

Business Partners, Financing, and the Commercialization of Inventions¹

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This draft: March, 2013

¹We have benefited from the comments of Victor Aguirregabiria, Serguei Braguinsky, Alberto Galasso, Bart Hamilton, Octavian Harare, Ig Horstmann, Alexander Kritikos, Illoong Kwon, Evgeny Lyandres, Robert Petrunia, Aloysius Siow, Sheryl Winston Smith, Scott Stern, Peter Thompson, Tereza Tykvova and seminar participants in a number of conferences. Thomas Astebro, HEC Paris, 78351 Jouy en Josas, France, Email: astebro@hec.fr. Carlos Serrano, Universitat Pompeu Fabra, Ramon Trias Fargas, 25-27, 08005 Barcelona, Spain, Email: carlos.serrano@upf.edu.

Abstract

This paper studies the effect of business partners on the commercialization of invention-based ventures, and it assesses the relative importance of the complementary human and social capital, and financial capital these partners may add to the original inventor-entrepreneur. Projects run by partnerships were five times more likely to reach commercialization, and they had mean revenues approximately ten times greater than projects run by solo-entrepreneurs. These gross differences may be due both to partners impacting business success and to selection. After controlling for selection effects and observed/unobserved heterogeneity, the smallest estimate of partner human/social capital approximately doubles the probability of commercialization and increases expected revenues by 29% at the sample mean. The results indicate that the decision to form a business partnership is an important determinant of the large heterogeneity in entrepreneurial success, and that obtaining human and social capital accounts for a large portion of this effect.

1 Introduction

The distribution of returns to entrepreneurship is skew and it is particularly uneven for technological entrepreneurship.¹ The large observed heterogeneity in entrepreneurial success has been associated with, inter alia, liquidity constraints, the skills of the entrepreneur, investment in own complementary skills, and the quality of the venture (e.g. Evans and Jovanovic, 1989; Astebro, 2003; Lazear, 2005; and Parker and van Praag, 2006). This paper takes a different tack by examining whether entrepreneurial returns are affected by the decision to form a business partnership.

Guy Kawasaki, one of the more famous Silicon Valley investors, write in his book “Art of the Start” (2004, p. 10): “History loves the notion of the sole innovator: Thomas Edison, Steve Jobs,... History is wrong. Successful companies are started, and made successful, by at least two, and usually more, soulmates. After the fact, one person may come to be recognized as ‘the innovator,’ but it always takes a team of good people to make any venture work.”

While Mr. Kawasaki’s statement may seem obvious to most (see e.g. Copeland and Malik, 2006), researchers have had a difficult time substantiating the claim. The size of the founding team has been found only marginally significant and not robustly related to start-ups’ sales growth (Eisenhardt and Schoonhoven, 1990; Kor, 2003), general firm performance (Haleblian and Finkelstein, 1993) raising venture capital and going IPO (Beckman et al., 2007) and new business survival (Astebro and Bernhardt, 2003). However, Cressy (1996) found team size to be a significant predictor of new business survival, and Astebro and Bernhardt (2003) found it to be significantly related to raising bank financing. In all these articles the size of the founding team was presumed exogenous to business outcomes.

In this paper we document and estimate the economic impact of adding business partners to the original inventor-entrepreneur. We further assess the relative importance of the skills, contacts,

¹See Astebro and Chen (2012) for a review of the evidence.

and money these business partners might bring. To study the economic impact of adding business partners is challenging for two reasons. The first challenge is that partnership formation may be endogenous. This can arise in a number of ways. For instance, business partners may be more likely to join inventors with high quality inventions or inventions with better prospects and these inventions are more likely to be commercialized, inducing a positive correlation between business partnership and revenues. Another possibility is that inventors with high quality inventions – who may be more likely to be liquidity constrained – are more likely to seek partners to obtain financing. A second challenge is that the complete contributions of partners financial, human, and social capital are typically hard to observe. In this paper we address endogeneity issues and are fortunate to have indicators of all three contributions from business partners.

A key feature of our field microdata is the focus on a sample of independent inventors which we know were originators of inventions. Business partners are defined as those who join the original inventor to try and commercialize the invention, contributing at least one of the following: human, social, or financial capital.² We use several strategies to control for the endogeneity of the partnering decision. First, we control for the quality of the invention and the observed commercialization investments by the inventor and external investors. Including realized investment levels will control for selection on the pre-investment prospects of ventures which are unobserved to the econometrician but observed by both the inventor and investors.³ Second, we control for selection on measurable inventor and invention characteristics into partnerships using a propensity score weighted model. In the third approach, we explicitly control for unobserved heterogeneity. Using another key feature of our data – the human, social, and financial capital contributions of business partners – we can compute estimates of the joint impact of partners’ human and social

²The definition of business partners does not include work-for-hire (e.g. legal, accounting or other work for pay).

³The idea of using realized investment levels to control for the (unobserved to the econometrician) pre-investment prospects of ventures has been extensively used in industrial organization and macroeconomics to estimate production functions and total factor productivity (see e.g. Olley and Pakes, 1996).

capital and the effect of partners' financial capital on gross revenues.

We rely on data from a comprehensive survey of Canadian inventors consisting of 772 independent inventors that had asked the Canadian Innovation Centre to evaluate their inventions between 1994 and 2001. The survey reveals that in approximately 21 percent of the projects the inventor was joined by business partners.⁴ The primary reason for the inventor to create a partnership was to obtain human capital (65%), followed by obtaining financing (51%), and finally to obtain social capital (42%), indicating a broad array of resources provided by partners. These partners take on substantial risk. The average pre-revenue external investments are approximately \$29,500 (2003 Cdn \$), when the average probability of commercialization is 0.11.

The survey indicates a very important role for business partners in commercialization success; the rate of commercialization of projects run by partnerships (0.30) is five times larger than those run by solo entrepreneurs (0.06); the revenues of projects undertaken by partnerships are almost ten times as large as those run by solo-entrepreneurs; and fully 72 percent of the total revenues of all projects were generated by projects run as business partnerships.

The bulk of our empirical analysis quantifies how much of these gross effects represent the returns to obtaining human and social capital versus obtaining additional financing, while controlling for selection of projects into partnerships. After controlling for selection effects and observed/unobserved heterogeneity, our smallest partnership estimate approximately doubles the probability of commercialization and increases expected revenues by 29% at the sample mean. The marginal impact of partners' human and social capital on entrepreneurial returns is 10% larger than the one of financial capital and 128% larger than a proxy of the quality of the venture.

Taken together, these results indicate that the decision to form a business partnership is an

⁴In comparison, Burton, Anderson, and Aldrich (2009, p. 116) report that 27% of start-ups were business partnerships (excluding spouses). Partnerships where other people made a distinctive contribution to the founding of the business but were not awarded ownership were more frequent; 40% (Burton et al., 2009). A dominating majority of partnerships are started by two people (Ruef et al., 2003; Burton et al., 2009).

important determinant of the large heterogeneity in entrepreneurial success, and that obtaining complementary human and social capital accounts for a large portion of this effect. Moreover, as long as the initial entrepreneur can appropriate part of the gains from collaborating with other individuals, the formation of business partnerships can increase the entrepreneurs' incentives to innovate.

Our findings suggest that a major policy leverage to increase commercialization rates and revenues for early-stage businesses is to lubricate the market for finding skilled partners. This will take different forms than the typical policy levers to stimulate the provision of formal venture financing, and is likely to be less costly.

Our work contributes to the literature on the choice of entrepreneurship. In a related paper, Lazear (2005) develops a theory of entrepreneurs as jacks-of-all-trades where he assumes that the entrepreneur must invest in his/her worst skill to increase business performance. We instead analyze the value for entrepreneurs of adding business partners providing skills. Furthermore, our work is distinct to Holmes and Schmitz (1990), who develop a theory of entrepreneurship with specialization and business transfers. We abstract from the possibility that the inventor may transfer her invention to others.⁵ Finally, our work relates to the literature on liquidity constraints for start-ups. Evans and Jovanovic (1989) studied the degree to which personal wealth provides a binding liquidity constraint for a single individual's choice between entrepreneurship and wage work. We instead focus on individuals who may find partners to relax liquidity constraints for commercialization success.

⁵Our data contains only five inventions where ownership was transferred and these are deleted from analysis.

