as a control for firm quality – high quality firms should be able to raise more long term debt. We therefore include the log of initial total assets as a measure of firm size. As another control for the firm's track record, we add a dummy equal to 1 when the firm is a real start-up. Last, we introduce a year dummy in order to control for potential changes in the yield curve that could affect the tradeoff between long- and short-term debt (see, again, Barclay and Smith [1995]).

Table 4 gathers all results using the date-zero (1994/1998) share of short-term bank debt as a dependant variable. Columns 1-3 in both tables use the employment expectation error, while columns 3-6 use the development expectation error. All regressions allow for a broad form of correlation of error terms for firms within the same industry. As can be noted noted, the number of observations drops dramatically because initial capital structure is available only for a subset of firms (basically those large enough at the end of the creation year to fill in tax forms).

In table 4, columns 1 and 4 report the results including the abovementioned controls. In line with results from Barclay and Smith [1995], larger projects use less short-term debt, as do projects with more tangible assets. More importantly to us, the expectation error about future performance is strongly positively correlated with date zero use of short term debt. The coefficient is significant and stable across specifications, but hovers around 0.03, which is economically small. Given that the standard deviation is 0.6 on expectation errors and 0.4 on shares of short term debt, approximately one twentieth of the variation in short-term debt is explained by optimism. This, however, could be due to measurement error of the bias. The identification strategy we develop in the next section will allow us to deal with this question.

How much do the reported results account for the plausible upward biases discussed above? First, as argued above, our estimate of β could be biased upwards if short-term bank debt could cause bad performance. To deal with this, columns 2 and 5 include a dummy equal to 1 when the firm disappears before its third birthday.[15] Quite comfortingly, the inclusion of the "Death" dummy does not affect our estimates, although some of them lose a little bit of statistical significance. It can be noticed, however, that the "Death" dummy comes out very significant, which suggests that either (1) bankers observe some aspects of the project quality/risk that econometricians do not see, and hence force the firm to accept short-term finance, or (2) short term debt propels firms into liquidity crises and death, and that entrepreneurs of these firms mechanistically have a larger expectation error. Hence, provided the Death dummy captures everything on firm performance, the residual correlation between expectation error and short-term debt becomes more meaningful.

The case for project-specific risk – our second reason for a positive bias – is more tricky. We included in our regressions industry controls, and allowed for a correlation of error terms within industries. Assuming the industry classification correctly accounts for sector heterogeneity, this should help us to get rid of some of the industry shocks. Some project categories, however, cannot be classified in a given industry. Think, for example, of internet-related projects: given their level of risk, these could have possibly been financed through short

[15] We also ran regressions using firm profitability after two years (return on assets) as a measure of subsequent performance. Results were not very different. We chose not to report them because banks are likely to focus more on risk rather than overall profitability when making their lending decisions.

term debt. The fact that they failed renders their entrepreneurs's expectations error positive, and the inclusion of industry dummies will not help us. To account for this, we added as additional controls in equation (5) all entrepreneur and project specific variables used in table 3 to explain optimism. Regressions results are displayed in table 4, columns 3 and 6. As it turns out, they slightly affected our results, but they remained significant. What remains unclear, though, is whether these added controls stand for their own direct effects or the effects of optimism (we saw for instance that education could trigger overoptimism). Such are the limits of the nonstructural approach.

All in all, these first results are encouraging and suggest that our upward bias may not be too large. This, however, remains to be confirmed by a proper instrumenting strategy, to which we turn now.

4.4 Optimism and Short Term Debt: An Instrumental Variable Approach

In this section, we look for instruments of the expectation *bias*, that is, variables affecting the bias of the entrepreneur, but not directly their financing decision. We propose here three instruments motivated by evidence drawn from clinical psychology: sunlight exposure, depression rate and religious belief. These variables are computed at the regional level (there are 22 regions in France).

- **Depression Rate:**
  - *Data:* As an indicator of individual propensity to fall into depression, we use the average share of recorded depressions in a regional population. Data on regional depression rates are obtained from the INSERM web site (a French public insitution devoted to medical research) for both 1993 and 1998. This dataset uses a survey to provide an approximation of the number of people (male or female) admitted to a psychiatric hospital and for whom the diagnosis was either "(affective) mood troubles" or "neurotic troubles, stress, somatic troubles". Some of the patients remain in the hospital, part time or full time, while others return home. We then use population estimates from the labor force survey (*Enquête emploi*, conducted by INSEE, the statistical office) to compute the depression rate at the individual level. Finally, we impute, for each entrepreneur in our sample, the regional depression rate in 1993 for firms started in 1994 and the regional depression rate in 1998 for firms started in 1998. Computed this way, the average depression rate is of course very small, since many depressions are not diagnosed or simply not

treated in the hospital. In the median region in 1994, the fraction of inhabitants admitted to the hospital for depression is a tiny 0.11%. The pervasiveness of depression does not seem to be related to latitude. Regions in the center of France (Auvergne, Limousin) and in the north (Northern Normandy) have the highest depression rate (0.24%). Similarly, a region in the center (Centre), one in the west (Vendée) and one in the north (Southern Normandy) have the lowest depression rates (0.08%).

