Luck and entrepreneurial success[◊]

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Abstract

We conduct a large survey of Swiss entrepreneurs to assess the importance of luck in entrepreneurial performance. In keeping with the literature, we first measure luck with what entrepreneurs consider as unexpected performance. That proxy explains less than 7% of performance. Yet unexpected performance is an incomplete measure of luck, since things like appropriate education are also ex-ante random draws. We therefore ask entrepreneurs to give us their assessment of luck. Even that proxy, however, does not explain more than 17% of performance. Toil, experience, and talent are more important. So are education and business contacts. A battery of tests shows that our estimates are unbiased.

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Those who have succeeded at anything and don't mention luck are kidding themselves.

Larry King, American television and radio host

1 Introduction

Some entrepreneurs turn their ideas into great riches; others are unable to make anything out of theirs. The goal of this study is to investigate what fraction of firm performance depends on luck. The question we are asking is very basic. We want to know how much of entrepreneurial success and failure is the result of deliberate actions, and how much is just coincidence. Are entrepreneurs masters of their destinies or does fate decide for them? Put somewhat differently, we are looking for evidence for the belief that good education, hard work, and dedication, the pillars of work ethic, pay off.

Finding an answer would seem to be quite useful. If success were only the consequence of pure chance, for instance, there would be little for academics to understand when studying entrepreneurial behavior. For practitioners, it would mean that careful planning is fairly futile. Not much would be gained from educating and training entrepreneurs, either. And there would be no reason to stigmatize unsuccessful entrepreneurs (Landier (2006)).

As far as we know, little research has been conducted on the importance of luck as a determinant of entrepreneurial success. We use the term luck, accident, and chance interchangeably. In the finance literature, the analysis of how luck affects performance seems to be confined to the many papers that have examined financial markets, starting with Fama, Fisher, Jensen, and Roll (1969). Hartzmark (1991), for example, shows that the ability of superior traders regresses toward the mean, which indicates that it is luck and not skills that drives performance. Chevalier and Ellison (1999) estimate fund managers' performance alphas and test whether proxies for skills can explain the cross-sectional variation in alpha. They find evidence for a systematic link between the managers SAT scores and the fund's outperformance. However, the explanatory power of skills is only about than 3%. This would seem to imply that luck is responsible for 97% of the variation in performance. Similarly, Kosowski, Timmermann, Wermers, and White (2006) find that a sizable minority of managers pick stocks well enough to more than cover costs, which suggests that luck plays an important role. Barras, Scaillet, and Wermers (2009) confirm this by showing that skilled managers of actively managed funds are exceptionally rare.

In the corporate finance literature, the relevance of luck has attracted comparatively less attention. Some studies have analyzed the influence of luck on executive pay (e.g., Bertrand and Mullainathan (2001)). In the entrepreneurship literature, at least one study is dedicated to the issue of luck, namely Gompers, Kovner, Lerner, and Scharfstein (2009). They report that entrepreneurs who are successful in their first venture are more likely to be successful in their subsequent one. They conclude that successful entrepreneurs have persistent (predictable) market timing abilities and managerial skills as opposed to sheer luck.

Consistent with that paper, one could define luck as unpredictable performance. To measure it, we would need the correct model for expected performance. That seems to be the approach implied by the literature. The mutual funds literature, for example, uses style benchmark returns as proxies for expected performance and the implied alphas as a reflection of fund manager skills (e.g., Chevalier and Ellison (1999)); the residual would therefore seem to reflect pure random effects (luck). The problem with this approach is that we cannot be sure that the model of expected performance is correct. Moreover, the relevant drivers of performance are always measured with error. Hence, it is not clear how much of any model-implied residual performance truly reflects random chance. Still, the first step in our analysis is to follow that approach and use the model of expected performance implied by the extant literature to measure the unexpected component of performance.

The second step of the analysis relies on an extensive survey of entrepreneurs to assess the unexpected component of performance. We ask them whether the performance of their venture is better, worse, or as expected. We therefore rely on their implicit model of performance and use that information to entertain two measures of luck: good and bad luck, respectively. Good luck is a binary variable that identifies entrepreneurs with better than expected performance, whereas bad luck is a binary variable that identifies entrepreneurs with worse than expected performance. We then examine whether these two variables have any power to explain unexpected performance in the preceding model. This yields a lower bound on the importance of luck.

A potential shortcoming of our first two proxies for luck is that we implicitly assume that the drivers of performance in the model are the result of deliberate choice and not themselves an accident. Having the right education, being in the right industry, or picking the right organization could indeed be fortuitous. To gauge how much of firm performance is coincidence and how much is skills and dedication, we therefore ask entrepreneurs directly. Since these opinions could be affected by factors such as previous performance, education, or risk preferences, we take into account the possible influence of these variables. Moreover, we compare the opinion of entrepreneurs to that of non-entrepreneurs.

To our knowledge, this is the first study to measure luck directly. The analysis is based on 8,241 completed questionnaires in a 2007 survey of 63,202 individuals in Switzerland. About one third of the respondents are entrepreneurs who have registered their business between 2002 and 2006, the rest are non-entrepreneurs, including managers and state employees. Our sample of entrepreneurs is similar to that used by Landier and Thesmar (2009) in their analysis of entrepreneurial overconfidence.

We measure performance alternatively as industry-adjusted sales, aggregate income, and return on initial invested capital (ROI). Regressing these variables on various proxies for skills, personal characteristics, and firm characteristics, suggests that luck could be responsible for about 70% of performance. This estimate is lower than that reported in Chevalier and Ellison (1999). Their main model has an R-squared of only 3%, leaving 97% to luck. One possible interpretation is that luck is more pervasive in capital markets than in entrepreneurial ventures.

As it turns out, our luck proxies are related to the unexplained component of performance in our regression model. When we add those proxies for good and bad luck in the regression equation, they have highly significant coefficients. Their marginal contribution to the explanatory power of the regression, which we measure following the approach in Lindeman, Merenda, and Gold (1980) and Kruskal (1987), however, is a mere 7%. Given the measurement error associated with these variables, and given the fact that, as we just said, some drivers of performance, such as gender or entrepreneur's age, are themselves random draws, 7% is probably a lower bound on the importance of luck.

We then ask respondents to rank the importance of six potential determinants of firm performance, namely experience, talent, effort, education, social network, and luck. Based on what survey participants tell us, this list is complete. Accordingly, these six factors are responsible for 100% of the cross-sectional variation in firm performance. Among these factors, luck is clearly the least important one. Education, experience, and effort matter more. Based on the evidence, luck can at best explain one sixth (or 17%) of the variation in performance.

We run a battery of robustness tests concerning our conclusions. For example, the entrepreneurs of successful firms could be blinded by their achievement and assign luck a lesser role than it deserves. Overconfident entrepreneurs might tend to believe the same. Experienced or educated entrepreneurs might also be skeptical. In contrast, risk averse entrepreneurs might believe the opposite. The evidence does not support any of these conjectures. Entrepreneurs seem to have well-balanced convictions. Interestingly, employees and managers have almost exactly the same beliefs. Hence, there is no reason to reject 17% as an upper bound measure of the importance of luck.

The main contribution of this paper is twofold. First, we show that luck plays a role in determining entrepreneurial performance. Prior research has assumed it does, but it has never shown that directly. Second, we find that luck plays a surprisingly small role in determining entrepreneurial performance – namely less than 17%. We arrive at this estimate using survey responses. Traditional investigations do not have that kind of information. They therefore suffer from the problem of not knowing the correct model of expected performance. Moreover, they implicitly attribute to deliberate choice performance drivers that are actually, at least in part, random draws.

A limitation of our study is that our conclusions might not extend to settings other than entrepreneurial ventures. Established firms are probably different. Yet if uncertainty correlates with accident, then luck would seem to play an even smaller role in those firms.

The paper is organized as follows. The next section discusses the data and their source. Section 3 presents the investigative design in more detail. Section 4 examines the empirical results. And Section 5 draws conclusions.

2 Sample and sample characteristics

The sample comes from a survey conducted at the end of 2007 in Switzerland. We used two questionnaires: one for entrepreneurs and one for a control group of managers and employees. The questionnaire contains 54 questions, most of them with subparts, and is nine pages long. The questionnaire was translated from German into Italian and French, the three official languages in Switzerland. The survey questionnaires can be downloaded from the Internet at http://www.ifm.unibe.ch/.

In 2007, we sent the questionnaire for entrepreneurs to 40,000 randomly selected chairmen of the board, co-owners of companies with limited liability, and sole proprietors of new start-ups. We took their addresses from the official Swiss Commercial Register. To make sure these individuals have the relevant information, we focused on recently founded firms, namely in 2002, 2004, or 2006. To assure a random sample of firms, we applied stratified sampling with starting year, legal form, and region as strata. We sent the questionnaire for the control group to 23,202 individuals. These are managers, public employees, teachers, engineers, mechanics, and commercial clerks randomly picked from the official Swiss telephone guide. We used profession and region as strata.

To increase the response rate, we included a cover letter and a return, postage-paid envelope. As a further incentive, respondents could order an analysis report. After two weeks, we sent people a reminder, and gave those who might have misplaced the questionnaire the possibility of getting a new copy by physical mail or e-mail, or from a Web site we created in the Internet. More than 300 ordered a second copy of the questionnaire by mail. Furthermore, we set up a telephone hotline to answer questions about the questionnaire or the survey. Anonymity was promised to each respondent.

The survey sample contains responses from 8,245 individuals. The response rate of more than 13% is comparable to other studies that report a response rate between 7 and 12% for CFOs (Trahan and Gitman (1995), Graham and Harvey (2001), Brav, Graham, Harvey, and Michaely (2005)) and between 16 and 19% for entrepreneurs (Bosma, Van Praag, Thurik, and De Wit (2004) and Forbes (2005)). Out of the 8,245 responses, 3,104 are entrepreneurs and 5,141 are treated as employees. We define entrepreneurs as individuals that hold a participation in the private firm he works for (e.g., Bitler, Moskowitz, and Vissing-Jørgensen (2005), Landier and Thesmar (2009)).[1]

[1] As a robustness we later use a narrower definition of entrepreneurs following Gompers, Lerner, and Scharfstein (2005). There, entrepreneurs have an equity participation and are at the same time the firm's founders or cofounders. 2,778 individuals in our sample are entrepreneurs according to this more restrictive definition.

In conducting our survey, we follow the procedure suggested by Graham and Harvey (2001). Appendix A contains an extensive description of the survey and how it was conducted. The appendix also discusses tests suggested by Graham and Harvey (2001) to assess potential survey biases, such as a non-response bias, a survivorship bias because only entrepreneurs of surviving firms answer our survey, or a self-selection bias. Our analyses and tests suggest that these biases are likely to play no significant role in our results as shown in Appendix A and throughout the paper.

Figure 1 shows the distribution of the fraction of equity owned by the entrepreneurs in our sample (broader definition). In line with Bitler, Moskowitz, and Vissing-Jørgensen (2005), about 70% of our entrepreneurs hold 100% of the firm's equity, and 90% control at least 50%.[2] As shown in Table 1, 44% of the entrepreneurs are sole proprietors, and 24% are shareholders in corporations. Interestingly, 89% of our entrepreneurs have founded their firm, 4% have inherited it, and the rest has bought it from someone else (not shown). As for funding, in 87% of the cases, the firm is funded initially by the founder alone, in 9% by family and friends, and in 1% by strategic investors (not shown).

The firms of the entrepreneurs in the sample are very small when they are started. According to Table 1, the median company starts out with one employee, the average one with 3, and the largest one with 330. By the time they make it into our sample, firms have grown somewhat. The median company has 2 employees, the average 5.62, and the largest 1,190. Most entrepreneurs claim they had no trouble coming up with the start-up money and had no business plan (not shown). Moreover, the companies that acted as incubators for the entrepreneurs in the sample are fairly evenly distributed across firm size: 24% of the entrepreneurs worked for companies with more than 250 employees, and 29% for companies with fewer than 10 employees.