2 Sampling Method and Data

We focus our empirical analysis on a sample of independent inventors; that is, individuals who decide to develop inventions outside their regular employment duties. Many inventors may not have great entrepreneurial or business skills and may lack the financial capital necessary to commercialize their inventions. Further, they may lack the benefits of working in a large organization in terms of access to a multitude of internal resources such as a lab, funding, skilled colleagues, and an established marketing and distribution network. They may thus find it particularly useful to have others join them in their commercialization efforts. Studying independent inventors should thus likely provide an excellent opportunity to examine the role of partnership mechanisms and their outcomes.

However, it is costly, given their scarcity, to find independent inventors among the general population. To economize on search costs, we therefore use a list of independent inventors, self-identified through their use of the Canadian Innovation Centre (CIC) in Waterloo, Canada. (For further information on the CIC see Appendix E.) Our sample frame consists of inventors that had asked the CIC to evaluate their inventions between 1994 and 2001. A survey resulted in 772 analysis observations. Survey methodology details are available in Appendix A.⁶

As in most surveys we expected sampling and response biases. We estimate sampling bias by using a probit model of the probability of being able to trace the private address/phone of the inventor. We also estimate the probability of response from the traceable sample. We multiply the probabilities of tracing and response and invert the product for use as selection weight in

⁶To summarize Appendix A, we developed a list of 6,405 inventors who had submitted ideas for review between 1994 and 2001. Of this number, we were able to trace 1,352 current addresses using the yellow pages and internet searches. Of these, 1,272 addresses led to actual contacts, resulting in 830 completed telephone interviews for an overall adjusted response rate of 61%. We then remove 53 partially answered surveys and 5 observations where the IP was sold or licensed, leaving 772 observations for analysis. We used a survey Centre to collect the data which followed the statistical methods and best practices of the American Association of Public Opinion Research, <http://www.aapor.org>.

the analysis (see Holt, Smith, and Winter, 1980). The results were qualitatively similar using the sampling and response probabilities as when not using them. This indicates that while there were trace and response sampling biases, these did not covary strongly with the correlations in the model. Results reported in the body of the text are without the sample selection corrections. Results with the sample selection corrections applied are available in Appendix D, Tables D1 and D2.⁷ There is also the potential for missing item (question) response bias. We therefore imputed missing items five times assuming data were Missing At Random (MAR) using a switching regression approach and report estimation results averaged across the five complete samples.⁸

To understand the composition of the inventor sample better, we further drew a comparison sample from the general Canadian population. We queried a sample of 300 Canadians from the general population based on sampling quotas for province, work experience, and gender, to reflect similarities in the aggregate with the inventors on these three variables. Comparisons were made on background characteristics and are reported in Appendix C.

A key variable in our survey was whether the inventor formed a business partnership for the commercialization of the invention. To obtain this information we asked the inventor in the phone interview (verbatim) "Did you ever team up with other people trying to commercialize the

⁷The trace model, which contained demographic information, address location identifiers, year and the CIC evaluation, was significant, explaining approximately 5% of sampling variance. It has been suggested to us that private address traceability is a function of whether the project was successful or not and that therefore there is a success bias in our sample. It is not clear to us how this correlation would appear since the difficulty we have in tracing inventors depend on whether they have a surname that is common or not. (See Appendix A and Table A1 for details.) Nevertheless, applying a correction for the ability to trace an address reduces the incidence of potential survival bias due to address non-traceability. The response probability model was also significant, explaining approximately 3% of response variance. Applying a correction for the probability of response reduces the incidence of survival or other bias due to survey non-response.

⁸In multiple imputation, missing values for any variable are predicted using existing values from other variables. The predicted values replace missing values, resulting in a full data set. This process is performed multiple times. Standard statistical analysis is performed on each imputed data set. Results are then combined. Multiple imputation restores not only the natural variability in the missing data, but also incorporates the uncertainty caused by estimating missing data. Uncertainty is accounted for by creating different versions of the missing data and observing the variability between imputed data sets. For an introduction to multiple missing data imputation see Graham and Hofer (2000). See van Buuren, Boshuizen, and Knook (1999) for the switching regression imputation method which we use. The number of imputed items (selected variables) varied from 53 (labor supply), 44 (investments), 16 (invention quality), to 2 (partnership formation). Means, coefficient estimates and standard errors are computed over five complete datasets using the formulae in Little and Rubin (1987, equations 12.17–12.20.)

invention?", if yes, we further inquired about the reasons for the formation of the partnership (verbatim): "Why did you team up with other people?" with the following options read aloud: "You needed to have your skills complemented by their skills", "They had contacts that were useful", "You needed the capital they provided", "They had resources that were useful (land, equipment, plant)" and "Other". Each option required a "Yes" or a "No" reply before continuing. The category "Other" also required the respondent to detail the particular reason and all words in the reply were coded and analyzed. In analysis the two categories prior to "other" are collapsed into one. The questions imply that there is some form of matching where the partner provides something which the inventor does not have. Follow-up interviews with a few inventors indicated that the questions accurately reflect the decision to form a business partnership, and not the decision to hire an employee, or to engage a consultant or other service provider (e.g. a lawyer or a banker) for cash payment.

An important feature of the data is that we know who had the original idea for the invention so that we can make some simplifying assumptions about the process of business partnership formation. We assume that partners are asked to join the business, rather than the business formation decision-making process being made jointly. This simplifies statistical inference considerably as there need only be one decision equation. We were, however, concerned that the inventor may have formed a business partnership to develop the invention and that this may be correlated with business partnership formation in the commercialization stage. We therefore also asked (verbatim): "I am now going to read you several alternatives regarding the circumstances of your invention's genesis. Did you..." with one option being: "You belonged to a team that together came up with the idea." We coded whether they belonged to a team that together came up with the idea as a binary dummy variable and control for this event in analysis.

Another key variable in our analysis is an assessment of the inventions' quality. This variable

was not obtained from the phone survey of the inventors, but from the administrative records of the CIC. The program helps inventors, before significant R&D expenditures are made, to evaluate an invention. (For more details on the program see Appendix E.) The average time between the evaluation and eventual market launch was approximately two years (Åstebro, 2003). Further, total commercialization investments for inventions that later reached the market averaged Cdn. \$276,350, but R&D expenses for all inventions up to the date of evaluation had averaged only Cdn. \$22,518 (2003 values). Both statistics confirm that the evaluations were made at an early stage.

Our key dependent variable is the log of all future business revenues (appropriately discounted). The details of the method to compute the discounted present value is reported in Appendix B. Other studies have used business survival, raising of venture capital, time to IPO or time to commercialization as proxies for business success. For this sample we believe that commercialization revenues is an appropriate measure of business success as most of these businesses have limited opportunity to raise formal venture capital or be listed on major stock exchanges, and business survival may be capturing the subjective value of staying an entrepreneur.

It is likely that the entrepreneurs were not able to respond particularly accurately when answering our phone calls. Indeed, some of these inventions were developed up to ten years before the phone conversation. We are thus likely to experience measurement error which will bias any regression estimates towards zero. Had we chosen to obtain more contemporary data we would likely reduce such noise, but on the other hand would have had to deal with a greater degree of truncation of data on commercialization revenues. We chose to avoid as much as possible truncation of the dependent variable at the cost of more noisy data.

Another concern may be that entrepreneurs may embellish on their roles and downplay the roles of others if the business is successful (this bias is generally known as the "attribution bias".)

This particular bias, if it exists in this survey, will then likely deflate the proportion of entrepreneurs responding that they obtained the assistance of business partners if the invention was successful, and also deflate the reported investments made by others than the entrepreneurs in the case that the invention was successful. This will bias down the impact of business partners on success.

2.1 Summary statistics

While the identification of inventors relies on a specific, focal, invention submitted to the CIC it does not imply that the individuals are predominantly one-shot inventors. To the contrary, the sample is dominated by long-term serial inventors. Fifty-three percent of them had spent six or more years developing inventions, and 75% had worked on more than one invention. Eleven percent developed the invention as part of their normal duties at work. Twenty-six percent were stimulated by something at work, a majority of which (73%) were not required to innovate at work.