- *Psychology:* The psychology literature documents large variations in depression rates across regions. These variations can be due to historical influences combined with the strong levels of transmission of psycho-pathologies from parents to children (Cohen, Slomkowski and Robins [1999]). Cultural variations in "social support" can also lead to this effect. Symister and Friend [2003] show that social support is associated with high self-esteem, which in turn increases optimism and leads to decreased depression rates. We believe our local depression rate is a good candidate for predictor of local optimism, as the psychology literature also documents a strong negative link between depression and optimism: according to Alloy and Abramson. [1979], depressed people exhibit more realistic beliefs. Taylor and Brown [1988] argue that being mentally healthy actually requires the ability to sustain overoptimistic beliefs. Agents who do not have this ability are subject to depression.

- **Sunlight:**

  - *Data:* As an indicator for sunlight exposure, we use the number of minutes of sunlight. These data are provided by Meteo France, the public body in charge of collecting weather data over the French territory and of making weather forecasts. For each region, Meteo France provided us with the number of minutes of sunlight received in 1994 and 1998 in a weather station that is representative of regional weather. For each individual, we imputed the percentage of minutes of sunlight at the regional level. For firms started in 1994, we took 1994 data on sunlight, while for firms started in 1998, we took 1998 data on sunlight. In 1994, the yearly percentage of daylight minutes with sunlight in the median region received was 38%. There is here, of course, a clear correlation between latitude and sunlight exposition. Both Provence and Languedoc, on the mediterranean coast received the most sunlight in the country (68% of daylight minutes with sunlight). North Normandy and Pas de Calais both in the north of the country received the least (less than 34% of sunlight minutes).

- *Psychology:* The psychology literature documents a highly positive impact of light exposure on mood. Depressive feelings can result from low light intensity levels and subjects feel better when they are exposed to more light (Summers and Schur [1992]). "Seasonal Affective Disorder" has been documented as a prevalent form of depression that can be treated with light therapy (Magnusson and Boivin [2003]).

- **Religious beliefs:**
  - *Data:* Our indicator of the individual propensity to hold religious beliefs is the fraction of people who feel that they "belong to a religion" within the region. The data source we use is the Survey on Household Behavior (Enquête Permanente sur les Conditions de Vie des ménages, INSEE). Every year since 1998, the October wave of the survey includes questions on religious beliefs. Some 5,600 persons in France are asked whether they (1) practice religion regularly (2) practice relision occasionally, (3) do not practice but feel religious or (4) do not practice religion or feel religious. Using survey data for 1998, we compute the weighted regional fraction of people who answered (1), (2) or (3) to this question. According to this index, the median French region has some 74% of its inhabitants who feel religious (though only some 11% observe a regular religious practice). Again, the geographic distribution of religious beliefs does not confine itself with the north-south axis. The most religious regions are in the east (Franche Comté, Alsace, Lorraine) and in the west (Limousin, Poitou Charentes). The least religious ones are to be found both on the meditarrenean coast (Languedoc, Provence) and in the north-west (Picardie, Normandy). Data constraints prevent us from using the distribution of religious beliefs in 1994; hence, we use 1998 religious beliefs to predict optimism about firms started both in 1994 and 1998. This is not unreasonable, since the cross region variability in religious attitudes is fairly stable over time. Using the 2002 wave of the EPCV survey, we looked at the correlation between the frequencies of religious beliefs in both 1998 and 2002. The correlation coefficient hovered around 50%, and the regression coefficient was close to 0.7.
  - *Psychology:* Strong religious beliefs tend to be correlated with positive physical and mental health outcomes (Seeman, Dubin, and Seeman [2003]). In particular, religious coping is linked to decreased occupational stress and higher well-being in the course of stressful events such as job loss or illness. The effectiveness of religious coping is due to an increased sense of control over the stressful episode

(Tix and Frazier [1998]) and the use of a religious cognitive framework to provide meaning and positive interpretation to negative events (Park and Cohen [1993]). The first years of a start-up being a high-stress episode in which the founder is deeply emotionally involved, we see the local intensity of religious beliefs as a natural candidate to predict optimistic beliefs in our context.