Firms are fairly evenly distributed across 13 industries (not shown). Most companies are either in IT or commerce (17 and 16%, respectively), the fewest are in agriculture and energy (2 and 1%, respectively). Seventy-four percent of the entrepreneurs had no exit plans

[2] It is somewhat surprising to find that some entrepreneurs have less than 20% ownership. There are two possible explanations. First, our survey participants might be presidents but not founders. Second, founders might have divested much of their business already. Bitler, Moskowitz, and Vissing-Jørgensen (2005) make similar observations in their sample. Our results are robust to excluding the few observations where ownership is less than 20% (not shown).

when they started their firms; only 2%were thinking of an eventual IPO; the rest anticipated liquidation, a family succession, or a sale to a competitor, an employee, or a private equity firm (not shown).

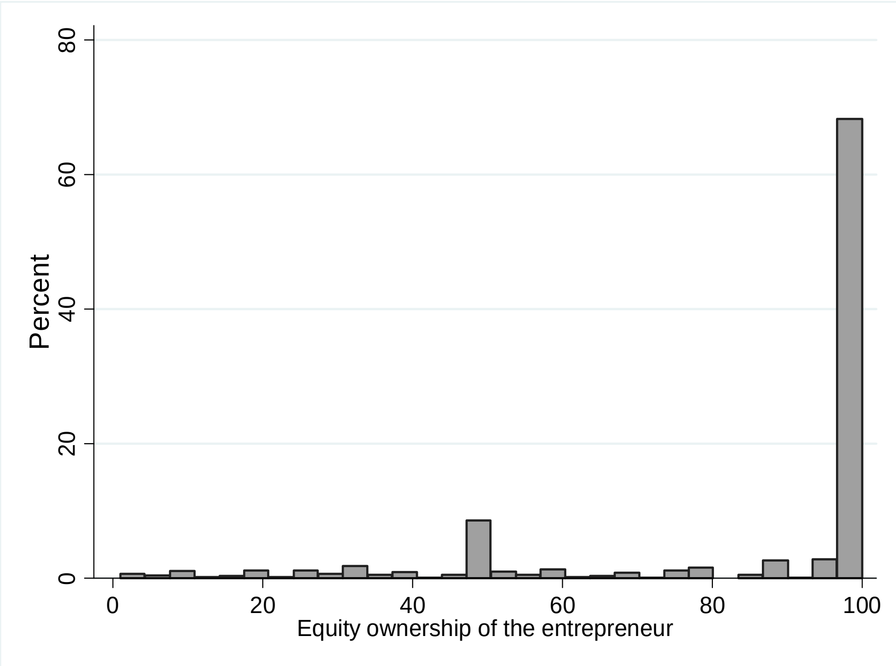

Figure 1: Distribution of equity ownership held by entrepreneurs

3 Investigative Design

We conduct our analysis in two parts. The first part of the analysis estimates a performance regression to assess the unexplained variation in performance. As a first approximation, that component of performance could reflect pure random events. We then introduce a first set of proxies for good and bad luck that are based on the assessment of the entrepreneurs. This allows us to compute the R-squared that are explained by those luck variables and thus obtain a lower bound on the importance of luck. The crucial assumption in this calculation is that we have the correct model for expected performance and valid proxies for its determinants. Moreover, we have to assume that the drivers of expected performance are unrelated to luck. Since these assumptions might not hold, we then gauge the importance of luck by examining what people tell us about luck. The second part of the analysis therefore studies how entrepreneurs assess and rank the importance of luck compared to other drivers of entrepreneurial performance. Moreover, we analyze how consistent that ranking is. We begin with a detailed description of the variables we use.

3.1 *Performance regressions*

Our main interest is to determine the role of luck as a determinant of performance. We therefore estimate the following cross-sectional regression model:

$$\text{Performance}_i = \alpha_i + \beta(\text{skills, personal characteristics, control variables})_i + \varepsilon_i \quad (1)$$

where ε_i is a disturbance term. With the exception of one control variable (entrepreneur's age), and in keeping with the literature, the functional form we choose for the model is linear (the results are robust relative to various nonlinearities and interaction terms). Representative papers that follow this approach are, among others, Bitler, Moskowitz, and Vissing-Jørgensen (2005) and Gompers, Kovner, Lerner, and Scharfstein (2009). As in Bitler, Moskowitz, and Vissing-Jørgensen (2005), performance is measured alternatively as the natural logarithm of the industry-adjusted sales and the natural logarithm of the industry-adjusted aggregate income. We also study the industry-adjusted return on the capital originally invested in the firm (ROI).

Since our survey generates direct proxies for luck, we then estimate equation (1) augmented with our luck variables as follows:

$$\text{Performance}_i = \alpha_i + \beta(\textit{luck}\text{, skills, personal characteristics, control variables})_i + \varepsilon_i \quad (2)$$

To assess the importance of luck, we first obtain an upper bound estimate by assuming that all the unexplained variance in regression (1) is due to luck. However, having the right personal characteristics or skills could also reflect a lucky draw. Hence, the preceding logic could underestimate the importance of luck. To obtain a lower bound, we then compute the increase in R-squared when adding proxies for *luck* in the regression equation (1). We compute the increase in R-squared in two ways. First, we simply take the difference in R-squared between regressions (2) and (1). This procedure assumes that our luck variables are orthogonal to the other independent variables in the model. However, this is unlikely to hold because having the right personal characteristics also could be luck. Second, we employ a procedure suggested by Lindeman, Merenda, and Gold (1980) that averages the marginal contribution that each variable makes to the R-squared of the regression (Kruskal (1987)).

Specifically, the procedure averages the increase in explained variance obtained when adding proxies for *luck* to all possible variations of the regression model (i.e., specifications with different combinations of the regressors).[3] The drawback of this method is that its statistical properties are not well understood. The advantage is that it decomposes the R-squared of the full model into contributions of the different regressors (Grömping (2007)).

Because entrepreneurs are unlikely to be drawn from a random sample of individuals, we run a Heckman (1979) two-stage regression. Put differently, entrepreneurs might possess (unobservable) characteristics that are positively related to the various activities of entrepreneurship and therefore to entrepreneurial performance (Hamilton (2000)). Therefore, we have to correct this possible bias by running the first stage that models the decision of pursuing an entrepreneurial career with the following probit regression:

$$\text{Entrepreneur}_i = f(\text{skills, personal characteristics, identification variables})_i + \nu_i. \qquad (3)$$

where ν_i is a disturbance term. Entrepreneur is a binary variable equal to one if the person is an entrepreneur, and zero otherwise. Although non-linearity of the probit model might already fulfill the exclusion restrictions (Wooldridge (2002), Li and Prabhala (2007)), we include several identification variables such as having entrepreneurial parents. The estimated inverse mills ratio is included in the performance regressions.

3.1.1 Performance measures

We asked respondents about sales, earnings, personal income, and initial invested capital. Based on the replies, we construct three performance measures. The first is the natural logarithm of the industry-adjusted sales, where the industry-adjustment is done by taking the difference between the log of sales of the firm and the log of the median sales in the industry by firms that were started in the same year. We classify firms into 13 different industries. Industry allocation is based on what respondents say. Table 1 shows that the average firm in our sample has CHF 2 million in sales, with a median of CHF 200,000 (the exchange rate is

[3] For example, to obtain the relative importance of x_1 in the case of a regression with two independent variables (x_1, x_2), we take the average of two marginal R-squared. The first marginal R-squared is that of the univariate regression with x_1 as the only regressor. The second is the increase in R-squared when going from a regression with x_2 as the only regressor to a regression with both independent variables as regressors.

about CHF 1.02 to the USD). The sales of the smallest firm are zero, those of the largest are CHF 2.5 billion.

Our second performance measure is the natural logarithm of the industry-adjusted aggregate income in the year 2006, defined as the sum of firm earnings and personal income (Bitler, Moskowitz, and Vissing-Jørgensen (2005)). For tax purposes, entrepreneurs might choose to draw cash salaries and wages from the firm rather than dividends. The problem with this measure is that entrepreneurs report only total personal income, not the income derived from the firm under investigation. Hence, in the case of part-time entrepreneurs, personal income is an upward biased measure of the income derived from the firm. When investigating performance measures that involve personal income, we will therefore focus on full-time entrepreneurs and ignore part-timers.

The third measure of performance is the industry-adjusted return on the capital originally invested in the firm (ROI), which we compute as the ratio of aggregate income in the year 2006 divided by initial invested capital. Table 1 shows that the average (median) aggregate income (firm earnings plus personal income) is CHF 169,000 (119,000), and the average (median) ROI is 421% (220%). To minimize the impact of potential outliers, we winsorize ROI at the 5 and 95 percentiles.

Our sample is more comparable with that of Bitler, Moskowitz, and Vissing-Jørgensen (2005) than with that of Gompers, Kovner, Lerner, and Scharfstein (2009). Whereas, for example, Bitler, Moskowitz, and Vissing-Jørgensen (2005) show median sales of $168,000, only 46.9% of the firms in Gompers, Kovner, Lerner, and Scharfstein (2009) are at the stage of generating revenues, and only 7.3% are profitable. In comparison, 96% of our sample firms report positive aggregate income. The fraction of profitable firms in Bitler, Moskowitz, and Vissing-Jørgensen (2005) is even higher.

The reason for the difference from Gompers, Kovner, Lerner, and Scharfstein (2009) is that they focus on venture-capital (VC) backed entrepreneurs while we look at entrepreneurs in general. Their performance metrics are exit transactions such as IPOs and trade sales rather than the measures we use. Our dataset includes only 60 entrepreneurs (2% of the sample) with VC or business-angel financing.

3.1.2 Luck

Gompers, Kovner, Lerner, and Scharfstein (2009) study whether entrepreneurs who start their second business after a successful first venture do better than first-time entrepreneurs. Since entrepreneurs seem to be able to repeat their past success, the authors conclude that skills are a significant determinant of entrepreneurial success—market timing in the first venture predicts market timing in the second. Implicitly, Gompers, Kovner, Lerner, and Scharfstein (2009) define luck as the unexpected component of performance.

We use the same definition of luck. The problem is that, without the true model of expected performance, it is difficult to tell whether a given measure of unexpected performance really measures luck or the effect of omitted variables in the expectations model. To get around this problem, we ask entrepreneurs directly. Our specific question is: "How was the business performance of your firm since it was started?" Respondents can choose from "better than expected," "as expected," and "worse than expected." On the basis of the answer, we construct two variables: good luck and bad luck. Good luck is a binary variable that identifies entrepreneurs with better than expected performance, whereas bad luck is a binary variable that identifies entrepreneurs with worse than expected performance.