With regards to the inventions, 21% were rated as of high quality by the CIC and given a positive recommendation, suitable to develop further at least as a part-time effort. The other 79% were deemed of low quality and inventors were recommended to stop further development. Most numerous were sports/leisure products (28%), followed by 16% security or safety applications, 14% automotive, 14% medical or health, and 13% which had environmental or energy applications. Inventions involving high technology (9%) and industrial equipment (14%) were also relatively frequent. Descriptions of some inventions reveal most to be “user-driven”. Successful consumer-oriented inventions included a new milk container design, a washable sanitary pad, and a home security light timer that imitates typical use. Other inventions had business applications. These inventions included an aligner and printer for photographic proofs, a tractor-trailer fairing that

enhances fuel efficiency, a re-usable plug to insert in wooden hydroelectric poles after testing for rot, and a computerized and mechanically integrated tree harvester. Thus, the inventions varied substantially in technological complexity and market potential. The median invention development effort was performed in 1997, and 95% of respondents had attempted to develop their focal invention before 2003.

The pre-commercialization investments in the inventions reveal to be far larger than in the ordinary start-up. For example, the 1992 Characteristics of Business Owners database report that the majority of U.S. start-ups (approximately 60%) were started or acquired with no cash outlay or with less than \$5,000 (U.S. Department of Commerce (1997)). In contrast, the average R&D investment for the inventors is approximately Cdn. \$22,500 and the additional commercialization investment is another Cdn. \$24,800 (2003 values).

3 Partnerships and the commercialization of inventions

Table 1 reports some descriptive statistics on partnerships and solo-entrepreneurs. In Panel A, we show that in approximately 21% of the projects the inventor was joined by someone to commercialize the invention. The primary reason for the inventor to create a partnership was to obtain human capital (65%), followed by obtaining financing (51%), and social capital (42%). Stated differently, 79% are without a partnership; and among the partnerships, in 16% of the cases there were only financing provided, in 37% there were both financing and human/social capital provided by partners, and in 47% of the partnerships there were only human/social provided.

The fact that a significant number of inventors are joined by someone to commercialize their invention suggests that there may be benefits to partnership. Indeed, we find that working with partners is positively correlated with the probability that inventions are commercialized. Table 1B shows that partnerships have a probability of commercialization of 0.30, which is about five times

larger than that of projects run by solo-entrepreneurs (0.06). The presence of partners is also positively correlated with revenues. Projects run by solo-entrepreneurs had mean present value of revenues of \$24,196; mean revenues from projects run by partnerships were approximately ten times as much; \$232,397. While solo entrepreneurship dominates the data there appears to be enough variation to examine partnership selection mechanisms and benefits. Importantly, not all partners provide financing indicating a potential value added effect through human and social capital.

While there appears to be benefits to forming partnerships a natural question is then why not all projects are run as partnerships? There are various reasons for this not occurring. Potential partners typically operate locally and individually and may be hard to find by inventors (Mason 2009; Harrison et al., 2010). Further, partnerships are formed only if the potential partner is qualified enough and/or if she loosens liquidity constraints to motivate the fixed cost of forming a partnership. Finally, partnership may not be formed due to a lack of "chemistry", or various other behavioral reasons that lies outside the scope of this paper.

In appendix F we develop a formal model of the partnership formation process. The key components of the model are that inventors have varying and limited wealth, their inventions have varying pre-partnership quality, inventors meet partners with positive probability which carry varying human and social capital, and partners can release an inventor's liquidity constraint by providing financing. There is a fixed costs of forming a partnership. A key model prediction is that the probability to form a partnership increases when invention quality increases. The model further shows that the probability of partnership increases when the human/social capital of the partner that the inventor meets increases. Finally, we demonstrate that the probability of financing from partners increases with invention quality. The model thus clarifies various endogenous selection mechanisms that must be econometrically controlled for when estimating

the economic impact of partnerships. In the next subsection we demonstrate the existence of these selection mechanisms.

3.1 Selection into business partnerships

Selection on invention quality To investigate selection on invention quality, we use two proxies for invention quality: the CIC assessment and the inventor’s own R&D expenditures prior to partnership formation.⁹ We first classify inventions into two categories; high quality inventions will be those with a CIC positive assessment, the rest of the inventions are deemed of low quality. It is immediately apparent that partners are more likely to join inventors with high quality inventions, as shown in Table 1B. Partnerships are twice more likely to have high quality inventions than solo-entrepreneurs, 35% versus 18%. Stated differently, 34% of inventions rated as high quality were eventually joined by a partner, while only 17% of inventions with low quality were joined by a partner. Similar results were obtained when the inventions were categorized using the inventor’s own R&D expenditures. Partners were more likely to join inventors with higher R&D expenditures. The average R&D expenditures by the inventors that were eventually joined by partners was \$90,364; solo-entrepreneurs spent on average \$4,725. To control for varying capital requirements by technology and for varying costs of capital we include industry and year dummies in a regression of the probability of partnership formation on invention quality. Estimates survive the inclusion of these industry and year controls (see Table 2). The Table also reveals that the two quality measures are positively correlated with each other.

Selection on demand for financing An additional reason for why partners join inventors is to provide external financing. For instance, if inventors with high quality inventions –who may be more likely to be liquidity constrained– are more likely to seek partners to obtain financing,

⁹We separate between the idea creation and commercialization phase by the date of the CIC assessment.

it can induce a positive correlation between invention quality and partnership for financing. This issue can potentially lead to an upward bias of the estimated effect of partnership on commercialization outcome. To study selection on demand for financing, we test whether the probability to form a partnership to obtain financing increases with invention quality. Using the same quality indicators and controls as before as predictors, Table 3 presents Probit regressions with a dummy = 1 if a partnerships with financing was formed, and zero otherwise. The table shows support for this prediction. However, it appears that most of the invention quality variation that determines partnership financing is best captured with pre-partnership R&D expenditures.

Both tests for selection indicates that partnerships are formed because high quality ideas attract business partners and because high quality ideas have greater demands for financing, even after controlling for industry and year effects. Examining the impact of partners will then need to control for project quality.

4 The economic impact of partners' human/social capital

4.1 Baseline econometric model

To study the contribution of partners in the commercialization of inventions we adopt the following econometric specification:

$$y_i = \begin{cases} y_i^* & \text{if } y_i^* > 0 \\ 0 & \text{if } y_i^* \leq 0 \end{cases}$$

with y_i^* as a latent variable indicating commercialization success, and

$$y_i^* = \alpha q_i + \beta d_i + \delta X_i + \mu_j + \tau_t + e_i$$

where y_i is the log of commercialization revenues; q_i is unobserved (to the econometrician) invention quality¹⁰; d_i is a dummy that equals one if a partnership was formed to commercialize invention i ; X_i represents regressors that vary across inventions and specifically includes investment levels by all parties, and e_i is a normally distributed zero mean, independently distributed residual component. The terms μ_j and τ_t correspond to industry and CIC application year effects as implemented by a set of dummy variables, and β captures the effect of partner’s human/social capital on the commercialization revenues conditional on a partnership being formed. We use the log form to allow for multiplicative effects of inputs.

Table 4 reports the effects of forming a partnership and control variables on the latent variable y_i^* . We use a Tobit model as there are a large number of inventions that are never commercialized and have zero revenues.¹¹ To provide intuition, we use a standard decomposition technique of the coefficient β into the marginal effect on the probability of commercialization, and the marginal effect on expected log revenues, both estimated at sample means (see e.g. McDonald and Moffitt, 1980).¹² The first column (Model 1) shows the estimated coefficient for the partnership dummy controlling for industry and year effect. Joint t-tests indicate that industry dummies (t=1.74) and year dummies (t=1.70) are only marginally significant. After controlling for industry and year dummies the size of β is 15.25. Taking this value and evaluating the marginal effects of partnership at the mean of the sample imply that an invention project run as a partnership has

¹⁰Formally, the variable q_i stands for any invention unobserved component that affects commercialization outcomes that is not accounted for the explanatory variables and the partnership effect.

¹¹We also experimented with a Heckman selection specification, but we could not find a variable that could be reasonably assumed to affect the probability to commercialize but not revenues conditional on commercialization. Without an exclusion restriction estimations were very unstable or did not converge.

¹²Consider the following Tobit model. Let the dependent variable be $y = y^*$ (if $y^* > 0$) and $y = 0$ (if $y^* \leq 0$), and the latent variable $y_i^* = \beta X + e_i$. The marginal effect on the observed log of expected revenues y is $\frac{\partial E(y|X)}{\partial x_k} \beta_k \Phi\left(\frac{X\beta}{\sigma}\right)$, where x_k is a regressor of interest, \bar{X} is a matrix of the sample means of the regressors, β_k is the corresponding Tobit estimated coefficient of the regressor x_k , and Φ is the cdf of the standard normal distribution. If x_k is a dummy, the marginal effect is the difference between the difference of the predicted values of of the dummy evaluated at the sample mean of the rest of the regressors. Because our dependent variable is the log of revenues, the marginal effect of partnership in revenues can be approximated by exponentiating the marginal effect of partnership on the log of revenues.

approximately a 0.22 greater probability of commercialization than one run by a solo-entrepreneur, and its expected revenues are eight times higher than a solo-entrepreneur project. (Since the controls are only marginally significant the gross differences in Table 1B are quite similar; 0.24 and 9.6, respectively.)