All these instruments are likely to have strengths and weaknesses, in particular since the bulk of the identifying power rests on cross regional, rather than longitudinal, variation. Their weaknesses are however likely to differ. The depression rate could be higher when local economic conditions worsen. Under these circumstances, projects are likely to fare less well, and bankers could be willing to lend more short term. This would induce a positive correlation between the depression rate and short term loans. While there is no perfectly satisfactory way to deal with this, we will include the local level of unemployment[16] as a control both in the first and the second stage regressions. Our two other instruments are less subject to this specific critique, but face others. The sunlight variable is very correlated with latitude; hence, if in the south of France creditor rights are less well enforced, or if economic activity is in general weaker there, commiting to repay short term debt may be the only way to obtain financing. Again, it is not completely possible to escape this critique, but we add a north/south dummy as a control variable. This dummy is equal to 1 when the region is north of the Loire, a river that cuts France in half and is generally thought to be the frontier between the South and North of the country. Note that Aquitaine and Rhone Alpes, two among France's most prosperous regions, are located in the South. Our last instrument, religious belief could be proxying for social capital. There is no a priori reason to expect a positive relation between social capital and short term debt. Using the EPCV survey described above, we have tried to add regional indices of social capital (share of people involved in associations, share of people practicing religion instead of just feeling religious). These indices did not come out as significant determinants of beliefs nor capital structure.

These caveats in mind, we now turn to our first stage regression. We estimate:

$$\Delta_{it,r} = \alpha + \beta_1.\text{DEP}_{rt} + \beta_2.\text{SUN}_{rt} + \beta_3.\text{REL}_r + \gamma.\text{controls}_{it,r} + \varepsilon_{it,r} \qquad (6)$$

where $\Delta_{i,r}$ is the expectation error (employment or development based) of entrepreneur i, starting his firm at date t, in region r. REL_r stands for the regional pervasiveness of religious beliefs as measured in 1998. SUN_{rt} is the share of sunlight time in region r at date t. DEP_{rt} is the regional depression

[16] There are no regional GDP series in France.

rate in region r in 1993 for firms started in 1994, and the same rate in 1998 for firms started in 1998. Controls$_{it,r}$ include (1) industry and year dummies, (2) a dummy equal to 1 when the firm is a real start-up, (3) the regional unemployment rate measured in the year where the firm is started/taken over and (4) the "north" dummy. Given that our instruments are constant within a region, the estimation procedure allows the $\varepsilon_{it,r}$ to be correlated with each other within a given region. We show linear estimation results to facilitate interpretation, but an ordered logit provides similar estimates.

Estimates for equation (6) are provided in table 5. Columns 1-2 use the employment expectation error as a dependent variable, while columns 3-4 use the development expectation. We first provide the results with industry and year dummies as sole controls (columns 1 and 3), and then include the local unemployment rate and the "north" dummy. As it turns out, the number of minutes of sunlight is the strongest of our instruments; the correlation with expectation is positive, as expected, significant and relatively stable across specifications. In line with the message delivered by the low R^2, its economic significance is, however, small. As argued above, this may simply mean that uncertainty is high and that the expectation error above the bias has a large variance. In the first specification, one standard deviation increase in sunlight time (about one hour per day) increases expectation errors by 0.035, or one twentieth of expectation error standard deviation. Our other instruments are significantly correlated with the development expectation error, but again, the economic effects are small (they have the same order of magnitude as sunlight). Note that they have the predicted sign in all specifications.

Hence, although our regional variables have little predictive power over expectation error, they make correct candidates as instruments of the expectation bias. The second-stage regressions are reported in table 6. Columns 1-2 report results using the employment expectation error variable and columns 3-4 use development expectation errors. Columns 1 and 3 include the same control as in the preceeding section (size, tangibility, industry and year dummies). Columns 2 and 4 add the north dummy and the local unemployment rate. We use standard, linear, two stage least square, except that we cluster error terms at the regional level.

With respect to estimates shown in table 4, asset tangibility, and to a lesser extent firm size have similar effects. When included (results not displayed), the Death dummy coefficient is now small and significant. As far as expectation errors are concerned, we lose some statistical significance, but given the weak power of our instruments, the surprise is rather that some results remain significant, at the 10 or 5% level. The coefficient on expectation errors – which this procedure allows to interpret as the coefficient on the bias – hovers around 1, a coefficient 20 times larger than the estimates from tables 4 and 5. A plausible explanation is that, if anything, the straight OLS estimates of those tables were driven down by measurement error, not up by other suspected simultaneity biases. The economic significance of the effect predicted by our theory could now be fairly (too) high. A one-standard-deviation increase in expectation error (0.6) yields an approximate increase of short term debt by 60 percentage points, some 1.2 standard deviation.