There are two possible shortcomings with our proxies for luck. The first is that they have, in principle, three components: the actual deviation from expected performance, which we call luck, and two potential biases: an overconfidence bias and a look back bias. To see this, note that our survey gives us Δ, the difference between the entrepreneur's ex post stated subjective expectation of performance $E_S\left(\tilde{Y}_T \middle| I_T\right)$ and the realized performance $\tilde{Y}_T$, both measured at time T, the time of the survey. This difference Δ, however, can be decomposed into three parts (see also Landier and Thesmar (2009)):

$$\begin{aligned}\Delta &= E_S\left(\tilde{Y}_T \middle| I_T\right) - \tilde{Y}_T \\ &= E_S\left(\tilde{Y}_T \middle| I_0\right) - \tilde{Y}_T + E_S\left(\tilde{Y}_T \middle| I_T\right) - E_S\left(\tilde{Y}_T \middle| I_0\right) \\ &= \underbrace{E\left(\tilde{Y}_T \middle| I_0\right) - \tilde{Y}_T}_{\substack{\text{deviation from expected} \\ \text{performance (luck)}}} + \underbrace{E_S\left(\tilde{Y}_T \middle| I_0\right) - E\left(\tilde{Y}_T \middle| I_0\right)}_{\text{overconfidence bias}} + \underbrace{E_S\left(\tilde{Y}_T \middle| I_T\right) - E_S\left(\tilde{Y}_T \middle| I_0\right)}_{\text{look back bias}}\end{aligned} \tag{4}$$

where $E\left(\tilde{Y}_T \middle| I_0\right)$ is the rational expectation of $\tilde{Y}_T$, conditional on the information I at time zero. The first component is the rational expectation error $\varepsilon = E\left(\tilde{Y}_T \middle| I_0\right) - \tilde{Y}_T$, which is truly *luck*. It is the difference between the expected performance $E\left(\tilde{Y}_T \middle| I_0\right)$ (under the assumption of having the correct model), relative to the realized performance $\tilde{Y}_T$. The second component represents the *overconfidence bias*, the difference in the ex ante expectation of performance between the subjective model $E_S\left(\tilde{Y}_T \middle| I_0\right)$ and the true (rational) model $E\left(\tilde{Y}_T \middle| I_0\right)$. For example, entrepreneurs might be overoptimistic and (unreasonably) expect their firms to perform better than true expectations would warrant. If so, Δ would be an upward biased estimate of luck. Education, especially management education, could help control for overconfidence and therefore attenuate this bias. To control for this bias and get a more accurate estimate of luck, we include measures of overconfidence, risk aversion, education, and other personal characteristics in our regressions. The third component in the expression for the ex-post measure of unexpected performance is *look back bias*, namely the difference between the subjective expectation of performance at time T and the subjective expectation at time zero, $E_S\left(\tilde{Y}_T \middle| I_T\right) - E_S\left(\tilde{Y}_T \middle| I_0\right)$. Entrepreneurs might not remember exactly what they expected at time zero. Alternatively, they might learn over time and adjust their expectations. Thus, this look back bias might even reduce the potential overconfidence bias.

The second possible shortcoming of our luck proxy is a survivorship bias, since badly performing firms eventually cease to exist and cannot be surveyed. In Table 1 we find that 37% of the respondents claim they had good luck, while only 13% say they had bad luck. The remaining 50% say their performance is as expected.[4] In a very large sample that extends over a long time period, we would expect to see a more symmetric distribution. However, the years 2002, 2004, and 2006 were characterized by very favorable economic conditions with a GDP growth in Switzerland of 2.1% relative to a long-term average of 1.5%. Thus, it is not clear that an unbiased luck measure should have a symmetric distribution during the sample years.[5]

4 Comparing ex ante expectations to ex post realizations, Landier and Thesmar (2009) find that 30% - 45% of their entrepreneurs end up with realizations away from expectations.

5 In fact, there are only small differences in our luck variables if we compare firms who started in the year 2002 with those who started in the year 2004 or 2006. Our results are qualitatively unchanged when including only the entrepreneurs that started their firm at the end of the sample period, namely in 2006. There should be much less survivor bias in this cohort of firms since they haven't had the time to fail. Hence, sample selection is unlikely to materially affect our conclusions.

3.1.3 Skills

Our proxy variable for skills is based on two broad sets of variables, namely education and experience. To assess the extent of education of a person, we follow Parker (2004) and count the number of years of education. We label that variable *education*. Entrepreneurs have, on average, 14.5 years of education compared to employees who have an average of 13.9 years (Table 2). We also use the measure of *balanced management education* proposed by Lazear (2004). This variable takes values between 0 and 5, depending on the number of the following five functional management areas the individual is educated in: marketing, finance and accounting, strategy, human resource management, and organization. The average value in our sample is 1.09 for entrepreneurs and 0.65 for employees.

Proxies for experience include *working experience* (in years, as in Parker (2004)), *industry experience* (years of working in the firm's industry, as in Evans and Leighton (1989)), *managerial experience* (years of managerial experience, following Kim, Aldrich, and Keister (2006)), *previously successful entrepreneur* (binary variable equal to one if the previous venture was financially successful, and equal to zero otherwise, as suggested by Gompers, Kovner, Lerner, and Scharfstein (2009)), and *previously unsuccessful entrepreneur* (dummy variable equal to one if the previous venture was financially unsuccessful). We use the measures of previous success to capture skills not captured by education and experience.

As shown in Table 1, entrepreneurs have an average 24.4 years of working experience, 11.9 in managerial positions, and 15 in the firm's industry. The cross-sectional variation in working, industry, and managerial experience is fairly substantial. The upper quartiles of these variables, for example, are generally more than twice as large as the lower quartiles. More than 20 percent of the entrepreneurs were successful in their prior venture, and only 8 percent were unsuccessful. This asymmetric distribution could reflect the possibility that unsuccessful entrepreneurs are stigmatized and therefore are reluctant to start another venture.

3.1.4 Personal characteristics

Personal characteristics covers various characteristics: gender, marital status, number of children, nationality, risk aversion, overconfidence, and effort. We define *risk aversion* as one minus the percentage of additional hypothetical wealth the respondent would invest in risky assets, namely stocks, mutual fund shares, warrants, puts, calls, structured products, hedge or private equity funds, real estate, commodity futures, commodity funds, and equity invested in the own firm (Cohn, Lewellen, Lease, and Schlarbaum (1975)). *Overconfidence* is the percentage of additional hypothetical wealth the respondent would invest in his/her own company, respectively in the company he works for (Malmendier and Tate (2005)). Table 1 reports an average risk aversion value of 0.3 and an average value of overconfidence of 0.21. This means that the average entrepreneur would be willing to invest 70% of a hypothetical wealth increase in risky assets, but only 21% in his own firm. The correlation between the two variables is only -0.32 (significant at the 1% level). Hence, there are no concerns about multicollinearity.

Bitler, Moskowitz, and Vissing-Jørgensen (2005) show that, consistent with moral hazard models, effort is a significant determinant of entrepreneurial performance. Their proxy for effort is the number of hours worked by survey respondents. We do not have that information. Hence, we use a binary variable equal to one if the person says he is a *part-time entrepreneur*, namely someone with another employment besides his company. Part-time entrepreneurs put less time into their company and should therefore not be as successful as full-time entrepreneurs. Table 1 shows that 30 percent of our entrepreneurs are part-time entrepreneurs. Effort, however, has at least two dimensions (Bitler, Moskowitz, and Vissing-Jørgensen (2005)). One is the number of hours actually worked, and the second is how efficiently those hours were spent. The entrepreneurship literature captures these two dimensions with *age* and *age squared* (Parker (2004)). Presumably, efficiency diminishes with age, an effect that is captured by the squared value of age. We follow Van Gelderen, Thurik, and Bosma (2006) and use these variables as direct proxies for effort. As an additional measure of efficiency, we include a variable that identifies entrepreneurs who were *previously unemployed*. We expect these entrepreneurs to be less efficient.

3.1.5 Firm specific control variables and other variables

We control for firm specific variables such as size, organizational form, ownership, VC backing, and leverage. Our proxies for size are the natural logarithm of the *initial capital* raised at the start of the company (Gimeno, Folta, Cooper, and Woo (1997); Bitler, Moskowitz, and Vissing-Jørgensen (2005)), the natural logarithm of the *number of employees*

(Bitler, Moskowitz, and Vissing-Jørgensen (2005))), and the natural logarithm of *sales*. Furthermore, we include a binary variable that captures regions with a mainly *protestant population*.

Few firms (2%) in our sample claim they have received *VC backing*. Unfortunately, there are not enough observations to run separate tests as in Gompers, Kovner, Lerner, and Scharfstein (2009), but we control for the potential VC influence.[6] We also control for *leverage*, which is particularly important in the regressions involving aggregate income and ROI.

3.1.6 Identification variables

Although exclusion restrictions might be unnecessary in the Heckman selection model due to the non-linearity of the probit model, we include several variables in the selection equation that are not in the performance regressions. If those identification variables are good predictors of the decision to become an entrepreneur (the first stage), the estimated coefficients in the performance regression (the second stage) should be unbiased (Little and Rubin (2002)). A first identification variable is a binary variable which indicates individuals who claim that they made their *career* choice *by chance*. We include this variable because Landier and Thesmar (2009) believe that people do not become entrepreneurs by accident. Additional selection variables are *motivation achievement*, a psychological trait often mentioned in the management literature (Zhao and Seibert (2006)) and *net wealth* (e.g. Holtz-Eakin, Joulfaian, and Rosen (1994)). Other variables that come from the social capital theory are the *firm size of the previous employer* (Gompers, Lerner, and Scharfstein (2005), Sørensen (2007)), having *entrepreneurial parents* (Blanchflower and Oswald (1998)), and being a *member of a business network (*Honig and Davidsson (2000)). All these variables have been shown to affect a person's choice of becoming an entrepreneur. For convenience, all variable definitions are provided in Appendix B.

[6] According to Brav and Gompers (1997), VC backed IPOs perform better than IPOs without VC financing. Direct evidence of the positive impact of VC firms on sales growth is provided by Lee, Lee, and Pennings (2001). VC firms provide consulting assistance (Lee, Lee, and Pennings (2001)), enforce professionalism by hiring a marketing VP (Hellmann and Puri (2002)), facilitate access to supplier or customer networks (Hochberg, Ljungqvist, and Lu (2007)), provide the legitimacy needed to obtain suppliers, employees and customers (Stuart, Ha, and Hybels (1999)), and improve innovation strategies (Da Rin and Penas (2008)).

4 Results

The analysis follows the two steps described in section 3. We first report the regression results of equations (1) and (2) to obtain objective measures of the importance of luck. In the second part, we investigate the survey responses for a subjective measure.

4.1 Regression analysis

4.1.1 Selection regression

The sample for the selection equation is made up of 7,489 observations including 2,348 entrepreneurs and 5,141 non-entrepreneurs (employees). We begin the analysis with firms that fit the broader definition of entrepreneurs, in line with Bitler, Moskowitz, and Vissing-Jørgensen (2005). We run a probit regression with the dependent variable equal to one if the respondent is an entrepreneur, and zero otherwise. The first regression in Table 3 shows coefficients and t-statistics based on the probit model of the Heckman procedure. The regression arguments are grouped in variables that measure skills, personal characteristics, firm-specific characteristics, and identification variables. The McFadden's adjusted R-squared of the probit regression is 28%; 78% of the observations are correctly predicted (56% of the entrepreneurs, and 81% of the employees).

Among the various proxies for skills, *education* and *balanced management education* have a positive and significant coefficient. An additional year of education, for example, increases the probability of pursuing an entrepreneurial career by 0.8% (not shown). *Managerial experience* has a positive effect as well. However, more *industry experience* tends to discourage that career choice. Moreover, individuals with *entrepreneurial experience* are more likely to try again, but only if they were unsuccessful the first time.

Of the personal characteristics, *risk aversion* has a negative effect (Stewart Jr. and Roth (2001)), while *overconfident people* are more likely to choose an entrepreneurial career, consistent with Cooper, Dunkelberg, and Woo (1988) and Bernardo and Welch (2001). Age has a nonlinear impact. The probability of becoming an entrepreneur first increases until age 33, and then declines.

Moreover, unemployed individuals are more likely, whereas married and people with more children are less likely, to try an entrepreneurial career, consistent with Evans and

Leighton (1989). Females are significantly less likely, and individuals in mainly protestant regions are more likely to become entrepreneurs.

Looking at the identification variables, four out of six are significant. Our paper is the first to test and find that entrepreneurs are more likely to say they made their career choice by chance. This is contrary to Landier and Thesmar (2009), who argue that people do not become entrepreneur by accident, but rather out of overconfidence. We show that both – overconfidence and chance – play a significant role in the entrepreneurial decision.

The regression also includes binary variables for six different geographic regions. They have mostly significant coefficients (not shown).

4.1.2 Performance regressions

Table 3 also reports tests of equation (1) after controlling for self-selection with a Heckman two-stage procedure. The number of observations differs across performance proxies as not all respondents provide information on all three measures. We have 2,348 observations for sales, 1,511 for aggregate income, and 1,433 for ROI.