The positive correlation between commercialization success and partnership formation has to be interpreted with caution as there is selection on invention quality. We therefore add two proxies for invention quality: the CIC assessment and the log of R&D expenditures. The second column in Table 4 (Model 2) shows that the effect of partnership formation on expected commercialization success then decreases from 15.25 to 11.68, a 23 percent reduction. The drop in the coefficient estimate indicates that there is clear selection on measurable project quality into partnerships. However, the partnership coefficient still remains significant and large. At the sample means, partnerships are associated with an increase in the probability of commercialization of 16 percentage points, and an increase in the expected revenues by a factor of 3.5. The large magnitudes of these effects indicate additional partnership effects.

The remaining partnership effect may be due in part to selection on unobservable invention quality. To control for this possibility we continue by including a measure of total commercialization investment. Rational investors will invest as a function of qualities of the project that drives commercialization performance.¹³ Including realized investment levels will therefore control for selection on the pre-investment prospects of ventures which are unobserved to the econometrician but observed by investors (Olley and Pakes, 1996). In addition, the amount of external financing provided by partners should capture the partnership effect on revenues from relaxing liquidity constraints.

In Model 3 of Table 4 we analyze the effect of total commercialization investments. The third

¹³See Olley and Pakes (1996) for more details on the application of the "control function" approach in the estimation of production functions.

column adds the natural logarithm of post-partnership commercialization investments; the sum of all cash provided both by the inventor and external financiers to commercialize the invention after the formation of a partnership. The results show that the commercialization investment is positively correlated with partnership formation (and thus unobservables determining this decision) because the partnership coefficient declines significantly (35.5%) when adding the commercialization investment. As observed, the investments are also strongly correlated with the two observable measures of project quality. Including investments reduces one quality measure to insignificance and the other to marginal significance. This suggests that investors clearly consider invention quality. But while the introduction of commercialization investment reduces the partnership coefficient considerably, the partnership effect remains positive and statistically significant. For instance, evaluating the effects of partnerships at the mean of the sample, partnerships increase the probability of commercialization by 8 percentage points, and increase expected revenues by 65%.

To examine whether inventors are liquidity constrained and the degree to which partners relax these liquidity constraints, in Table 5 we separate between the natural logarithm of the inventor's cash contribution and the natural logarithm of the sum of all cash contributions by all external financiers.¹⁴ External financiers may be banks, friends and family, and business partners. A first result from this analysis is that the size of the coefficient for external financing is almost four times lower than the coefficient for own financing in Model 3. This result is consistent with the idea

¹⁴Unfortunately, due to survey structure we cannot simultaneously identify own and external investments from own and others R&D. R&D expenditures are therefore included in the measures of financing. The survey enquired: 1. First, we would like to know how much money was spent on developing XX. Include all costs for product development, marketing research, making of prototypes, etc. How much did you spend before you contacted the CIC for an evaluation? 2. How much did you spend after you contacted the CIC for an evaluation? 3. I will now read a list of sources of funds that you may have used to pay for the costs of developing your invention. Please tell me for each source whether you have actually used it or not. 4. Consider the total amount of money you have spent on this invention so far. How large a proportion of this amount was your own money? These data allow us to identify either the effect of commercialization investment (using question 2) or external financing (using question 4).

that inventors are capital constrained. If they were not constrained the coefficients for internal and external financing should be equal.¹⁵ Thus, selection into partnerships to release liquidity constraints is likely to occur. External financing is also positively correlated with the partnership effect, but not very much. Quantitatively, the partnership coefficient is reduced from 10.28 (in model 2) to 9.26 (in model 3), a reduction by 10%. The results indicate that partners may often not be the main external financier.

Our previous analysis did not include the labor supply for the inventor and the partner. But it is possible that labor input may depend on the quality and prospects of the venture. The inventor may for example be trading off time in the venture with working part-time as an employee and the partner may be investing in several ventures at the same time. We therefore add labor supply as control. In particular, we inquired about the sum of the number of hours provided by the inventor and all partners post CIC evaluation to commercialize the invention. Including the log of this number (with log of zero hours set to zero) will allow us to approximately isolate partner human/social capital from hours of input by the partner. Results are reported in Model 4 in Tables 4 and 5. Controlling for labor inputs, the partnership coefficient drops by 0% in Table 4 and 5% in Table 5. The low conditional correlation between the partnership dummy and total hours indicate that it is the inventor whom perform the majority of commercialization efforts, and that the main contribution by partners is skills, rather than hours. However, the magnitudes of the other parameters generally drop, indicating that labor efforts are positively correlated with invention quality, total commercialization investments, and the amount of external financing. Nevertheless, the partnership coefficient remains significant and large.

Whatever is left of the partnership coefficient after accounting for selection on quality, commercialization investment, labor supply, and external financing can be attributed to the effects

¹⁵This result is consistent with the finding that smaller and younger firms have higher growth-cash flow sensitivities than larger and more mature firms (see e.g. Fazzari, Hubbard, and Peterson, 2000).

of the partner’s human/social capital, but as well to omitted variable bias. In the next section we therefore attempt to further control for additional selection on inventor-invention observed characteristics and selection on unobservables to isolate the effect of partner human and social capital on commercialization success.

4.2 Accounting for selection on observables and unobservables

The control function approach used in the previous analysis should in principle account for the effects of unobserved heterogeneity. It does so even though we have noisy measures of invention quality because we also include in the estimation the total investments (and efforts). Nevertheless, there still exists the possibility that a partner’s decision to join an inventor may depend on other inventor/invention characteristics that *do not* affect the observed post-partnership commercialization investment (and efforts), but *do* affect the commercialization outcomes. An example of this possibility might be a kinship partner which follow sequentially a rational investor. Assume the rational actor invests optimally but do not know that the kinship partner will join. The kinship partner join the effort purely (we assume) because of social pressure, and invests money, but may add zero or even negative value to the business. If this kinship partner had invested knowing his/her poor impact on the venture or if the rational actor had known of the kinship partner, we would have been able to observe this knowledge in the investments and there still would be no omitted variable bias. However, in the above (rather contrived) case there is an omitted variable bias: that of kinship. Alternatively, omitted variable bias can also arise from decision biases such as optimism. To account for the presence of selection on unobservables that cannot be captured with our survey data, below we develop an empirical strategy which leverages the survey data to its fullest and exploits an identifying restriction based on our model of selection into partnerships (see model in appendix F.)

Another potential limitation of the control function approach is the presence of an omitted variable that affects both the level of commercialization investment across projects and the partner's decision to join an inventor, but does not directly affect the gross revenues of the project. The issue is that the effect of such omitted variable on the observed commercialization investment may distort the monotonic relationship between the entrepreneurs's decision variable "commercialization investment" and the unobserved invention level state-variable "invention quality". An example of this variable might be the previous inventor's entrepreneurial experience, which can increase both the likelihood of partnership formation in this project and reduce the factor price of external capital, inducing higher commercialization investment for a given level of "invention quality." To confront this possibility, we controlled for a some additional observables of the inventor and invention (e.g., inventor's prior business and innovative, etc.) within the framework of a control function approach, and found no significant differences in the estimated parameters of interest. In the analysis that follows, we will make use of very detailed information from our survey on the inventor and invention's characteristics in a propensity-score weighted model.

4.2.1 Propensity-score weighted model: Accounting for selection on observables

To account for the possibility that there remains inventor or invention unobserved heterogeneity and measurement error unaccounted in our previously identified selection effects, we begin exploiting a large number of detailed inventor and invention characteristics and use a propensity-score weighted model described by Hirano, Imbens, and Ridder (2003).¹⁶ Woolridge (2007) discusses a

¹⁶In another attempt to endogenize partnership formation we estimated an IV model with "the invention was stimulated at work" as exogenous predictor of partnership. It seems reasonable to presume that if the stimulus for the invention was at work it may make it easier for the inventor to find partners, but should not necessarily directly affect returns. The variable indeed was a significant predictor of partnership ($t=2.94$, $p<0.01$) but results were not stable. This is a situation where the instrument simply is too weakly identified.