5 Conclusion

This paper argues that differences in beliefs exist, have real effects, and therefore do matter in the design of financial contracts. We test a simple model of contracting with optimistic entrepreneurs with data on entrepreneurial expectations and outcomes. We show that there is substantial heterogeneity in beliefs in the data and that this heterogeneity can be partly explained by sociodemographic and psychological characteristics of the entrepreneur. We then establish a positive, robust correlation between optimism and the use of short term debt, using an instrumental variables identification strategy. This correlation is consistent with the main prediction of our financial contracting model.

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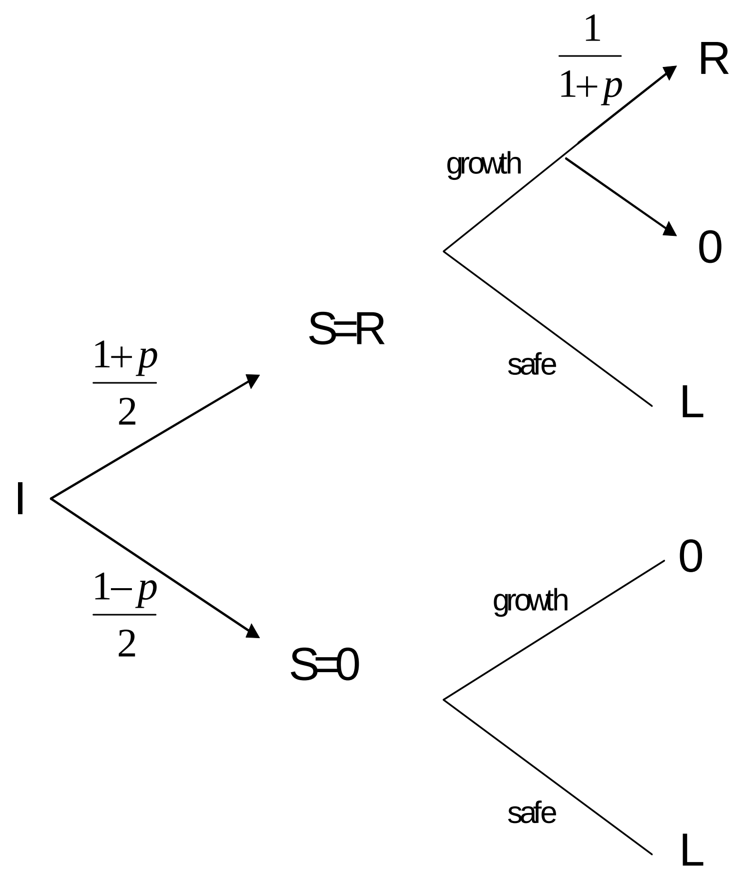

Figure 1: The Business Plan as seen by a Realist

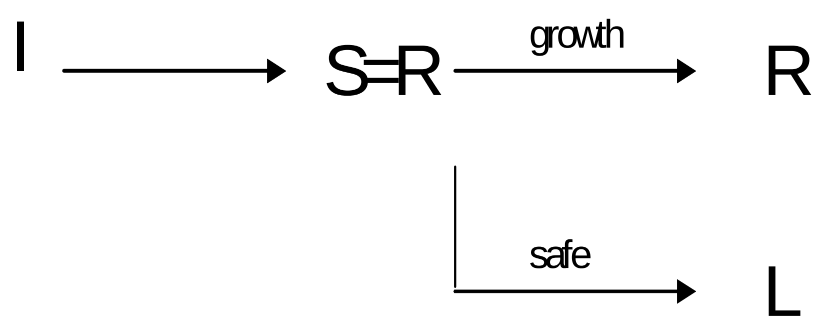

Figure2: The Business Plan as seen by an Optimist

Table 1: Size and Capital Structure of New Firms in 1994 and 1998

	Firm really created		Firm changing hands	
	Sole Prop.	Corp.	Sole Prop.	Corp.
Employment (employees)	0.4	2.5	1.0	5.4
Fixed assets (000 euros)	17	52	71	85
Total Sales (000 euros)	117	244	142	484
Observations	11,007	12,179	8,181	7,415
Equity / (debt + equity)	0.69	0.63	0.52	0.66
Observations	4,639	12,083	10,828	5,181
Short term loans / Bank loans	0.45	0.46	0.27	0.39
Credit lines / Bank loans	0.34	0.36	0.19	0.31
Observations	250	2,750	536	2,305

Source: 1994 and 1998 SINE surveys and tax files. Size indicators and capital structure are measured at the year of firm creation. We restricted ourselves to firms that were first present in the tax file during the survey year (hence 1994 for the first wave, and 1998 for the second one). There are fewer observations for the detailed capital structure because the tax files do not report detailed financing for small businesses (with sales below 230,000 euros). "Corporations" corresponds to firms whose owner enjoys formal limited liability.