Success or failure in the previous entrepreneurial venture is unrelated to performance. This finding contradicts Gompers, Kovner, Lerner, and Scharfstein (2009), who find performance persistence among successful serial entrepreneurs. To investigate where the difference in results might come from, we repeat the estimation with the same variables that Gompers, Kovner, Lerner, and Scharfstein (2009) use, except for the variables that describe the characteristics of the VC firm, since we do not have that information. With that specification and their OLS approach, we find that previously successful entrepreneurs do indeed repeat (not shown). The same holds when we replicate the analysis with a Heckman two-stage approach (not shown). However, when we add our variables for skills, personal characteristics, and luck the importance of previous entrepreneurial success goes away. Hence, the reason we obtain different results is that we have additional variables that control for person-level characteristics. Thus, one possible interpretation is that the variable "previously successful entrepreneurs" is a proxy for variables not included in Gompers, Kovner, Lerner, and Scharfstein (2009), especially managerial experience, balanced management education, and, possibly, luck. A look at Appendix C confirms that experience and education are correlated. Hence, being successful in one venture could be a proxy for the experience gained, which is correlated with the education, the right personal characteristics, and, possibly, the proper dose of luck.

The results also show that having been unemployed before becoming an entrepreneur has a negative effect on two out of three performance measures, possibly because formerly unemployed people find it harder to obtain capital or because they are relatively less effective entrepreneurs. This finding is consistent with Evans and Leighton (1989), and suggests that pushing unemployed people into entrepreneurship is not necessarily a good idea.

We also find that neither risk aversion nor overconfidence generally affect performance. If anything, overconfidence has a negative impact on ROI. Interestingly, a mean comparison test shows that entrepreneurs are significantly more overconfident and less risk averse than managers (Table 2). Moreover, overconfidence has a positive and significant coefficient in an OLS regression of sales (not shown). Since the inverse mills ratio is significant there might be a selection problem in standard OLS regression equations. This finding supports the notion that tests for the influence of individuals' characteristics (e.g., a CEO's overconfidence) on decision making (e.g., Malmendier and Tate (2005)) and value should use a Heckman procedure with a first stage selection model where the characteristic is allowed to affect a person's choice to control for a potential self-selection bias.

The results indicate that the first of our proxies for effort, part-time entrepreneur, has a significantly negative correlation with sales,[7] consistent with the prediction that entrepreneurs who dedicate less time to their firm do not do as well—more effort improves performance. This result confirms those of Bitler, Moskowitz, and Vissing-Jørgensen (2005). As mentioned above, we also measure effort with age and age squared, in line with Van Gelderen, Thurik, and Bosma (2006). The coefficient on age is positive and that on age squared is negative in the sales regression, although these coefficients are statistically zero.

Finally, sales are negatively correlated with gender (female), but positively with being married and with the number of children. Females could face tighter capital constraints (Parker (2004)). Their firms might therefore be smaller than those of their male counterparts. In addition, individuals who are married or have kids might feel a stronger pressure to succeed to support their family (see, for example, Bernheim, Shleifer, and Summers (1985)

[7] Recall that we have to exclude part-time entrepreneurs from the aggregate income and ROI regressions because they report personal income, including that from other positions they occupy.

for the strategic bequest motive). Divorced individuals and foreigners do not seem to have a differential impact on sales.

With regard to the firm-specific controls, ownership has a negative and significant effect on sales, no significant correlation with aggregate income, and a positive association with ROI. The negative association between ownership and sales is consistent with the OLS findings in Bitler, Moskowitz, and Vissing-Jørgensen (2005). However, ownership might be endogenous. Intuitively, one could argue that entrepreneurs might not have sufficient capital to fund large firms. The problem is that we control for firm size with the logarithm transform of the number of employees. Still, we run a two-stage least squares regression with the same instruments as Bitler, Moskowitz, and Vissing-Jørgensen (2005). Specifically, our instruments are binary variables that identify whether the entrepreneur is the founder and whether he has inherited the firm, age, and age squared. Under that specification, ownership has a positive impact on performance (not shown). However, the test of overidentifying restrictions rejects the validity of the instruments, and the instruments are potentially weak according to the F-test proposed by Staiger and Stock (1997). Therefore, we do not further pursue instrumental variables estimation.

As an additional control variable, the regressions include a binary variable that identifies sole proprietorships. This organizational form means 100% equity ownership. We find that sole proprietorship has a positive effect on ROI and aggregate income, but a negative one on sales. As we just pointed out, the latter result could reflect a size effect, since sole proprietorships are generally one-man shows.

Moreover, we find a positive and highly significant association between initial invested capital and sales, but no significant relation with aggregate income. The same relation holds when we include *number of employees* as a proxy for size. In the ROI regression, we include the *logarithm of sales* instead of initial capital. While sales have a positive influence on ROI, number of employees does not have a significant coefficient. In Bitler, Moskowitz, and Vissing-Jørgensen (2005) both proxies for size are always positively associated with performance. One reason for the difference might be that our sample is based on relatively young firms that might not have reached their profitability potential yet.

VC backing is unrelated to performance. Finally, note that the coefficient of the binary variable which indicates protestant regions is also insignificant.

Assuming our performance model is correct, we can measure the role of luck with the unexplained portion of the cross-sectional variation of firm performance. In the case of sales, luck would therefore be responsible for 67% of that variation; in the case of aggregate income, the contribution would be 84%; and in the case of ROI, it would be 90%. If so, performance would be for the most part the result of luck. The problem is that our model might be misspecified or that we might have omitted important variables. Moreover, the value of some drivers of performance, such as gender, are not actually chosen by the individual but rather randomly assigned to him or her fate. If so, even the explained component of performance could reflect elements of luck.

We therefore examine whether *any* fraction of performance is related to luck as perceived by the entrepreneur. Table 4 replicates the analysis by including our two variables for luck, *good luck* and *bad luck*. To save space, we report only the coefficients associated with these two variables. The other coefficients remain essentially the same as in Table 3. Both dummy variables are highly significant in all three performance regressions. The subjective impression of entrepreneurs is therefore confirmed by the data: perceived luck explains some of the unexpected variation in performance. Note that good and poor luck have a symmetric effect—the absolute value of their coefficients is practically identical except for return on invested capital.

To assess how much our explicit measures of luck can explain, we take the difference in the R-squared for the regressions estimated with and without our luck variables. Using this method, luck explains 5.1%, 4.1%, and 4.2% of the variation in the three performance measures, respectively. This method, however, is only valid if luck is orthogonal to the other independent variables. However, being female or having the right risk aversion could also be luck, at least in some cases. Hence, we also compute the marginal R-squared following Lindeman, Merenda, and Gold (1980) and Kruskal (1987). This method becomes computationally more demanding the larger the number of arguments in the model (Grömping (2007)). We therefore aggregate the independent variables in the following five indices: skills (education and experience), luck, personal characteristics, firm-specific variables, and region. For education and experience, for example, we multiply the observation of each variable in the group by its coefficient estimate of Table 4 and sum across variables in the group. That yields the first observation of the skills index. We follow the same procedure to generate our five indices. We then treat these indices and the inverse Mills ratio as the new regression arguments, and apply the R-squared decomposition method of Lindeman, Merenda, and Gold (1980) and Kruskal (1987). Each index has a regression coefficient equal to one by construction. With this approach, the contribution of luck to the R-squared of the regression is 7.5%, 8.3%, and 5.1%, respectively (Table 5).

Since our proxies for luck are measured as binary variables, these numbers provide only *lower bounds* for the importance of luck. For a better measure of the marginal contribution of luck, we need a different approach. We therefore examine what survey participants answer to direct questions about the relative importance of luck.

4.2 Opinion of entrepreneurs

We asked the survey participants to assess the importance of six performance factors according to a Likert scale. The possible responses they could choose from ranged from *very important* (5) to *very unimportant* (1). We specified six factors, namely luck, experience, talent, effort, education, and social network. We also gave the participants the possibility of mentioning other factors. Only 9% of the entrepreneurs used that opportunity. Moreover, there was no systematic additional success factor.[8]

About 3,000 entrepreneurs participated in the survey. Table 6 details the answers. Column (1) reports the average score assigned to each individual factor across entrepreneurs—remember, the highest score is a 5 and the lowest a 1. Column (2) averages the ranking assigned to each individual factor across entrepreneurs. Column (3) shows the proportion of participants who rank a given factor as the most important, and the proportion who ranked it as the least important. Finally, column (4) indicates for each success factor the proportion of entrepreneurs who give it a score of 5 and 1, respectively.

4.2.1 Ranking of success factors

According to Table 6, luck has an average score of 3.19, which is significantly lower than that of the other five success factors, which, for their part, are deemed to be equally important (column (1)). Average ranks confirm this interpretation: with an average rank of 4.50, luck's

8 The most mentioned additional success factors are stamina, confidence, and family support. However, only 1% of the entrepreneurs mentioned those factors.

relevance comes far after that of the other factors, especially effort, talent, and experience (1.58, 1.61, and 1.94, respectively). Education and availability of the proper networks position in the middle of the scale of importance (column (2)).

Column (3) of the table points out that only about 15% of the respondents think luck is the most important key to success, whereas a whopping 78% regard it as the least important. Among the other factors, effort comes out on top of the rankings—about 75% of the entrepreneurs in the sample consider it as the most important condition for success, and only 15% believe it is the least important. Education and networks rank once again in the middle ground. Finally, column (4) underscores the low relevance of luck: only about 14% of the entrepreneurs in our sample give it the highest score of 5, and as many as 11% give it the very lowest score of 1. In comparison, effort receives the highest score in 72% of the cases and the lowest score in 0.1% of the cases. Interestingly, we also find that almost 58% of the survey participants maintain that start-ups need no luck for success.

Table 7 and Table 8 show the results of a Bonferroni multiple comparison tests which reveal the following order of importance: effort and talent are the most important success factors, followed by experience, education, and network. Luck is by far the least important success factor.

These results have a striking implication for the contribution that luck makes to performance. If the six factors of success were genuine and independent determinants, and if they were equally important, then each one would be responsible for $1/6^{th}$ (17%) of firm performance. Since luck, however, is actually the least important success factor, it should explain less than 17% of entrepreneurial performance (the remaining factors have roughly the same importance).[9]

The obvious reservation at this point is that these rankings are self-reported opinions—and opinions are probably colored by various personal situations. In what follows, we therefore try to assess whether there is evidence of bias in our upper bound estimate of the importance of luck. That analysis is conducted in Table 9.

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[9] The 17% could still be an upward biased estimate if we systematically omitted factors deemed more important than luck. However, as mentioned above, we do not see any evidence for this.

4.2.2 Analysis of different subsamples

We first test whether successful entrepreneurs are more likely to ascribe their success to superior abilities and planning, whereas unsuccessful entrepreneurs blame their failure to bad luck (see Miller and Ross (1975) and Zuckerman (1979) for similar arguments). We therefore split the sample according to performance. Well performing firms have sales that are above the median sales in the group of peers with the same age and in the same industry. As panel A of Table 9 shows, however, the ranking of luck among our six factors of success is the same regardless of firm performance. It always ranks at the bottom, with the same average score and rank across subsamples. The relative ranking is also unaffected for the other five factors. The only marginal effect we can find is that the entrepreneurs of firms that do better believe more strongly that no luck is necessary for start-ups to succeed—the corresponding proportions are 55% among unsuccessful firms and 62% among successful ones.

In panel B, we repeat the analysis and split the sample into firms that, according to their entrepreneur, have performed worse than anticipated, as anticipated, or better than anticipated (i.e., our luck variable in the first part). This should be a more powerful test of performance-driven bias, since entrepreneurs are sorted by their own beliefs. The results, however, are very similar to the ones above.

Another variation of our test is presented in Panel C, where we sort the sample into firms with a previously successful entrepreneur, firms with a previously unsuccessful entrepreneur, and firms with a first-time entrepreneur. The ranking of success factors is again unaffected by this partition.

In general, we find no evidence that performance affects the judgment of entrepreneurs and induces a self-attribution bias (e.g., Puri and Robinson (2007)). Consequently, we cannot reject the claim that entrepreneurs' opinion concerning the importance of luck corresponds to reality.