We also experimented with including all the inventor and invention characteristics in the production function. This produced results qualitatively similar to the ones reported in Tables 4 and 5 and were deemed to be of no major interest. Results available on request from the corresponding author.

related approach, but Hirano et al.'s method may produce more efficient estimates. We estimate the propensity to form a partnership with logistic regression using as predictors the previously used variables: Positive, pre-partnership R&D expenditures, industry and year dummies, as well as a range of additional pre-determined pre-partnership inventor and invention characteristics to calibrate the propensity to form a partnership.¹⁷ The range of inventor and invention characteristics is quite large and includes whether there were several people involved in the development of the invention. Matching partnership observations to non-partnership observations with similar propensity scores we can behave as if there was random assignment to partnerships on inventor and invention characteristics, under the condition that there is ample partnership and non-partnership observations for each score. We examined this requirement and deleted 48 observations where there was no common support, leaving 724 observations for subsequent analysis. The region of common support for the score is [.02, .91], capturing the 1st to the 99th percentile. Because there is considerable overlap in the score distributions between partnership and non-partnership observations between the 1st to the 99th percentile the so-called balance property is satisfied and we can safely rely on the scores to provide reasonable matching.

Results of the inverse propensity-score weighted Tobit are provided in Model 5 of Tables 4 and 5. As seen, the estimate of the partnership coefficient is again reduced, indicating that there is also selection on observable inventor and invention characteristics. The coefficient however does not decrease that much, it drops by an additional 6.3% and 9.7%, in Tables 4 and 5 respectively. Therefore, after controlling for these selection effects, the partnership coefficient still remains large. The size of the effect is either 46% or 52% of the gross partnership coefficient in Model 1,

¹⁷We included inventor gender, marital status, age, education, work experience, managerial experience, business experience, family business experience, years experience inventing, number of inventions developed, invention developed at work, invention stimulated at work, invention developed together with someone else, full-time, part-time, un- or self-employed when inventing. Burton, Anderson, and Aldrich (2009) show that many of these demographics are related to partnership formation. We also included the following invention characteristics: positive, pre-team R&D expenditures, pre-team number of hours of effort, industry dummies, year dummies, and whether the fee paid to the CIC for the review was partly subsidized by a third party.

respectively. The estimate from Table 4 implies that expected revenues of commercialized inventions increase by 29% going from solo-entrepreneurship to partnership, and that the probability of commercialization increases by 0.06 percentage points, which is a 97% percent increase over the commercialization rate of solo-entrepreneurs, both non-trivial impacts. The estimates of the impact of partnerships from Table 5 are somewhat stronger. Partnerships increase the probability of commercialization by 0.09 percentage points, and increase expected revenues by 49%.

Another result to note is that once we control for inventor and invention characteristics prior to collaboration, the coefficient for own financing becomes negative. This may be the case because our propensity score method uses observables that are correlated with the borrowing capacity of the inventor. If the borrowing increases, then equity financing may be reduced.

A propensity-score estimator strategy allows us to exploit our survey data on observed inventor and invention characteristics to the fullest. It does so by controlling for the possibility of selection effects into partnerships that are directly accounted for commercialization investment, the R&D expenditures, the CIC review, and a long list of variables associated with the inventor and the invention. Nonetheless, there still remains the possibility of unobserved heterogeneity that cannot be accounted for our detailed list of observables. For instance, a positive shock to the prospects of commercialization that impact the decision to form a partnership but does not affect commercialization investment. The next subsection addresses the possibility of selection on unobservables.

4.2.2 Accounting for selection on unobservables

Finally, we address the possibility that there is unobserved heterogeneity and measurement error of our identified selection effects. Here we utilize the fact that some partners only provide financial capital. We decompose the partnership effect as follows: Partnership = partner with human/social

capital [$P(hc)$] + partner without human/social capital but with financing [$P(not_hc_fin)$]. The identifying restriction we consider is that the financial contribution of partners exclusively affects commercialization investments by relaxing liquidity constraints. Under this assumption, once we control for invention quality and commercialization investment a partner that exclusively provides financing should not affect revenues in any other way, i.e., the coefficient for $P(not_hc_fin)$ should be zero ($\gamma = 0$). If the estimated coefficient for $P(not_hc_fin)$ is zero, $\hat{\gamma} = 0$, then the coefficient for $P(a)$ (label this $\hat{\beta}$) should represent the economic value of partner's human/social capital. Alternatively, if $\hat{\gamma}$ is positive, then there will likely be selection on unobservables and therefore $\hat{\beta}$ may have an upward bias.

Model 6 in Table 4 (5) replaces Partnership with dummies for $P(hc)$ and $P(not_hc_fin)$. In Table 4 we find that $\hat{\beta} = 7.09$ ($p < 0.01$), and $\hat{\gamma} = 6.52$ ($p = 0.08$). Results in Table 5 are similar. Therefore, it appears that $\hat{\beta}$ is upwards biased due to selection on unobservables.

We proceed to separately identify the contribution of the partner's human/social capital from selection on unobservables. Rather than imposing further parametric restrictions to obtain point identification, we construct a lower bound for $\hat{\beta}$. The effect of selection on unobservables may differ between partners who provide human/social capital and partners who only provide financing. We consider that conditional on inventor's assets the partnerships that receive only financing have on average higher quality than the rest of the partnerships. In appendix F we derive this result in a model of selection into partnerships. The result is fairly general: partners that on average provide lower contributions can only compensate the opportunity cost of forming a partnership in projects of high quality.¹⁸ This implies that the ventures where partners did not contribute human/social capital but provided financing are more likely to involve high quality inventions than in the rest of the ventures. In our econometric setting, this result is equivalent to have

¹⁸The result depends on a positive complementarity between the invention quality, commercialization investment, and human and social capital. This is satisfied by most production functions.

$cov(P(hc), q) < cov(P(not_hc_fin), q)$. The sign of this inequality allows us to calculate a lower bound of the partner’s human/social capital: $\beta^L = \hat{\beta} - 0.224\hat{\gamma}$.¹⁹ Evaluating the right hand side of the bound at the estimated $\hat{\beta}$ and $\hat{\gamma}$, we obtain $\beta^L = 5.63$ (std. err. 1.99, $p < 0.00$) and $\beta^L = 6.95$ (std. err. 2.06, $p < 0.00$) for the estimations presented in Table 4 and Table 5, respectively. Because we can safely assume that an upper bound for β is $\hat{\beta}$, the best estimate of partner’s human/social capital must lie in the range $\beta \in (5.63, 7.09)$. The lower bound represents a partnership coefficient that is lowered from 7.54 in Model 4 to 5.63 in Model 6 of Table 4, a 25% reduction. The lower bound is 37% of the gross partnership coefficient in Model 1. The lower bound remains economically meaningful. For example, the mean probability of commercialization increases from 0.06 to 0.12 at the estimated lower bound effect, and the impact on expected revenues is a 38% increase. As the lower bound estimate is higher for results in Table 5 we refrain from reporting those details. Note that this method returns estimates quite similar to those from the method controlling for observed heterogeneity.

As stated in the sampling methods and data section there is the potential for selection bias due to address traceability and non-response. We therefore estimate a model for the probability of address traceability and a model for the probability of response from the traceable sample. We multiply the probabilities of tracing and response and invert the product for use as selection weight in the analysis (see Holt, Smith, and Winter (1980)). Results of regressions when applying these weights are reported in Table D1 and D2 in Appendix D. These results are qualitatively similar to those reported in the text where weights are not applied (Table 4 and 5). This indicates that while there were trace and response sampling biases, these did not covary strongly with the correlations in the model.

¹⁹Define $bias(\hat{\beta}) = \frac{cov(P(hc), Q)}{Var(P(hc))}$ and $bias(\hat{\gamma}) = \frac{cov(P(not_hc_fin), Q)}{Var(P(not_hc_fin))}$. $bias(\hat{\gamma}) = \hat{\gamma}$ since our theoretical model implies that the true value of γ is 0, while $bias(\hat{\beta}) = \hat{\beta} - \beta$. Rearranging and using that $Cov(P(hc), Q) < Cov(P(not_hc_fin), Q)$, the lower bound β^L for $\hat{\beta}$, is $\beta^L = \hat{\beta} - (\frac{Var(P(not_hc_fin))}{Var(P(hc))})\hat{\gamma} = \hat{\beta} - 0.224\hat{\gamma}$. We have replaced $Var(P(hc))$ and $Var(P(not_hc_fin))$ with their sample counterparts.