Table 2: The Sample Distribution of Expectation Errors

	1994 Survey	1998 Survey
Firm really created		
Employment exp. error = -1	12.1	12.1
Employment exp. error = 0	71.5	68.4
Employment exp. error =+1	16.6	19.5
Development exp. error = -1	27.3	26.1
Development exp. error = 0	55.3	53.7
Development exp. error = +1	17.4	20.3
Firm changing hands		
Employment exp. error = -1	16.6	17.9
Employment exp. error = 0	73.7	69.7
Employment exp. error =+1	9.7	12.5
Development exp. error = - 1	39.4	36.6
Development exp. error = 0	50.0	50.6
Development exp. error = +1	10.6	12.8

Source: Ex ante expectations from 1994 and 1998 SINE surveys. Ex post realizations are from the tax files. The development expectation error is the difference between expectation (a dummy equal to 1 when the entrepreneur initially expects "further development" of his firm) and realization (a dummy equal to 1 if the firm's sales grow by more than 3% over the firm's first two years of existence). The employment expectation error is the difference between an employment expectation (a dummy equal to 1 if the entrepreneur expects to hire in the next 2 years) and an employment realization (whether employment indeed grows by one body, or not). The sample is broken down into firms newly created and already existing firms taken over by the entrepreneur. The sample is also broken down into the 1994 and 1998 survey waves. Reading: expectation errors are therefore equal to +1 when high expectations were not met by realizations, -1 when low expectation were met by good realizations, and 0 when realizations ended up in line with initial expectations.

Table 3: Explaining the Heterogeneity of Beliefs: The Employment and Development Expectation Errors

	All Emp.	1994 Emp.	1998 Emp.	All Dev.	1994 Dev.	1998 Dev.
Entrepreneur Characteristics						
High School Grad.	.03	.04	.03	.06	.05	.07
	(.008)***	(.01)***	(.01)***	(.01)***	(.01)***	(.02)***
College Grad.	.07	.06	.06	.1	.09	.1
	(.01)***	(.02)***	(.01)***	(.02)***	(.02)***	(.02)***
Grandes Ecoles	.07	.05	.08	.13	.12	.14
	(.01)***	(.02)**	(.02)***	(.02)***	(.03)***	(.02)***
Age > 38 years	-.009	0	-.02	-.009	-.004	-.02
	(.007)***	(.009)	(.01)***	(.007)***	(.01)	(.009)***
Entrepreneur is Male	.01	.02	.008	-.009	-.03	-.005
	(.008)*	(.01)	(.01)	(.01)*	(.01)***	(.02)
Serial Entrepreneur	.008	-.004	.02	.07	.07	.07
	(.009)	(.01)	(.01)*	(.009)***	(.01)***	(.01)***
Project Characteritics						
Experience in Industry	-.008	-.009	.004	-.04	-.04	-.03
	(.007)	(.01)**	(.01)	(.009)***	(.01)***	(.01)***
Motive: New Idea	.06	.06	.06	.07	.06	.08
	(.01)***	(.02)***	(.01)***	(.01)***	(.02)***	(.02)***
Motive: Autonomy	.02	.007	.03	.03	.05	.01
	(.006)***	(.01)	(.008)***	(.008)***	(.01)***	(.01)
Real Start-Up	.1	.09	.1	.16	.17	.14
	(.009)***	(.02)***	(.01)***	(.01)***	(.01)***	(.01)***
Year = 1998	.004	.	.	.006	.	.
	(.002)**			(.002)**		
	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	31824	14376	17448	31824	14376	17448
R^2	.05	.06	.06	.09	.1	.11

Source: SINE surveys conducted among entrepreneurs both in 1994 and 1998 for entrepreneur characteristics, expectations, and project characteristics. Accounting data from tax files for sales growth and employment change. Note: Sample includes both start-ups and non start-ups. All regressions include year and 4-digit industry dummies. They allow for a general form of correlation of error terms within industries. Reading: In columns 1 to 3, the dependant variable is the "employment"-based expectation error. In columns 4 to 6, the dependant variable is the "development"-based expectation error. Columns 1 and 4 provide estimates based on the whole sample. Columns 2 and 5 provide estimates based on firms started/taken over in 1994. Columns 3 and 6 provide estimates based on firms started/taken over in 1998. Asterisks indicate the level of statistical significance. *** stands for 1% level of significance, ** for 5% and, * for 10%.