There are, however, other possible biases. In section 4.1.1 we found that entrepreneurs are on average overconfident and less risk averse. Conceivably, the more confident and less risk averse among them might underestimate the importance of luck. We therefore test if the ranking remains the same if we sort the sample by the degree of risk aversion and overconfidence of the entrepreneurs (Panels D and E). There is no difference across subsamples. Luck clearly remains the least important success factor. And also the ranking of the other factors is unaffected. Some entrepreneurs might even think that they can control outcomes that they have no influence over (e.g., Langer (1975)). While individuals with an internal locus of control believe that their life mainly depends on their personal decisions and effort, individuals with an external locus of control believe that luck and other external circumstances determine their life (Rotter (1966)). Therefore, we split our sample into entrepreneurs with an internal and an external locus of control (see Panel F). Although entrepreneurs with an external locus of control rank luck more highly than those with an internal one, luck is still by far the least important success factor.

Furthermore, we examine whether education, especially management education, or experience affect the perception of entrepreneurs. It could be, for example, that better educated or more experienced entrepreneurs believe they have more control and are therefore less exposed to chance. The analysis is in Panels G, H, and I. The evidence, however, rejects these hypotheses.

We also investigate if founders or starting entrepreneurs, i.e., individuals who recently started a company have different opinions. Especially, the result of the starting entrepreneurs could be interesting because in that sample, there is almost no survivorship bias. Panel J presents the results. Again, luck is the least important success factor and we do not find evidence that a potential survivorship bias affects our inferences.

Finally, it could be that entrepreneurs as a group have a warped perception of reality. As a comparison, we therefore study the ranking of success factors provided by managers and employees. The scores and rankings based on the survey of managers are almost identical, even in their numerical expression, to what entrepreneurs tell us. Luck is at the bottom of the ranking, and the other success factors are about equally important (Panel K).

In untabulated tests, we also compared the rankings across industries and found luck to be consistently the least important factor. Thus, we find no reason to believe that entrepreneurs have a distorted perception of the relative importance of the drivers of success.

In Table 10 we perform an ordered logit regression analysis with the ranking of luck as the dependent variable. Among the dependent variables are proxies for the biases we have investigated in the various panels in Table 9. The regression analysis is designed to test for the significance of the various potential biases which could affect the ranking of luck. The multivariate setting also allows us to test whether the ranking might be influenced if several biases were combined.

The results of Table 10 suggest that people with a high need for achievement or an internal locus of control rank luck lower. The result on internal locus of control is consistent with the interpretation that such individuals might think that they can manage outcomes that are completely outside their control. People with a high need for achievement might also overestimate the importance of effort and therefore underestimate that of luck. Furthermore, previously unsuccessful entrepreneurs rank luck higher, i.e., they experienced failure and therefore could have more realistic assessment of the importance of luck or they blame bad luck for their previous experience. However, the economic significance of these three factors, which could reflect potential biases, is low. For example, the regression suggests that the difference between internal and external locus of control amounts to an average difference in rank of 0.60 (4.50 – 3.90). This estimate is consistent with the difference found in Table 9, Panel F and is thus not significant enough to affect the overall ranking of luck.

In sum, there is no reason we can find to question the claim that the upper bound for the explanatory power of luck is 17%.

5 Policy implications

The data suggest many things one can do to encourage people to pursue an entrepreneurial career. Much of what is done in practice, such as education, proper training, and more financial support, seems to make sense. Public measures, for example, that would lessen risk aversion and boost confidence could also help. For example, most new ventures are started as sole proprietorships. The associated unlimited financial downside probably deters many individuals from becoming entrepreneurs. One way around that problem could be to make it easier to start new ventures under legal forms with limited liability. To achieve that, one could lower the minimum starting capital required for companies with limited liability, or provide public seed money to help entrepreneurs compile the minimum required starting capital. Another measure that could make sense is encouraging suitable business networks to help women overcome their apparent reluctance to choose an entrepreneurial career.

Helping entrepreneurs to be successful seems to be a more difficult task. Nevertheless, education, management as well as industry experience seems to strengthen performance. Besides, public policymakers should question those measures that motivate unemployed individuals to start an own business because their firms have a significantly lower performance, holding all other things equal.[10]

6 Conclusions

The media abound with stories about exciting entrepreneurial success. The obvious question that comes to mind is how much of that success is the predictable result of skills and personal characteristics, and how much the result of sheer luck. Are successful entrepreneurs a special breed of people or are they simply lucky? The evidence uncovered here suggests that entrepreneurs such as Bill Gates are indeed different people, and that their success seems to reflect much more dedication, skills, and personal characteristics than pure luck. Luck plays a surprisingly small role as a determinant of performance. This holds no matter how we measure performance (industry-adjusted sales, aggregate income, and return on initial capital). Among other things, entrepreneurs are typically hard workers, male, more educated (especially in general management), less risk-averse, more overconfident, and wealthier. They have worked for small firms in the past, can rely on business networks, and have fewer children. Often, they become entrepreneurs only by chance.

Of course, becoming an entrepreneur is no guarantee of success, although hard work, skills, experience, and education are crucial. Accident, it might be comforting to know, does not play a big role. In conclusion, coming back to the original question that motivated this paper: are entrepreneurs masters of their destinies or does fate decide? The answer seems to be the former.

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[10] Especially Germany introduced such measures in 2003 with Hartz II (Ich-AG, EXGZ).

Appendix A: Survey Design

Design

The sample comes mainly from a survey conducted at the end of 2007 in Switzerland. We used two questionnaires: one for entrepreneurs and one for a control group of managers and employees. To minimize possible input errors, we scanned the answers as opposed to entering them by hand.[11] The survey questionnaires can be downloaded from the Internet at http://www.ifm.unibe.ch/.

The questionnaire for entrepreneurs focuses on seven topics: company founding, current company data, professional background and education of the entrepreneur, personal characteristics, importance of luck, social environment, and personal financial circumstances. In conducting our survey, we follow the procedure suggested by Graham and Harvey (2001). Specifically, we first took a look at other questionnaires on entrepreneurship. Based on those questionnaires and a careful review of the existing literature, we drafted a first version of the questionnaire in German and circulated it to a group of academics for feedback. We revised the questionnaire on the basis of their critique and suggestions. Then we sought the advice of marketing and psychology scholars on survey design and execution. In particular, we discussed measures to maximize the response rate and minimize possible response biases like, for example, response set bias. Then, we sent the questionnaire to a group of entrepreneurs and managers for a pretest. After a revision of the questionnaire based on their suggestions, we asked a communication expert to look over the design and wording of the questionnaire. Then, we sent it out to several entrepreneurs and managers to make sure that every question was understandable. After some final changes, we finalized the questionnaire. The final version contains 54 questions, most of them with subparts, and is nine pages long. Because Switzerland has three official languages, the questionnaire was translated into Italian and French.

The questionnaire for non-entrepreneurs contains the same questions except for the two company-related sections. Moreover, we added three questions: one about the profession, one about the current employer, and one to find out whether the respondent ever founded a company. The questionnaire for the control group is six pages long; it contains 26 questions, most of them with subparts.

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[11] For that we used the software Cardiff TeleForm v10.

Definition of entrepreneur

In labor economics, researchers often equate entrepreneurship with self-employment, the argument being that self-employed individuals are residual claimants and therefore bear risk, a major entrepreneurial function (e.g. Parker (2004)). Under our broader definition, an entrepreneur therefore holds a financial participation in the firm he works for. This definition is consistent with the one in Bitler, Moskowitz, and Vissing-Jørgensen (2005) or Landier and Thesmar (2009). In contrast, in the spirit of Schumpeter's (1912) notion of innovation, the management literature tends to define entrepreneurs as new business initiators (e.g. Carland, Hoy, Boulton, and Carland (1984)). Under our stricter definition, entrepreneurs have therefore an equity participation and are at the same time the firm's founders or cofounders, consistent with the definition of Gompers, Lerner, and Scharfstein (2005). We use both definitions.

Sample selection and response rates

In 2007, we sent the questionnaire for entrepreneurs to 40,000 randomly selected chairmen of the board, co-owners of companies with limited liability, and sole proprietors of new start-ups. We took their addresses from the official Swiss Commercial Register. To make sure these individuals have the relevant information, we focused on recently founded firms, namely in 2002, 2004, or 2006. To assure a random sample of firms, we applied stratified sampling with starting year, legal form, and region as strata. We sent the questionnaire for the control group to 23,202 individuals. These are managers, public employees, teachers, engineers, mechanics, and commercial clerks randomly picked from the official Swiss telephone guide. We used profession and region as strata.

To increase the response rate, we included a cover letter and a return, postage-paid envelope. As a further incentive, respondents could order an analysis report. We also promised anonymity. After two weeks, we sent people a reminder, and gave those who might have misplaced the questionnaire the possibility of getting a new copy by physical mail, e-mail, or from a Web site we created in the Internet. More than 300 ordered a second copy of the questionnaire by mail. Furthermore, we set up a telephone hotline to answer questions about the questionnaire or the survey.

3,748 individuals filled out the questionnaire for entrepreneurs, for a participation rate of 9.4%. 3,104 are entrepreneurs according to our broader definition, and 2,778 are entrepreneurs according to the restrictive definition. Individuals not classified as entrepreneurs under the broader definition are considered as employees. 4,497 individuals filled out the questionnaire for the control group, which corresponds to a 19.4% participation rate. Of these individuals, 553 are managers, 301 public employees, 1,474 teachers, 568 engineers, 460 mechanics, 410 commercial clerks, and 731 other employees.

All together, 8,245 individuals filled out our questionnaires. The overall response rate of more than 13% is fairly high, considering the length of the questionnaire and the confidential nature of some of the questions. Other studies report a response rate between 7 and 12% for CFOs (Trahan and Gitman (1995), Graham and Harvey (2001), Brav, Graham, Harvey, and Michaely (2005)) and between 16 and 19% for entrepreneurs (Bosma, Van Praag, Thurik, and De Wit (2004) and Forbes (2005)). Only 4,410 individuals, however, filled out the questionnaire completely. To maximize the number of observations in our regression analysis, whenever there are missing data, we use nondisclosure dummies. These binary variables are equal to one if a given respondent does not disclose a particular piece of information, and equal to zero otherwise.

Non-response bias and other issues related to survey data

To examine the possible presence of non-response bias in the data, we follow various approaches. In a first experiment, suggested by Filion (1975) and Armstrong and Overton (1977), we compare the characteristics of the responding individuals to the characteristics of the overall population, namely those in the official Swiss Commercial Register. Comparison is with respect to legal form, registration year, and Canton of registration. The differences are small.

In a second experiment, suggested by Mayer and Pratt Jr. (1966), we compare the characteristics of the responding individuals to those of the people we wrote to, also with regard to legal form, registration year, and Canton of registration. These differences are also small.

In a third test, we compare the responses of individuals who returned the questionnaire on time with those of people who returned the questionnaire only later (see also Mayer and

Pratt Jr. (1966)). According to Filion (1975), the trend of responses over time predicts the direction of the non-response bias, as late respondents resemble non-respondents. As in Graham and Harvey (2001), we therefore test whether the median response of early respondents differs from that of late respondents. We do this for each of the 27 variables in the survey. According to a Wilcoxon rank-sum test, early answers differ from late answers for 12 of the 27 variables with 0.95 confidence (not tabulated). The differences are mostly related to firm characteristics. In contrast, there are no differences with respect to luck, education and experience, and personal characteristics. To examine the importance of this non-response bias, we replicate the analysis for early and late respondents, separately. Our conclusions are unaffected (not shown).

There could also be survivorship bias. Our sampling procedure could induce such a bias because, with the exception of firms started at the end of our sample period (i.e., in 2006), only surviving firms remain in the Commercial Register at any one time. Based on data from the Bundesamt für Statistik und Unternehmensdemographie,[12] we know that 81% of the firms stay in business a year after they were started, 77.2% after two years, 64.9% after three, 60.3% after four, and 49.2% after five years. To assess the potential impact of this survivorship bias, we repeat the analysis by restricting our attention to firms that were started in 2006. The survivorship bias in that subsample should be small, since these firms were just started. As it turns out, our main conclusions remain mostly unaffected.