5 Conclusion

Business partners appear frequently among start-ups (Burton et al., 2009; Ruef et al., 2003). This paper investigates the impact of business partners on invention commercialization success. Our survey suggests a very important role for business partners in commercialization success. Projects run by partnerships are five times more likely to reach commercialization, they have mean revenues approximately ten times greater than projects run by solo-entrepreneurs, and fully 72 percent of the total revenues of all projects were generated by projects run as business partnerships. These gross differences may be due both to selection and business partners' value added.

We use several approaches to control for selection into partnership and find that the effect of partners' human and social capital represents an increase in the probability of commercialization at least between 0.06 and 0.09 points. These are economically meaningful values as the probability of commercialization for solo-entrepreneurs is 0.06. The estimated effect of partner human and social capital on revenues is also large, representing approximately either a 29% or a 38% increase in expected revenues, depending on the specification. Our findings also indicate that inventors are capital constrained, and that external financing is positively correlated with the partnership effect, but not very much, suggesting that partners may often not be the main external financier.

Taken together, these results indicate that the decision to form a business partnership is an important determinant of the large heterogeneity in entrepreneurial success, and that obtaining complementary human and social capital accounts for a large portion of this effect. Moreover, as long as the initial entrepreneur can appropriate part of the gains from collaborating with other individuals, the formation of business partnerships can increase the entrepreneurs' incentives to innovate.

Our setting is admittedly unique. We likely examine a domain where good business partners'

human and social capital may be considerably more useful than in regular start-ups such as the mom-and-pop corner store. In this respect our sample is probably similar to that of projects that attract and receive angel financing (Goldfarb et al, 2009). At the same time our sample does not contain many projects that eventually receive formal VC funding and our results may reflect this fact.²⁰

Our work contributes to the literature in several ways. This paper contributes to the literature accounting for the large observed heterogeneity in entrepreneurial returns. This heterogeneity has been typically associated with, among other factors, liquidity constraints, the skills of the entrepreneur, investment in own complementary skills, and the quality of the venture (e.g. Evans and Jovanovic, 1989; Astebro, 2003; Lazear, 2005; and Parker and van Praag, 2006). To our knowledge this is the first paper to examine the performance consequences when an inventor-entrepreneur obtains business partners. We also examined how much of this impact is due to the partner's complementary human and social capital, and financial capital. The paper also contributes to the literature on the choice of entrepreneurship. Lazear (2005) develops a theory of entrepreneurship where he assumes that entrepreneurs must invest in his/her worst skill to increase business performance; Holmes and Schmitz (1990)'s theory of entrepreneurship focuses on specialization and business transfers; and Evans and Jovanovic (1989) study the degree to which an individual's financial wealth determines the choice between entrepreneurship and wage work. We, instead, focus on individuals who may find partners to complement their skills and/or relax their liquidity constraints for commercialization success. Moreover, the paper echoes previous concerns about selection into business angel and venture capital financial agreements potentially contaminating estimates of the value of such agreements for early stage businesses (see e.g., Hall and Lerner, 2010). We suggest some alternate and slightly novel approaches to solving

²⁰The fraction which received VC financing was 0.8%, too small to be analyzable in our study.

this contamination issue. Our results also provide some complementary evidence to studies of both business angel venture capital financing, which show that there real positive performance consequences –i.e., IPO and business survival rates– on early-stage ventures (see e.g., Hellmann and Puri (2000), Sorensen (2007), Kerr et al (2013)).

Our results would suggest that a major policy leverage to increase commercialization rates and revenues for early-stage businesses is to make it easier for inventors and partners to meet. This would take different forms than the typical policy levers to stimulate the provision of venture financing, and is likely to be less costly. Entrepreneurship clubs, breakfast networking meetings and other activities that intend to match inventors with potential partners come to mind as possible vehicles. The results also hint at how business partners may raise their ability to be successful.

References

- ASTEBRO, T. (2003): “The Return to Independent Invention: Evidence of Risk Seeking, Extreme Optimism or Skewness-Loving?,” *The Economic Journal*, 113 (484), 226–239.
- ASTEBRO, T., AND I. BERNHARDT (2003): “Start-Up Financing, Owner Characteristics and Survival,” *Journal of Economics and Business*, 55(4), 303–320.
- ASTEBRO, T., AND J. CHEN (2012): “The Returns to Entrepreneurship: Measurements, Methods, Old and New Results,” HEC Paris Working Paper.
- BAKER, K., AND G. ALBAUM (1986): “New Product Screening Decision,” *Journal of Product Innovation Management*, 3 (1), 32–39.
- BASS, F. M. (1969): “A New Product Growth Model for Consumer Durables,” *Management Science*, 15, 215–27.

- BECKMAN, C. M., M. D. BURTON, AND C. O'REILLY (2007): "Early teams: The impact of team demography on VC financing and going public," *Journal of Business Venturing*, 22 (2), 147–173.
- BURTON, M. D., P. C. ANDERSON, AND H. E. ALDRICH (2009): "Owner Founders, Nonowner Founders and Helpers," in *New Firm Creation in the United States, International Studies in Entrepreneurship*, ed. by P. Reynolds, and R. Curtin. Springer Science-Business Media.
- CAMPBELL, D., AND D. FISKE (1959): "Convergent and Discriminant Validation by the Multi-trait-Multi-method Matrix," *Psychological Bulletin*, 56 (2), 81–105.
- CHEMMANUR, T., AND Z. CHEN (2006): "Venture Capitalists versus Angels: The Dynamics of Private Firm Financing Contracts," Working paper, Boston College.
- COPELAND, M., AND O. MALIK (2006): "How to build a bulletproof startup," *Business 2.0*, June, 76–92.
- CRESSY, R. (1996): "Are business startups debt rationed?," *The Economic Journal*, 106, 1253–1270.
- CRONBACH, L. (1951): "Coefficient alpha and the internal structure of tests," *Psychometrika*, 16 (3), 297–334.
- EISENHARDT, K. M., AND C. B. SCHOONHOVEN (1990): "Organizational Growth: Linking Founding Team, Strategy, Environment, and Growth Among U.S. Semiconductor Ventures, 1978-1988," *Administrative Science Quarterly*, 35 (3), 504–529.
- EVANS, D., AND B. JOVANOVIĆ (1989): "An Estimated Model of Entrepreneurial Choice under Liquidity Constraints," *Journal of Political Economy*, 97(4), 808–827.
- FAIRLIE, R. W., K. KAPUR, AND S. GATES (2009): "Is Employer-Based Health Insurance a Barrier to Entrepreneurship?," Working Paper University of California, Santa Cruz.

- FAZZARI, S. M., R. G. HUBBARD, AND B. C. PETERSEN (2000): “Investment-cash flow sensitivities are useful: A comment on Kaplan and Zingales,” *Quarterly Journal of Economics*, 115 (2), 695–705.
- FISCHHOFF, B. (1975): “Hindsight Is Not Equal to Foresight: The Effect of Outcome Knowledge on Judgment under Uncertainty,” *Journal of Experimental Psychology: Human Perception and Performance*, 1(3), 288–299.
- GIURI, P., M. MARIANI, S. BRUSONI, G. CRESPI, D. FRANCOZ, A. GAMBARDELLA, W. GARCIA-FONTES, A. GEUNA, R. GONZALES, D. HARHOFF, K. HOISL, C. L. BAS, A. LUZZI, L. MAGAZZINI, L. NESTA, O. NOMALERI, N. PALOMERAS, P. PATEL, M. ROMANELLI, AND B. VERSPAGEN (2007): “Inventors and invention processes in Europe: Results from the PatVal-EU survey,” *Research Policy*, 36 (8), 1107–1127.
- GOLDFARB, B., G. HOBERG, D. KIRSCH, AND A. TRIANTIS (2007): “Are angels preferred series A investors?,” Working Paper, University of Maryland.
- GRAHAM, J., AND S. HOFER (2000): *Multiple Imputation in Multivariate Research*. Hillsdale, NJ: Erlbaum.
- GROSSMAN, S., AND O. HART (1986): “The costs and benefits of ownership: A theory of vertical and lateral integration,” *Journal of Political Economy*, 94(4), 691–719.
- HALEBLIAN, J., AND S. FINKELSTEIN (1993): “Top Management Team Size, CEO Dominance, and Firm Performance: The Moderating Roles of Environmental Turbulence and Discretion,” *The Academy of Management Journal*, 36 (4), 844–863.
- HALL, B. H., AND J. LERNER (2010): “The Financing of R&D and Innovation,” in *Handbook of the Economics of Innovation*, ed. by B. H. Hall, and N. Rosenberg, chap. 14. Elsevier North-Holland.