Table 4: Use of Credit Lines and Heterogeneity of Beliefs: Naive Regressions

	Empl.	Empl.	Empl.	Dev	Dev.	Dev.
	(1)	(2)	(3)	(4)	(5)	(6)
Empl. Exp. Error	.03	.02	.02	.	.	.
	(.01)***	(.01)***	(.01)**			
Dev. Exp. Error	.	.	.	.03	.03	.02
				(.009)***	(.009)***	(.009)**
Death in 2 y.	.	.13	.12	.	.13	.11
		(.03)***	(.04)***		(.03)***	(.04)***
Real Start-Up	-.009	-.009	-.02	-.02	-.02	-.02
	(.01)	(.01)*	(.02)**	(.01)*	(.01)**	(.02)**
Pct Tangible Assets	-.48	-.48	-.48	-.48	-.48	-.48
	(.03)***	(.03)***	(.03)***	(.03)***	(.03)***	(.03)***
Log (Initial Assets)	-.03	-.02	-.03	-.03	-.02	-.03
	(.007)***	(.007)***	(.008)***	(.007)***	(.007)***	(.008)***
Year = 1998	-.001	0	-.001	-.001	0	-.001
	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
						.
4-digit Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	5370	5370	4269	5370	5370	4269
R^2	.22	.23	.26	.22	.23	.26

Source: SINE surveys conducted among 30,000 entrepreneurs both in 1994 and 1998 for entrepreneur characteristics, expectations and projects characteristics. Tax files for capital structure, sales growth and employment change. Note: Sample restricted to newly created firms only. The dependent variable is the share of used credit lines in the firm's total bank loans in the year when the firm is created (1994/1998). All regressions use OLS and include year and industry dummies; the estimations of standard errors also allow for a general form of correlation of error terms within industries. Reading: Columns 1-3 use development expectation errors whose distribution is given in table 2 as explanatory variables and various controls. Columns 4-6 use the employment expectation error. Columns 1 and 4 are the simplest specification. Columns 2 and 5 add a dummy equal to one if the firm disappears before its third year of existence. Columns 3 and 6 further add entrepreneur and project characteristics used in table 3 (estimates not reported). Asterisks indicate the level of statistical significance. *** stands for 1% level significance, ** for 5% and, * for 10%.

Table 5: Explaining the Heterogeneity of Beliefs: Sunlight, Depression and Suicide Instruments

	Empl. (1)	Empl. (2)	Dev. (3)	Dev. (4)
Depression	-.14 (.31)	-.08 (.34)	-.77 (.32)**	-.63 (.33)*
Sunlight Exposition	.46 (.13)***	.5 (.18)***	.2 (.05)***	.34 (.12)***
Religious belief 1998	-.02 (.16)	-.04 (.2)	.43 (.16)***	.32 (.15)**
Real Start-Up	.	.11 (.02)***	.	.2 (.02)***
Unemployment rate	.	-.001 (.48)	.	-.23 (.34)
Northern France	.	.01 (.02)	.	.04 (.03)
Year = 1998	.02 (.006)**	.01 (.007)	.03 (.005)***	.02 (.005)***
4-digit Industry Dummies	Yes	Yes	Yes	Yes
Obs.	5371	5370	5371	5370
R^2	.11	.11	.13	.15

Source: SINE surveys conducted among 30,000 entrepreneurs both in 1994 and 1998 for entrepreneur characteristics, expectations and projects characteristics. Accounting data from tax files for sales growth and employment change. Note: Sample includes both taken-over and newly created firms. Dependant variable is "employment" based expectation error. All regressions include year and industry dummies and allow for a general form of correlation of error terms within industries. Columns 1-2 use the employment expectation error as the dependent variable, columns 3-4 use the development expectation error. Asterisks indicate the level of statistical significance. *** stands for 1% level significance, ** for 5% and, * for 10%.

Table 6: Credit Lines and Heterogeneity of Beliefs: IV Results

	Empl.	Empl.	Dev.	Dev.
	(1)	(2)	(3)	(4)
Empl. Exp. Error	.66	1.2	.	.
	(.44)	(.64)*		
Dev. Exp. Error	.	.	.87	1.08
			(.44)**	(.43)**
Unemployment rate	.	-.16	.	.63
		(.65)		(.47)
Northern France	.	.06	.	.006
		(.04)*		(.04)
Real Start-Up	-.08	-.13	-.19	-.24
	(.05)*	(.08)*	(.11)*	(.11)**
Pct Tangible Assets	-.52	-.55	-.47	-.46
	(.04)***	(.08)***	(.04)***	(.04)***
Log (Initial Assets)	-.009	-.008	-.04	-.04
	(.01)	(.02)	(.01)***	(.01)***
Year = 1998	0	-.009	0	-.009
	(.009)	(.01)	(.008)	(.009)*
4-digit Industry Dummies	Yes	Yes	Yes	Yes
Obs.	5370	5370	5370	5370

Note: Sample includes both newly created firms and firms taken over. The dependant variable is the share of credit lines in the year when the firm is created (1994/1998). All regressions use TSLS, instrumenting expectation errors with regional propensity to depression, regional propensity to hold religious beliefs and sunlight exposition. All regressions include year and industry dummies; the estimations of standard errors also allow for a general form of correlation of error terms within regions. Reading: Columns 1-2 use employment expectation errors, while columns 3-4 use developement expectation errors as explanatory variables. Asterisks indicate the level of statistical significance. *** stands for 1% level significance, ** for 5% and, * for 10%.