One final potential bias is self-selection. It could be that entrepreneurs of unsuccessful firms are reluctant to participate in a survey that exposes their failure. If so, successful firms would tend to be overrepresented in our sample. We cannot exclude this possibility, although we do not think the problem is serious. First, we guaranteed anonymity. Second, the questionnaire we sent came in an envelope very similar to that of the fiscal and the regulatory authorities. It seems that many people filled out the questionnaire thinking they participated in a mandatory survey. Third, successful firms are probably equally reluctant to disclose their success for fear of attracting competition. Fourth, close to 20% of our sample firms actually report negative earnings during a period of overall economic growth. And fifth, we checked whether early respondents differ from late respondents with respect to profitability. If unsuccessful entrepreneurs are hesitant to fill out the questionnaire, and if late respondents

[12] See BFS (2009) for details.

are similar to non-respondents, then late respondents should be less profitable than early respondents. Mean and median comparison tests, however, reject the hypothesis of a difference with respect to sales, firm earnings, and personal income (not shown). Hence, there is little reason to believe that our regression results are biased.

We have two further concerns. One is that respondents might not answer truthfully. We think this problem is minimal because the survey is anonymous. We make the respondents aware of this anonymity twice: in the personal letter and in the questionnaire. Our second concern is that the questions might have been misunderstood. We address this issue in four different ways: first, wherever possible, we used questions from past surveys in the literature. For example, to assess an individual's need for achievement, we used standard questions from McClelland (1961) in the psychology literature. Second, prior to sending out the questionnaire, we pre-tested the questions with several entrepreneurs and managers with different educational backgrounds and personal characteristics to make sure they are understandable. Third, we showed the questionnaire to a communications expert and made revisions based on her advice. Finally, we asked the respondents to indicate what questions were hard to understand. Only 9% claimed that the questionnaire was difficult to understand–and, in most cases, they struggled with only one question. Dropping these individuals from the sample has no material effect on our conclusions (not shown).

Appendix B: Definitions of all the variables used in the analyses

Variable	Description
Panel A: Measures of luck	
Career by chance	Binary variable equal to 1 if the individual claims that he made a career by chance, and equal to 0 otherwise;
Good luck	Binary variable equal to 1 if the entrepreneur claims his business performed better than expected, and equal to 0 otherwise;
Bad luck	Binary variable equal to 1 if the entrepreneur claims his business performed worse than expected, and equal to 0 otherwise. There are entrepreneurs claiming that business turned out as expected;
Panel B: Measures of skills	
Education	Years of education, as in Parker (2004);
Balanced management education	Number of different functional areas in management the entrepreneur is educated in, as in Lazear (2004). In particular, this variable ranges between 0 and 5, with 5 meaning that the individual is educated in marketing, finance and accounting, strategy, human resource management, and organization;
Age	Number of years since birth;
Working experience	Years of working experience, as in Parker (2004);
Industry experience	Years of working experience in the firm's industry, as in Evans and Leighton (1989);
Managerial experience	Years of managerial experience, as in Kim, Aldrich, and Keister (2006);
Previously successful entrepreneur	Binary variable equal to 1 if the prior venture of the serial entrepreneur was financially successful, and equal to 0 otherwise, consistent with Kim, Aldrich, and Keister (2006). A serial entrepreneur is an entrepreneur who started a business before the existing one;
Previously unsuccessful entrepreneur	Binary variable equal to 1 if the prior venture of the serial entrepreneur was not financially successful, and equal to 0 otherwise;
Panel C: Measures of personal characteristics	
Risk aversion	One minus the percentage of additional hypothetical wealth the respondent would invest in risky assets. Risky assets are stocks, mutual fund shares, warrants, puts, calls, structured products, hedge or private equity fund shares, real estate, commodity futures, commodity funds, and equity invested in own firm, as in Cohn, Lewellen, Lease, and Schlarbaum (1975);
Overconfidence	Percentage of additional hypothetical wealth the respondent would invest in his/her own company, respectively in the company the respondent works for, as in Malmendier and Tate (2005);
Need for achievement	Binary variable equal to 1 if individual has a high level of motivation achievement. Persons with a strong need for achievement set challenging goals and work hard to achieve them (see McClelland (1961)). Binary variable created on the basis of statements taken from Lynn (1969) and Tucker (1988);
Locus of control	Binary variable equal to 1 if individual has an internal locus of control. Individuals with an internal locus of control believe that their life mainly depends on their personal decisions and effort (Rotter (1966)). Variable created on the basis of statements taken from Koh (1996) and Entrialgo, Fernandez, and Vázquez (2000);
Part-time entrepreneur	Binary variable equal to 1 if entrepreneur has another job, and equal to 0 otherwise, similar to Giannetti and Simonov (2008);

Panel D: Firm-specific control variables and other variables	
Ownership	Entrepreneurial ownership in precent, as in Bitler, Moskowitz, and Vissing-Jørgensen (2005);
Sole proprietorship	Binary variable equal to 1 if firm is a sole proprietorship, and equal to 0 otherwise;
Initial capital	Capital raised at the start of the company, as in Gimeno, Folta, Cooper, and Woo (1997), adjusted for the formation year of the company by compounding at the risk free rate;
Current equity	Firm equity;
Sales	Firm sales;
Employment	Current number of employees, as in as in Bitler, Moskowitz, and Vissing-Jørgensen (2005);
Leverage	Current debt/equity ratio;
Venture capital backed	Binary variable equal to 1 if firm is venture capital or business angel backed, as in Brav and Gompers (1997);
Protestant region	Binary variable equal to 1 if entrepreneur lives in a region with mainly protestant population;
Panel E: Measures of firm performance	
Industry-adjusted log(sales)	Natural logarithm of firm sales minus the sample median in the industry with the same firm formation year;
Industry-adjusted log(aggregate income)	Natural logarithm of firm earnings plus personal income of the entrepreneur minus the sample median in the industry with the same firm formation year;
Industry-adjusted return on initial capital	Aggregate income after taxes as a percent of initial capital, winsorized at the 5 percent and 95 percent tails minus the sample median in this industry with the same firm formation year;

Appendix C: Correlation Matrix

Correlation matrix of all variables used in the second stage of the regression analysis. The sample comprises 2,458 entrepreneurs, defined as individuals who work at least part time in a company in which they hold a financial stake. All variables are defined according to appendix B. Bold denotes statistical significance at the 5% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)
Education (1)	1.00																								
Balanced management education (2)	**0.12**	1.00																							
Working experience (3)	-0.01	**0.08**	1.00																						
Industry experience (4)	-0.03	0.01	**0.56**	1.00																					
Managerial experience (5)	**0.09**	**0.16**	**0.66**	**0.42**	1.00																				
Previously successful entrepreneur (6)	**0.07**	**0.07**	**0.14**	**0.04**	**0.24**	1.00																			
Previously unsuccessful entrepreneur (7)	-0.01	0.00	0.01	**-0.05**	-0.02	**-0.16**	1.00																		
Good luck (8)	**0.05**	**0.07**	0.01	**0.09**	**0.06**	0.00	-0.03	1.00																	
Bad luck (9)	-0.01	0.00	-0.01	**-0.09**	**-0.06**	0.00	**0.07**	**-0.30**	1.00																
Risk aversion (10)	**-0.14**	**-0.05**	0.01	**0.05**	**-0.06**	**-0.08**	0.00	**-0.04**	0.02	1.00															
Overconfidence (11)	0.03	0.01	**-0.06**	**-0.04**	-0.01	**0.05**	0.01	**-0.05**	0.01	**-0.32**	1.00														
Part-time entrepreneur (12)	**0.10**	0.03	**-0.06**	**-0.16**	0.00	**0.13**	0.01	**-0.11**	**0.12**	-0.03	0.01	1.00													
Age (13)	**0.11**	**0.05**	**0.86**	**0.47**	**0.65**	**0.18**	0.03	-0.02	0.02	-0.02	**-0.06**	**-0.04**	1.00												
Previously unemployed (14)	**-0.04**	-0.01	0.03	**-0.05**	**-0.04**	-0.03	**0.06**	**-0.05**	**0.11**	0.01	-0.01	**-0.05**	**0.04**	1.00											
Female (15)	**-0.09**	0.00	**-0.11**	**-0.14**	**-0.18**	**-0.09**	0.01	-0.02	0.01	**0.04**	**-0.06**	0.00	**-0.08**	0.01	1.00										
Married (16)	**0.04**	0.01	**0.22**	**0.17**	**0.18**	**0.04**	0.00	0.02	**-0.05**	0.00	-0.03	-0.02	**0.25**	-0.01	**-0.08**	1.00									
Divorced (17)	-0.03	0.02	**0.07**	0.02	**0.05**	0.03	0.01	**-0.05**	**0.05**	-0.01	0.03	0.00	**0.10**	**0.05**	**0.07**	**-0.42**	1.00								
Number of children (18)	0.03	-0.01	**0.21**	**0.14**	**0.23**	**0.07**	0.02	**0.04**	**-0.04**	**-0.07**	0.02	0.02	**0.29**	-0.01	**-0.06**	**0.38**	**0.04**	1.00							
Foreigner (19)	0.03	**-0.09**	**-0.13**	**-0.07**	**-0.09**	0.00	0.03	**-0.04**	0.00	-0.03	**0.04**	**-0.05**	**-0.09**	0.02	0.02	0.00	0.00	-0.03	1.00						
Ownership (20)	**-0.14**	**-0.10**	0.03	**0.04**	**-0.05**	**-0.10**	-0.03	-0.02	-0.02	**0.04**	-0.02	**-0.10**	0.02	**0.05**	**0.06**	**-0.04**	**0.05**	-0.01	0.02	1.00					
Sole proprietorship (21)	**-0.17**	**-0.14**	**-0.05**	**-0.06**	**-0.16**	**-0.14**	-0.01	**-0.05**	0.02	**0.11**	-0.03	**-0.04**	**-0.06**	**0.10**	**0.14**	**-0.08**	**0.05**	**-0.06**	0.02	**0.49**	1.00				
Log(initial capital) (22)	**0.04**	**0.06**	**0.05**	**0.05**	0.10	**0.04**	0.00	0.02	0.03	**-0.11**	**0.10**	**-0.04**	**0.06**	-0.01	**-0.09**	0.02	0.02	**0.06**	-0.01	**-0.14**	**-0.19**	1.00			
Log(employment) (23)	**0.04**	**0.09**	0.03	**0.11**	**0.14**	-0.02	-0.01	**0.17**	**-0.16**	**-0.08**	**0.06**	**-0.24**	0.03	**-0.07**	**-0.06**	**0.05**	-0.03	**0.08**	0.01	**-0.13**	**-0.20**	**0.19**	1.00		
Leverage (24)	-0.05	0.01	-0.03	-0.04	-0.04	0.01	0	-0.04	0.04	0	0.02	0.01	-0.04	0.02	-0.03	0	-0.02	-0.01	-0.05	**-0.06**	**-0.10**	**0.11**	-0.01	1	
Venture capital backed (25)	**0.08**	**0.06**	-0.02	-0.03	0.01	0.03	0.03	-0.02	0.02	-0.03	0.02	-0.01	0.00	-0.03	-0.01	-0.01	0.01	-0.01	0.01	**-0.24**	**-0.11**	**0.09**	**0.11**	0.11	1.00

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Table 1
Summary Statistics of Entrepreneurs
Descriptive statistics for the various variables. The sample comprises 3,057 entrepreneurs, defined as individuals who work at least part time in a company in which they hold a financial stake. Only entrepreneurs that disclosed all information is included in these statistics. Variable definitions are provided in the Appendix.