- HARRISON, R. T., C. M. MASON, AND P. J. ROBSON (2010): “The Determinants of Long Distance Investing by Business Angels: Evidence from the United Kingdom,” *Entrepreneurship and Regional Development*, 22(2), 113–137.
- HELLMANN, T., AND M. PURI (2000): “The interaction between product market and financing strategy: the role of venture capital,” *Review of Financial Studies*, 13, 959–84.
- HIRANO, K., G. W. IMBENS, AND G. RIDDER (2003): “Efficient Estimation of Average Treatment Effects Using the Estimated Propensity Score,” *Econometrica*, 71(4), 1161–90.
- HOLMES, T., AND J. A. SCHMITZ (1990): “A Theory of Entrepreneurship and Its Application to the Study of Business Transfers,” *Journal of Political Economy*, 98(2), 265–94.
- HOLMSTROM, B. (1982): “Moral hazard in partnerships,” *Bell Journal of Economics*, 13, 324–40.
- HOLT, D., T. SMITH, AND P. WINTER (1980): “Regression analysis of data from complex surveys,” *Journal of the Royal Statistical Society*, 143 (4), 474–487.
- KAWASAKI, G. (1994): *The Art of the Start: The Time-Tested, Battle-Hardened Guide for Anyone Starting Anything*. Penguin, New York.
- KERR, W. R., J. LERNER, AND A. SCHOAR (2013): “The Consequences of Entrepreneurial Finance: Evidence from Angel Financings,” *Review of Financial Studies*, Forthcoming.
- KOR, Y. Y. (2003): “Experience-Based Top Management Team Competence and Sustained Growth,” *Organization Science*, 14 (6), 707–719.
- KREMER, M. (1993): “The O-ring theory of economic development,” *Quarterly Journal of Economics*, 108(3), 551–75.
- LAZEAR, E. P. (2005): “Entrepreneurship,” *Journal of Labour Economics*, 23(4), 649–81.
- LITTLE, R. J. A., AND D. RUBIN (1987): *Statistical analysis with missing data*. John Wiley &

Sons, New York.

MASON, C. M. (2009): “Venture Capital: A Geographical Perspective,” in *Handbook of Research on Venture Capital*, ed. by H. Landström. Edward Elgar Publishing Limited, Cheltenham, UK.

MCDONALD, J. F., AND R. A. MOFFITT (1980): “The Uses of Tobit Analysis,” *The Review of Economics and Statistics*, 62 (2), 318–321.

OLLEY, S., AND A. PAKES (1996): “The Dynamics of Productivity in the Telecommunications Equipment Industry,” *Econometrica*, 64 (6), 1263–1298.

PARKER, S. C., AND C. M. VAN PRAAG (2006): “Schooling, Capital Constraints, and Entrepreneurial Performance,” *Journal of Business & Economic Statistics*, 24 (6), 416–431.

REPULLO, R., AND J. SUAREZ (2004): “Venture capital finance: A security design approach,” *Review of Finance*, 8, 75–108.

RUEF, M., H. E. ALDRICH, AND N. M. CARTER (2003): “The Structure of Founding partnerships: Homophily, Strong Ties, and Isolation among U.S. Entrepreneurs,” *American Sociological Review*, 68(April), 195–222.

SORENSEN, M. (2008): “How Smart is Smart Money? An Empirical Two-Sided Matching Model of Venture Capital,” *Journal of Finance*, 52 (6), 2725–62.

TRAJTENBERG, M., G. SHIFF, AND R. MELAMED (2006): “The Names Game, Using Inventors Patent Data in Economic Research,” NBER Working Paper 12479.

URBAN, G. L., AND J. R. HAUSER (1993): *Design and Marketing of New Products*. Englewood Cliffs, NJ: Prentice-Hall.

VAN BUUREN, S., H. C. BOSUIZEN, AND D. L. KNOOK (1999): “Multiple imputation of missing blood pressure covariates in survival analysis,” *Stat Med*, 18, 681–694.

WOOLRIDGE, J. M. (2007): *Econometric Analysis of Cross Section and Panel Data*. MIT Press.

Table 1: Commercialization, Invention Quality, R and D Expenditures and Revenues by Solo-entrepreneurs and Teams.

All data are in Cdn 2003 dollars. Each missing item response has been imputed five times. Means are computed using the formulae in Little and Rubin (1987).

A. Percentage of projects with partnerships and contributions by partners

Percentage partnerships (%)	21.0
Contributions among partnerships (%)	
Only financing	16.1
With both financing and human or social capital	36.8
Without financing and with human or social capital	47.1

B. Characteristics of projects unconditional on commercialization

	All	Partnership	Solo-entrepreneur
Percentage with positive CIC review (%)	21.5	35.5	17.8
Mean R&D expenditures (\$) by inventor prior to the CIC review	22,518	90,364	4,725
Mean commercialization investment (\$)	24,823	70,690	12,792
Mean commercialization revenues (\$)	67,432	232,397	24,196
Probability of commercialization (%)	10.9	29.9	5.9

C. Characteristics of projects conditional on commercialization

Percentage with positive CIC review (%)	49.3	55.0	41.7
Mean R&D expenditures (\$) by inventor prior to the CIC review	166,009	282,354	10,882
Mean commercialization investment (\$)	110,343	169,732	31,158
Mean commercialization revenues (\$)	619,739	776,238	411,073

Table 2: Probit Regression Analysis of Selection into Partnership

Dependent variable is partnership, a dummy variable taking the value 1 if an innovation was commercialized as a partnership, 0 otherwise. All data are in Cdn 2003 dollars. Regressions include dummy variables controlling for industry and year. Standard errors in parenthesis. ***, ** or * mean the coefficient is significant at the 1 percent, 5 percent, or 10 percent level, respectively. Missing item data are multiple imputed. Coefficients and standard errors are computed using the formulae in Little and Rubin (1987).

Parameter estimates of effects of invention quality			
Positive	0.397*** (0.130)		0.211 (0.142)
R&D expenditures		0.080*** (0.016)	0.071*** (0.017)
Pseudo R^2 (%)	0.06	0.08	0.08
N	772	772	772

Table 3: Probit Regression Analysis of Selection into Partnership with Financing

Dependent variable is partnership with financing; a dummy variable taking the value 1 if an innovation was commercialized by a partnership with financing, 0 otherwise. All data are in Cdn 2003 dollars. Regressions include dummy variables controlling for industry and year. Standard errors in parenthesis. ***, ** or * mean the coefficient is significant at the 1 percent, 5 percent, or 10 percent level, respectively. Missing item data are multiple imputed. Coefficients and standard errors are computed using the formulae in Little and Rubin (1987).

Parameter estimates of effects of invention quality			
Positive	0.125 (0.152)		-0.029 (0.165)
R&D expenditures		0.055*** (0.019)	0.057*** (0.021)
Pseudo R^2 (%)	0.05	0.06	0.06
N	772	772	772

Table 4: Tobit Regression Analysis of Commercialization Revenues

Dependent variable = $\log(\text{commercialization revenues})$. Regressions include dummy variables controlling for industry and year. Standard errors in parenthesis. ***, ** or * mean the coefficient is significant at the 1 percent, 5 percent or 10 percent level, respectively. Missing item data are multiple imputed. Coefficient estimates and standard errors are constructed using the formulae in Little and Rubin (1987).