A Appendix: Data Description

Our dataset is created by merging two sources. The first one is composed of the 1994 and 1998 waves of the SINE survey. In each of these years, the French stastical office (INSEE) sent questionnaires to between a sixth and a fourth of all entrepreneurs who started, took over, or inherited a business in the current year. Answering this questionnaire was compulsory, so that a 85% reponse rate was achieved. Each survey wave (1994 and 1998) was then re-sent questionnaires three years after the business was started/taken over/inherited (in 1997 and 2001), in order to evaluate survival and young firm dynamics. The 1994 wave thus had 30,778 entrepreneurs present in 1994, and only 18,132 still there in 1997, yielding an attrition rate of 41% in three years. Part of this attrition is natural, and part of it is due to firms moving and not being found again by survey managers. The 1998 survey wave had 30,068 entrepreneurs surveyed in 1998, and 27,136 present in 2001.

We thus have a representative sample of new firms. This survey of new businesses has information on the entrepreneur's main socio demographic characteristics (age, education, social background), and on his *growth expectations* as he starts/takes over/inherits the business. Other qualitative questions relate to (1) the reasons for which the firm was started (2) the conditions under which it was started (financing, initial research, customer prospectives) and (3) the management of the first three years of operation (change in product line, agressive commercial policy conducted). The first two types of questions correspond to variables collected in the same year the business is started, while the last type of variables corresponds to answers collected three years after.

The questions asked in this survey are very qualitative in nature. Accounting information (have you used bank credit? who was the major contributor to the start-up capital?) is therefore hardly usable if we want to investigate the real effects of optimism on corporate finance. This is why we matched the SINE datasets with accounting data. The accounting data are compiled from tax reports (Bénéfices Industriels et Commerciaux). They are therefore fairly exhaustive and include all firms making more than 110,000 euros in annual sales. Fortunately, the French statistical system is highly centralized, and firms in both databases share the same 9-digit identifying number, the SIREN. The accounting data are – theoretically – available for every year since the firm first shows up, so they allow us to follow the firms from their start. The available variables are detailed balance sheet information, operating income, and employment. Balance sheet information is more detailed for slightly larger firms. Small firms in France can choose between two ways of reporting their income to tax authorities: the "simplified" and the "regular" tax regime. The regular tax regime becomes compulsory as soon as annual firm sales exceed 230,000 euros, and requires detailed information about the debt structure. Firms that fall into the “simplified” regime are not required to provide as much detail and just need to report the overall amount of financial debt. This will make our observation number drop severely when we wil look at debt.

We match the two datasets, and first remove those firms whose accounts are not reported within their first two years of existence by the tax reports (1994 or 1995 for the first wave, 1998 or 1999 for the second one). We end up with 39,540 firms started either in 1994 or in 1998, present in the SINE surveys, and whose accounts are reported within their first two years of existence. We thus lose almost 20,000 firms in the merging process, but these are overwhelmingly small firms, whose sales are below 110,000 euros, and therefore do not have to complete the tax forms that form the basis of the accounting data.

From the SINE survey we extract several types of variables, that we used in the subsequent analysis.

1. **AGE:** is the entrepreneur’s age, in years. In most regressions, however, we use instead a dummy equal to 1 when the entrepreneur’s age is above the median (37).

2. **EDUCATION:** education is broken down into four possible categories: high school dropout (reference), high school graduate (HSG), College graduate (CG), and Post graduate studies or “*Grande Ecole*” graduate (GE). The last category is especially interesting since the highly selective process to enter French *Grandes Ecoles* is likely to reinforce self-esteem and confidence. To be fair, the questionnaire does not allow us to break down this last category into greandes écoles and post graduate studies, which are relatively frequent in France. This is, however, possible using the Labor Force Survey. Looking at entrepreneurs from the 1991-1993 waves of this survey, we find that more than 80% of the postgraduate-Grande Ecole entrepreneurs are actually graduates from *Grandes Ecoles.*

3. **SERIAL ENTREPRENEURS**: a dummy equal to 1 when the entrepreneur has started at least one business before this one.