Variable	Mean	Min	Lower quartile	Median	Upper quartile	Max	S.D.	N
Panel A: Entrepreneurial luck								
Good luck	0.37	0.00	0.00	0.00	1.00	1.00	0.48	3,048
Bad luck	0.13	0.00	0.00	0.00	0.00	1.00	0.34	3,048
Panel B: Entrepreneurial skills								
Education	14.47	9.00	12.50	14.00	15.50	23.50	2.47	3,034
Balanced management education	1.09	0.00	0.00	1.00	2.00	5.00	1.39	3,034
Working experience	24.42	0.00	17.00	24.00	30.00	63.00	10.56	3,026
Industry experience	14.99	0.00	6.00	13.00	20.00	61.00	10.42	3,037
Managerial experience	11.93	0.00	4.00	10.00	18.00	50.00	9.89	3,008
Previously successful entrepreneur	0.23	0.00	0.00	0.00	0.00	1.00	0.42	3,051
Previously unsuccessful entrepreneur	0.08	0.00	0.00	0.00	0.00	1.00	0.27	3,051
Panel C: Personal characteristics								
Risk aversion	0.30	0.00	0.10	0.25	0.50	1.00	0.25	2,983
Overconfidence	0.21	0.00	0.00	0.11	0.28	1.00	0.23	2,983
Part-time entrepreneur	0.29	0.00	0.00	0.00	1.00	1.00	0.46	3,051
Age	45.10	20.00	38.00	44.00	52.00	86.00	10.20	3,035
Previously unemployed	0.04	0.00	0.00	0.00	0.00	1.00	0.20	3,103
Female	0.18	0.00	0.00	0.00	0.00	1.00	0.39	3,038
Married	0.64	0.00	0.00	1.00	1.00	1.00	0.48	3,057
Divorced	0.09	0.00	0.00	0.00	0.00	1.00	0.29	3,057
Number of children	1.36	0.00	0.00	1.00	2.00	9.00	1.29	3,068
Foreigner	0.16	0.00	0.00	0.00	0.00	1.00	0.37	2,958
Panel D: Firm-specific control variables and other variables								
Ownership (percentage)	85.31	1.00	80.00	100.00	100.00	100.00	25.91	3,104
Sole proprietorship (proportion)	0.44	0	0	0	100	100	50	3,087
Initial capital in thousand	193	0	22	53	116	16'500	831	193
Current equity in thousand	856	0	41	118	312	200,000	7,970	1,332
Initial employment	3	0	1	1	2	330	8.66	2,956
Current employment	5.62	0	1	1.75	4	1,190	36.76	2,979
Leverage (proportion)	0.72	0.00	0.00	0.00	0.25	47.08	2.94	1,301
Venture capital backed (proportion)	0.02	0.00	0.00	0.00	0.00	1.00	0.14	3,000
Protestant region	0.53	0.00	0.00	1.00	1.00	1.00	0.50	2,956
Panel E: Firm performance								
Firm sales in thousand	2,010	0	70	200	600	2,500,000	48,800	2,697
Aggregate income in thousand	169	-3,330	60	119	190	5,370	308	1,586
Return on initial capital	4.21	0.06	0.81	2.20	5.63	19.75	5.10	1,457
Personal income in thousand	110	0	50	62	125	1,000	123	2,960

Table 2
Summary Statistics of Entrepreneurs and Employees
Means (frequencies for binary variables), standard deviations, and differences in means between entrepreneurs and employees, z-values are based on a Mann-Whitney test. Entrepreneurs are defined as individuals who work at least part time in a company in which they hold a financial stake. The sample consists of 2,485 entrepreneurs and 3,467 employees. Variable definitions are provided in the Appendix. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) level.

	All individuals		Entrepreneurs		Employees		Difference in	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Means	z-value
Panel B: Entrepreneurial skills								
Education	14.12	2.34	14.47	2.47	13.92	2.24	0.55***	-11.89
Balanced management education	0.82	1.23	1.09	1.39	0.65	1.09	0.44***	-15.76
Working experience	28.27	11.81	24.42	10.56	30.59	11.92	-6.17***	23.37
Industry experience	19.49	12.63	14.99	10.42	22.30	13.07	-7.30	24.22
Managerial experience	12.35	11.60	11.93	9.89	12.62	12.56	-0.70***	-2.61
Previously successful entrepreneur	0.18	0.38	0.23	0.42	0.14	0.35	0.09***	-9.79
Previously unsuccessful entrepreneur	0.06	0.24	0.08	0.27	0.05	0.21	0.03***	-5.60
Panel C: Personal characteristics								
Risk aversion	0.38	0.28	0.30	0.25	0.43	0.29	-0.13***	19.74
Overconfidence	0.13	0.21	0.21	0.23	0.08	0.17	0.14***	-37.30
Age	50.50	13.00	45.10	10.20	53.74	13.42	-8.64***	28.56
Previously unemployed	0.03	0.16	0.04	0.20	0.02	0.13	0.02***	-6.00
Female	0.23	0.42	0.18	0.39	0.26	0.44	-0.08***	8.40
Married	0.68	0.47	0.64	0.48	0.70	0.46	-0.06***	5.70
Divorced	0.09	0.28	0.09	0.29	0.08	0.27	0.01	-1.11
Number of children	1.56	1.33	1.36	1.29	1.68	1.34	-0.32***	11.22
Foreigner	0.12	0.32	0.16	0.37	0.09	0.28	0.08***	-10.27
Panel D: Firm-specific control variables and other variables								
Protestant region	0.50	0.50	0.53	0.50	0.48	0.50	0.05***	-4.28
Identification variables								
Career by chance	0.67	0.47	0.73	0.44	0.63	0.48	0.10***	-8.94
Motivation achievement	0.37	0.48	0.43	0.50	0.33	0.47	0.10***	-8.34
Net wealth	12.56	1.81	12.63	1.85	12.52	1.79	0.11**	-1.84
Former employer: small firm	0.37	0.48	0.53	0.50	0.28	0.45	0.25***	-23.16
Entrepreneurial parents	0.27	0.44	0.32	0.47	0.23	0.42	0.09***	-8.44
Member of business network	0.10	0.31	0.16	0.37	0.07	0.25	0.09***	-13.03

Table 3
Performance of Entrepreneurial Firms
Heckman's two-step procedure with nondisclosure dummies (not reported). In the selection equation, the dependent variable takes value 1 if an individual is an entrepreneur and zero otherwise. Entrepreneurs are defined as individuals who work at least part time in a company in which they hold a financial stake. In the second stage, the dependent variables are the industry-adjusted logarithm of firm sales, the industry-adjusted logarithm of aggregate income, and the industry-adjusted return on equity, respectively. Variable definitions are provided in the Appendix. The sample compromises 7,495 individuals in the selection equation and 1,433 (return on initial capital) to 2,348 entrepreneurs (firm sales) in the performance regressions. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) level.

	Selection equation (probit)		Industry-adjusted log(firm sales)		Industry-adjusted log(aggregate income)		Industry-adjusted return on initial capital	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
Panel B: Entrepreneurial skills								
Education	0.024***	2.916	0.002	0.148	0.031**	2.200	0.143***	2.841
Balanced management education	0.089***	6.038	0.043**	1.976	0.030	1.234	-0.094	-1.090
Working experience	0.005	1.599	0.001	0.254	0.002	0.241	-0.022	-0.931
Industry experience	-0.007***	-3.536	0.010***	3.046	0.002	0.495	0.028**	2.033
Managerial experience	0.015***	6.765	0.011**	2.464	0.013***	2.652	0.012	0.662
Previously successful entrepreneur	0.023	0.475	0.087	1.205	0.074	0.907	-0.033	-0.112
Previously unsuccessful entrepreneur	0.309***	4.170	0.024	0.223	0.042	0.352	0.227	0.529
Panel C: Personal characteristics								
Risk aversion	-0.428***	-5.810	-0.082	-0.658	-0.096	-0.714	-0.483	-0.985
Overconfidence	1.090***	11.593	-0.046	-0.307	-0.252	-1.511	-2.869***	-4.696
Part-time entrepreneur			-0.416***	-6.294				
Age	0.072***	5.776	0.028	1.326	0.011	0.506	-0.114	-1.383
Age squared	-0.001***	-8.924	-0.000*	-1.919	-0.000	-0.738	0.001	1.370
Previously unemployed	0.484***	4.359	-0.418***	-2.651	-0.448***	-2.738	-0.524	-0.909
Female	-0.433***	-9.344	-0.229***	-2.757	-0.134	-1.430	0.097	0.280
Married	-0.083*	-1.682	0.167**	2.270	0.122	1.506	-0.260	-0.894
Divorced	0.136*	1.814	0.091	0.796	0.064	0.511	-0.762*	-1.659
Number of children	-0.070***	-4.363	0.068***	2.704	0.011	0.366	0.075	0.716
Foreigner	0.227***	4.050	-0.012	-0.151	0.046	0.519	1.018***	3.132
Panel D: Firm-specific control variables and other variables								
Ownership			-0.004***	-3.178	-0.001	-0.394	0.016***	3.150
Sole proprietorship			-0.603***	-8.993	0.147**	2.004	1.033***	3.826
Log(initial capital)			0.078***	7.126	0.013	1.012		
Log(sales)							0.169*	1.850
Log(employment)			0.310***	15.535	0.154***	6.090	-0.097	-1.001
Leverage			0.038***	2.899	-0.018	-1.025	-0.117**	-2.376
Venture capital backed			0.329	1.437	-0.110	-0.453	-0.949	-1.162
Protestant region	0.123***	2.735	-0.077	-1.074	-0.095	-1.205	-0.377	-1.291
Selection equation (identification variables)								
Career by chance	0.123***	3.136						
Need for achievement	0.057	1.505						
Log(net wealth)	0.073***	5.222						
Former employer: small firm	0.511***	13.709						
Entrepreneurial parents	0.044	1.118						
Member of business network	0.388***	6.763						
Inverse Mills ratio (λ)			-0.271**	-2.179	0.031	0.234	0.096	0.200
Constant	-2.802***	-8.075	-0.921*	-1.688	-0.905	-1.524	-0.537	-0.221
Region dummies	Yes		Yes		Yes		Yes	
Number of observations	7,495		2,349		1,499		1,421	
R-squared	0.284		0.326		0.155		0.101	
Adjusted R-squared	0.274		0.311		0.127		0.069	
Correctly predicted	78.00%							

Table 4
Performance of Entrepreneurial Firms

Heckman's two-step procedure with nondisclosure dummies (not reported). In the selection equation, the dependent variable takes value 1 if an individual is an entrepreneur and zero otherwise. Entrepreneurs are defined as individuals who work at least part time in a company in which they hold a financial stake. In the second stage, the dependent variables are the industry-adjusted logarithm of firm sales, the industry-adjusted logarithm of aggregate income, and the industry-adjusted return on equity, respectively. Variable definitions are provided in the Appendix. The sample compromises 7,495 individuals in the selection equation and 1,433 (return on initial capital) to 2,348 entrepreneurs (firm sales) in the performance regressions. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) level.

	Selection equation (probit)		Industry-adjusted log(firm sales)		Industry-adjusted log(aggregate income)		Industry-adjusted return on initial capital	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
Panel A: Entrepreneurial luck								
Good luck			0.583***	10.036	0.498***	7.848	1.619***	6.755
Bad luck			-0.587***	-6.535	-0.549***	-5.045	-1.268***	-3.273
Number of observations	7,495		2,349		1,499		1,421	
R-squared			0.377		0.196		0.143	
Adjusted R-squared	0.274		0.362		0.167		0.111	
Marginal contribution of the luck variables to the overall R-squared of the regression			0.051		0.041		0.042	

Table 5
Relative Importance of Skills, Personal characteristics, and Luck for Success: Decomposition of R-squared

Decomposition of the R-squared into contributions from different indexed regressors. The used method takes the average of all R-squared from all possible orderings of all regressors (see Lindeman, Merenda, and Gold (1980) and Kruskal (1987) for an introduction of the method. See Grömping (2007) for a discussion). Because of the large number of independent variables and computer memory limitations, we created an index for each set of variables on basis of the regression results of Table 4. Specifically, we first generated new variables by multiplying the regression coefficient in Table 4 with the associated variable. Afterwards, we summarized those generated variables according the panels to indexes. Those indexes are than used to compose the R-squared. The delta R-squared are in percent. The number in the brackets represents the rank of relative importance. The sample compromises 1,421 (return on initial capital) to 2,349 entrepreneurs (firm sales).