4. **EXPERTISE:** a dummy equal to 1 when the entrepreneur has previous experience within the industry. The exact phrasing of the question is: ”In your previous job experiences, did you acquire skills: (1) in the industry you are setting this business in? (2) in a similar activity? (3) in a very different activty? and (4) you have very diverse skills. The EXPERT dummy is equal to 1 when the entrepreneur answers (1).

5. **MOTIVATION: A NEW IDEA:** The question about the entrepreneur’s motivation is “was the main motivation that drove you into start-

ing a firm: (1) a new idea (2) a taste for entrepreneurship, for independance (3) an opportunity (4) other entrepreneurs among family or friends (5) until then unemployed. The answers are nonexclusive, but our IDEA dummy equals 1 when the entrepreneur selects (1).

6. **MOTIVATION: AUTONOMY :**Our AUTONOMY dummy equals 1 when the entrepreneur selects (2) in the above question.

7. **"DEVELOPMENT" EXPECTATION**: Here we use two types of variables. The entrepreneur is asked about his expectations for the next 6 or 12 months, roughly one year after it is started (which can be 1994 or 1998 depending on the survey wave). The question is phrased "What is your view of the future?", and the possible answers are: (1) the firm will develop, (2) the firm will keep its current balance, (3) I will have to struggle (4) I will have to shut down the firm (5) I will sell it (6) I do not know. Our EXPGR1 dummy equals to 1 when the entrepreneur answers (1) and 0 when he answers (2), (3) or (4). Entrepreneurs responding (5) or (6) were removed from estimation.

8. **"HIRING" EXPECTATION:** The second expectation variable is related to employement. Again, the entrepreneur is asked about his expectations for the next 6 or 12 months, roughly one year after it is started (which can be 1994 or 1998 depending on the survey wave). The question is phrased "Do you plan to hire in the next 12 months?", and the possible answers are: (1) yes, (2) no or (3) I do not know. Our EXPEMP1 dummy equals to 1 when the entrepreneur answers (1) and 0 when he answers (2). Entrepreneurs responding (3) were removed from estimation.

B Appendix: Some More Descriptive Statistics

Expectational variables form the focus of our study: summary statistics are displayed in table B1. Expectations are consistent with the business cycle: they improve in 1998 with respect to 1994. Unsurprisingly, a very small number (6%) of all founders already expect difficulties in the year they start their business.

Our empirical methodology partly consists of looking at the entrepreneurial determinants of these expectations. Summary statistics of these determinants, and their relation to firm size, are provided in table B2. It seems that, on average, more experienced entrepreneurs undertake larger projects. When entrepreneurs state "autonomy" as one of their primary motives, they tend

Table B1: Summary Statistics on Expectations

	1994 Survey	1998 Survey
Plans to hire within a year	0.26	0.31
Expects "development"	0.54	0.58
Expects "difficulties"	0.06	0.06
Observations	19,069	11,794

Source: 1994 and 1998 SINE surveys.

Table B2: Summary Statistics on Entrepreneurial Characteristics

	Non Corporation	Corporation	Small	Big
Has already started one business	0.02	0.15	0.07	0.13
Experience in the industry	0.59	0.56	0.55	0.65
Motive: Desire to implement own idea	0.09	0.22	0.15	0.16
Motive: Desire for autonomy	0.58	0.48	0.54	0.50
Entrepreneurs in family	0.44	0.45	0.45	0.44
High school graduate	0.14	0.20	0.17	0.18
College graduate	0.08	0.17	0.11	0.14
Post graduate studies or "Grandes Ecoles"	0.03	0.14	0.08	0.10
Age (years)	35	39	36	38
Male Entrepreneur	0.75	0.77	0.75	0.78
Observations	10,929	10,493	16,360	5,063

Source: 1994 and 1998 SINE surveys. Most variables are dummies, so that the reported means stand for percentage in the category. The only exception is age.

to create smaller firms. But when their motivation is the implementation of an original idea, the firm's size at start tends to be bigger. The existence of entrepreneurs within the family is an important determinant of the decision to start a business, since some 45% of all entrepreneurs already have an entrepreneur in their family. This is consistent with existing studies on entrepreneurs. As it turns out, most entrepreneurs are not even high school graduates, but this is especially true for the ones that start sole proprietorships or small firms (75% of sole proprietors are high school dropouts). When we focus on corporations, a little more than 50% of entrepreneurs turn out to be at least high school graduates, which is much more consistent with national statistics given the age structure of entrepreneurs.[17] Also, older entrepreneurs tend to undertake larger projects. Last, the data have a nontrivial amount of female entrepreneurs (between 25 and 30%), who –weakly– tend to start larger firms.

[17] The proportion of high school graduates among younger people tends to be greater than 50% in France.