	Industry-adjusted log(firm sales)	Industry-adjusted log(aggregate income)	Industry-adjusted return on initial capital
Entrepreneurial skills index	2.65	1.97	1.18
Entrepreneurial luck index	7.51	8.26	5.06
Personal characteristics index	4.24	1.49	2.65
Firm-specific control variables index	22.04	2.77	3.29
Inverse Mills ratio	0.96	0.02	0.48
Region index	0.26	0.86	1.57
R-squared of the model	37.66	15.38	14.23
Number of observations	2,349	1,499	1,421

Table 6

Relative Importance of Skills, Personal characteristics, and Luck for Success: The Opinion of Entrepreneurs

The first column shows the average score of a given success factor; the second column reports its average rank; the third column displays the percentage of entrepreneurs stating that the correspondent success factor is the most important, while the second number in this column is the percentage of entrepreneurs stating that the success factor is the least important. The fourth column shows the percentage of entrepreneurs who claim that the success factor is very important and the percentage who claim that the factor is very unimportant.

	Average score (1)	Average rank (2)	Most important vs. least important (3)	Very important vs. very unimportant (4)
Luck	3.19	4.50	15.47% ; 78.43%	13.88% ; 11%
Effort	4.66	1.58	74.86% ; 14.53%	72.35% ; 0.1%
Experience	4.47	1.94	60.43% ; 18.46%	57.71% ; 0.23%
Talent	4.63	1.61	70.99% ; 14.34%	67.98% ; 0.2%
Education	4.25	2.48	47.23% ; 28.3%	44.41% ; 0.49%
Network	4.19	2.62	47.11% ; 28.12%	44.09% ; 1.08%
F-Value (ANOVA equality test of means)	1,325***	1,553***		
Start-up need no luck for success	57.8%			
Minimum number of observations	3,018			

Table 7

Relative Importance of Skills, Personal characteristics, and Luck for Success: Difference in Average Score

The table displays the result of a Bonferroni multiple comparison test. Specifically, the first entry represents the difference between the average score of experience and the average score of luck. Asterisks denote statistical Bonferroni-adjusted significance at the 1% (***), 5% (**), or 10% (*) level.

	Luck	Effort	Experience	Talent	Education
Effort	1.47***				
Experience	1.27***	0.16***			
Talent	1.43***	0.03	0.16***		
Education	1.06***	-0.41***	-0.21***	-0.38***	
Network	0.99***	-0.47***	-0.28***	-0.44***	-0.07**

Table 8

Relative Importance of Skills, Personal characteristics, and Luck for Success: Difference in Ranking

The table displays the result of a Bonferroni multiple comparison test. Specifically, the first entry represents the difference in mean between the ranking of experience and the ranking of luck. Asterisks denote statistical Bonferroni-adjusted significance at the 1% (***), 5% (**), or 10% (*) level.

	Luck	Effort	Experience	Talent	Education
Effort	-2.92***				
Experience	-2.56***	-0.36***			
Talent	-2.90***	-0.03	-0.33***		
Education	-2.03***	0.87***	0.54***	0.87***	
Network	-1.88***	1.05***	0.68***	1.02***	0.15**

Table 9

Relative Importance of Skills, Personal characteristics, and Luck for Success: The Opinion of Entrepreneurs

The first column shows the average score of a given success factor, whereas the second column reports its average rank. Panel A splits the sample between good and poor performing firms, based on whether their sales are below or above the industry median of firms of the same age. Panel B splits the sample between entrepreneurs with unexpected poor performance, entrepreneurs with performance that corresponds to expectations, and entrepreneurs with unexpected good performance.

Panel A: Actual firm performance

	Bad performance		Good performance	
	Average score	Average rank	Average score	Average rank
Luck	3.20	4.50	3.18	4.50
Effort	4.65	1.62	4.68	1.56
Experience	4.47	1.97	4.45	1.95
Talent	4.64	1.60	4.62	1.60
Education	4.28	2.44	4.21	2.55
Network	3.20	2.56	4.15	2.67
Start-up need no luck for success	55.3%		62.4%	
Minimum number of observations	1,145		1,097	

Panel B: Firm performance compared to expectations

	Poor performance		Performance that meets expectations		Good performance	
	Average score	Average rank	Average score	Average rank	Average score	Average rank
Luck	3.29	4.26	3.18	4.52	3.17	4.55
Effort	4.57	1.74	4.64	1.60	4.72	1.50
Experience	4.46	1.94	4.47	1.90	4.46	1.97
Talent	4.58	1.73	4.60	1.63	4.68	1.54
Education	4.18	2.63	4.26	2.42	4.26	2.52
Network	4.31	2.45	4.16	2.62	4.17	2.70
Start-up need no luck for success	51.8%		56.3%		62.4%	
Minimum number of observations	384		1,476		1,103	

Panel C: Previous success

	Previously successful entrepreneur		Previously unsuccessful entrepreneur		Never started a business before	
	Average score	Average rank	Average score	Average rank	Average score	Average rank
Luck	3.17	4.45	3.40	4.15	3.18	4.55
Effort	4.66	1.57	4.59	1.71	4.67	1.57
Experience	4.46	1.94	4.53	1.79	4.46	1.96
Talent	4.62	1.59	4.55	1.76	4.64	1.59
Education	4.22	2.53	4.15	2.72	4.27	2.43
Network	4.14	2.70	4.17	2.60	4.20	2.61
Start-up need no luck for success	61.9%		49.8%		57.2%	
Minimum number of observations	687		231		2,054	

Panel D: Overconfidence

	High overconfidence		Low overconfidence	
	Average score	Average rank	Average score	Average rank
Luck	3.16	4.56	3.23	4.45
Effort	4.71	1.52	4.61	1.64
Experience	4.48	1.94	4.45	1.94
Talent	4.66	1.56	4.59	1.65
Education	4.29	2.43	4.22	2.52
Network	4.21	2.58	4.16	2.67
Start-up need no luck for success	58.4%		57.2%	
Average overconfidence	0.39		0.04	
Minimum number of observations	1,534		1,484	

Panel E: Risk aversion

	High risk aversion		Low risk aversion	
	Average score	Average rank	Average score	Average rank
Luck	3.20	4.53	3.18	4.47
Effort	4.68	1.57	4.64	1.59
Experience	4.52	1.85	4.41	2.03
Talent	4.63	1.63	4.62	1.59
Education	4.31	2.40	4.20	2.55
Network	4.21	4.53	4.16	2.64
Start-up need no luck for success	54.7%		60.8%	
Average risk aversion	0.52		0.11	
Minimum number of observations	1,486		1,532	

Panel F: Locus of control

	Internal locus of control		External locus of control	
	Average score	Average rank	Average score	Average rank
Luck	2.75	4.49	3.36	4.32
Effort	4.76	1.58	4.63	1.63
Experience	4.51	1.95	4.45	1.95
Talent	4.68	1.60	4.61	1.61
Education	4.32	2.48	4.23	2.52
Network	4.00	2.60	4.25	2.49
Start-up need no luck for success	65.5%		55.0%	
Average locus of control (dummy)	1		0	
Minimum number of observations	802		2,216	

Panel G: Education

	Higher education		Basic education	
	Average score	Average rank	Average score	Average rank
Luck	3.27	4.40	3.12	4.61
Effort	4.57	1.73	4.75	1.44
Experience	4.39	2.06	4.54	1.82
Talent	4.60	1.63	4.66	1.58
Education	4.23	2.48	4.28	2.47
Network	4.22	2.52	4.16	2.73
Start-up need no luck for success	61.3%		53.7%	
Average education	16.52		12.52	
Minimum number of observations	1,630		1,388	

Panel H: Management education

	Management education		No management education	
	Average score	Average rank	Average score	Average rank
Luck	3.21	4.49	3.17	4.52
Effort	4.64	1.61	4.68	1.55
Experience	4.45	1.96	4.48	1.92
Talent	4.63	1.59	4.62	1.62
Education	4.25	2.48	4.25	2.47
Network	4.19	2.62	4.18	2.63
Start-up need no luck for success	61.3%		53.7%	
Average management education	2.07		0	
Minimum number of observations	1,630		1,388	

Panel I: Experience

	Highly experienced		inexperienced	
	Average score	Overall rank	Average score	Overall rank
Luck	3.11	4.62	3.28	1.56
Effort	4.66	1.60	4.66	2.11
Experience	4.54	1.78	4.39	1.63
Talent	4.65	1.58	4.61	2.62
Education	4.31	2.34	4.19	2.48
Network	4.14	2.75	4.24	1.56
Start-up need no luck for success	62.0%		53.5%	
Average experience	16.53		12.52	
Minimum number of observations	1,515		1,502	

Panel J: Other definitions of entrepreneurs

	Founders		Starting entrepreneurs	
	Average score	Average rank	Average score	Average rank
Luck	3.20	4.49	3.24	4.48
Effort	4.66	1.58	4.65	1.59
Experience	4.45	1.95	4.45	1.96
Talent	4.63	1.60	4.58	1.68
Education	4.24	2.48	4.25	2.47
Network	4.19	2.60	3.24	2.51
Minimum number of observations	2,724		898	

Panel K: Employees

	All employees		Managers	
	Average score	Average rank	Average score	Average rank
Luck	3.13	4.54	3.25	4.39
Effort	4.59	1.71	4.58	1.69
Experience	4.44	1.98	4.42	1.94
Talent	4.63	1.59	4.59	1.60
Education	4.43	2.05	4.30	2.33
Network	3.91	3.17	4.17	2.64
Minimum number of observations	4,745		1,126	

Table 10
Opinion of entrepreneurs: Biases in Ranking
Ordered logit regressions. The dependent variable equals the ranking of luck. Furthermore we show a regression with entrepreneurs only and a regression with all entrepreneurs. Variables definitions are provided in the Appendix. The sample compromises 7,763 individuals and 3,013 entrepreneurs. Asterisks denote statistical significance at the 1% (***), 5% (**), or 10% (*) level.

	Entrepreneurs only		All individuals	
	Coefficient	t-Statistic	Coefficient	t-Statistic
Panel A: Entrepreneurial luck				
Good luck	0.002	0.029		
Bad luck	-0.017	-0.151		
Panel B: Entrepreneurial skills				
Education	-0.006	-0.354	-0.027***	-2.790
Balanced management education	0.039	1.439	-0.014	-0.789
Working experience	0.021***	3.063	0.008**	2.067
Industry experience	0.014***	3.202	0.012***	4.852
Managerial experience	0.001	0.216	0.004*	1.809
Previously successful entrepreneur	-0.088	-0.992		
Previously unsuccessful entrepreneur	-0.249*	-1.902		
Panel C: Personal characteristics				
Risk aversion	-0.011	-0.070	0.158*	1.869
Overconfidence	0.023	0.138	0.075	0.634
Motivation achievement	0.122*	1.677	0.104**	2.258
Locus of control	0.725***	8.496	0.677***	12.719
Part-time entrepreneur	-0.092	-1.131		
Age	0.017	0.656	-0.003	-0.248
Age squared	-0.000	-1.416	-0.000	-0.721
Previously unemployed	-0.092	-0.496	-0.203	-1.509
Female	-0.109	-1.110	0.008	0.148
Married	0.024	0.264	0.078	1.340
Divorced	-0.023	-0.166	0.139	1.583
Number of children	0.036	1.173	0.020	1.100
Foreigner	0.010	0.103	0.051	0.716
Log(net wealth)	-0.017	-0.696	0.003	0.244
Entrepreneur			0.094*	1.847
Panel D: Firm-specific control variables and other variables				
Ownership	0.001	0.715		
Sole proprietorship	0.164*	1.932		
Log(initial capital)	-0.006	-0.468		
Log(employment)	-0.028	-1.123		
Leverage	0.018	1.017		
Venture capital backed	-0.116	-0.469		
Protestant region	0.005	0.051		
Industry dummies	Yes		No	
Region dummies	Yes		Yes	
Number of observations	3,013		7,763	
Pseudo R-squared	0.027		0.014	
LR Chi-squared	240.87		316.05	