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
					Propensity Score Weighted	
	Tobit	Tobit	Tobit	Tobit	Tobit	Tobit
Partnership effects						
Partnership	15.25*** (2.38)	11.68*** (2.14)	7.54*** (1.94)	7.54*** (1.92)	7.06*** (1.84)	
Partner with human/social capital						7.09*** (2.01)
Partner without human/social capital but with financing						6.52* (3.69)
Control variables						
Positive evaluation		5.44*** (2.15)	3.02 (1.98)	3.05 (1.98)	2.19 (1.94)	3.11 (1.98)
R&D expenditures		1.57*** (0.35)	0.54* (0.33)	0.48 (0.33)	-0.30 (0.29)	0.49 (0.33)
Commercialization investment			1.61*** (0.28)	1.14*** (0.31)	1.00*** (0.31)	1.19*** (0.32)
Commercialization labor				1.05** (0.44)	1.32*** (0.48)	1.01** (0.44)
Constant	-25.07*** (4.70)	-34.22*** (5.43)	-31.78*** (4.98)	-32.71*** (5.05)	-25.76*** (4.49)	-32.17*** (4.98)
Sigma	14.88*** (1.44)	13.37*** (1.28)	11.97*** (1.13)	11.81*** (1.11)	9.51*** (0.91)	11.87*** (1.12)
Pseudo R^2 (%)	0.09	0.13	0.18	0.19	0.14	0.18
N	772	772	772	772	724	772

Table 5: Tobit Regression Analysis of Commercialization Revenues with Inventor's and Other's Capital

Dependent variable = $\log(\text{commercialization revenues})$. Regressions include dummy variables controlling for industry and year. Standard errors in parenthesis. ***, ** or * mean the coefficient is significant at the 1 percent, 5 percent or 10 percent level, respectively. Missing item data are multiple imputed. Coefficient estimates and standard errors are constructed using the formulae in Little and Rubin (1987).

	Model 2	Model 3	Model 4	Model 5	Model 6
				Propensity Score Weighted	
	Tobit	Tobit	Tobit	Tobit	Tobit
Partnership effects					
Partnership	10.28*** (2.08)	9.26*** (2.08)	8.83*** (2.02)	7.98*** (1.92)	
Partner with human/social capital					8.45*** (2.10)
Partner without human/social capital but with financing					6.66* (3.81)
Control variables					
Positive evaluation	5.03*** (2.06)	4.30** (2.05)	4.29** (2.02)	4.02** (2.05)	4.31** (2.03)
Own financing	1.90*** (0.36)	1.74*** (0.36)	0.81** (0.37)	-0.56* (0.28)	0.86** (0.37)
External financing		0.43** (0.22)	0.22 (0.21)	0.40* (0.22)	0.25 (0.22)
Commercialization labor			1.73*** (0.44)	2.13*** (0.46)	1.70*** (0.44)
Constant	-36.38*** (5.54)	-35.37*** (5.42)	-33.67*** (5.17)	-24.01*** (4.50)	-33.22*** (5.12)
Sigma	13.02*** (1.24)	12.83*** (1.22)	12.31 (1.17)	9.22*** (0.88)	12.39*** (1.18)
Pseudo R^2 (%)	0.15	0.15	0.17	0.12	0.17
N	772	772	772	742	772

Appendix: Data and Tables

Appendix A: Further Details on Inventor Sample and Sampling Process

The sample is drawn from the universe of inventor-entrepreneurs using the services of the CIC. One important feature of our sample is that there was full personal contact information recorded for the inventor by the CIC at the time of assessment (name, title, home telephone number, home address, business telephone number). This proved a benefit over studies that use patents to track inventors (c.f. Giuri et al. (2007); Trajtenberg, Shiff, and Melamed (2006)). Patent records provide only the name and only sometimes the address of the inventor. A drawback was that the CIC as a rule only recorded the initial of the first name, making it more difficult to find exact name matches when searching telephone directories for updated information.

Using records from the Canadian Innovation Center, in 2004 we extracted a list of 6,405 records with inventors who had submitted ideas for CIC review between 1994 and 2001. This list was edited down to 4,425 records, deleting all but one application from the same inventor. Similarly to Giuri et al. (2007) we then used a tiered match search algorithm to search for the inventors' current home addresses and home phone numbers using the Yellow Pages. The results appear in Table A1.

We were able to match 45% of records (1,978 records). In contrast, Giuri et al. (2007) obtained 64% exact matches of patent holders in the White and Yellow pages. The percentage of matches was lower than that of Giuri et al. (2007) for several reasons. First, we identified 610 records (14%) where there were more than one match but typically fewer than four. Although it would have been possible to call these to find the inventor, we did not do so due to budget constraints. Second, as our records contained only the initial of the first name, we had more inventors with multiple matching records (41.5%). Finally, our sample consisted of 25% stayers and 75% movers, while the European survey contained 64% stayers; since our inventors moved more often, it was more difficult to trace them.

The Survey Research Centre mailed out 1,841 letters on Friday January 30th 2004, the difference being used for two pre-test rounds and the elimination of another 8 records that upon closer scrutiny had inventors with multiple submissions. After 71 refusals to participate were obtained the final sample size was 1,770. Contact attempt results are presented in Table A2.

Many numbers in the sample did not lead to contact with an inventor, for any of the following reasons, moved, not in service, wrong number, and the person reached was not the inventor. By excluding these numbers (dispositions 3, 4, 5, and 10), we can calculate a traceable rate by dividing the remaining contacted numbers over the sample total. Excluded dispositions corresponded to 418 observations. The traceable rate was $1352/1770 = 76\%$. The response rate can be calculated among the remaining cases by multiplying the contact rate by the cooperation rate. Using disposition codes to represent the number of such observations, the response rate is,

$$\frac{7 + 8 + 9 + 11 + 12 + 13 + 14}{1 + 2 + 7 + 8 + 9 + 11 + 12 + 13 + 14}, \frac{13 + 9}{8 + 9 + 11 + 12 + 13 + 14}$$

which equals 61%.

Table A1: Address Match Results

	Number	Percentage
Record where details did not change	948	21.4%
Record with new phone number, same address	160	3.6%
Record with new address, same phone number (local move)	371	8.4%
Record with new address and phone number	499	11.3%
Excessive number of name matches with no matching address/phone (> 3)	1,355	30.6%
Multiple name matches with non-matching address and phone (≤ 3)	610	13.8%
No matching record	482	10.9%
Total	4,425	100%

Table A2: Contacts Attempt Results

Disposition Code	Description	# of Records
1	No Answer/Answering Machine	79
2	Busy	2
3	Not in service	164
4	Wrong Number	136
5	Moved	18
6	Callback - No interview started	0
7	Callback - partial interview	2
8	Refusal	390
9	Refusal - partial interview	49
10	Person did not submit invention to CIC	100
11	Person not available during study hours	7
12	Other	22
13	Complete	781
14	Deceased	21
Total		1770

Appendix B:
Method for Computing Discounted Present Value of Future Commercialization Revenues

The method follows Åstebro (2003) Data on revenues X_1, \dots, X_N for year $1, \dots, N$, are collected for 84 commercialized inventions for which 41 had revenues right censored by the survey date 2003. For products that were not yet discontinued by the time of the survey, indexed by l , information on X_l, \dots, X_N is not available. For these, the revenues from l to N was estimated using forecasts.

First, the expected duration of product sales, $E(N)$, was estimated to have a geometric duration distribution function with the parameter $\alpha = 0.09$. The expected duration for innovation j at time l is therefore $E(N|N < l) = (l + 1/\alpha)$.

Second, we forecasted $X_l, \dots, X_{E(N)}$ using the sales forecast model of Bass (1969). The model estimates the diffusion of new consumer durable products with the formula $F(t) = 1 - e^{-(p+q)t} / [1 + (q/p)e^{-(p+q)t}]$, where $F(t)$ can be interpreted as the fraction of cumulative sales that occur in period t , and p and q are estimated parameters. Over 100 publications reveal typical parameter values of $p = 0.04$ and $q = 0.3$ (Urban and Hauser (1993, p.82)). These values define a product life cycle with the peak of sales in the sixth year, and the cumulative sales volume reaching 99% after 20 years of sales. Innovations in this sample with completed spells show similar sales patterns. We thus used the above mentioned values of p and q to forecast sales during the expected remainder of innovation j 's life cycle $X_l, \dots, X_{E(N)}$ for up to 20 years of sales if N was right censored for innovation j at time l .

Finally, all observed and expected future revenues were discounted to 2003 using the real interest rate, estimated as the posted yearly Government of Canada bond rate adjusted for inflation.

Regression results were insensitive to excluding forecasted revenues.

Appendix C:

Demographic Statistics for Inventor and Matched Sample from General Population

The modal inventor age is 45-54 and the modal educational attainment is high school, although about 26% of the inventors had some professional or graduate education. Only 16% of the inventors reported they were unemployed, home-makers, retired, disabled, or on sick leave during the time that they were developing their focal invention. Most (58%) were full-time employees, while 32% were self-employed when developing their invention (multiple answers possible).

The combined samples from the general population matched with the inventors contains unusually high fractions reporting that they are or have been self-employed (63 percent), or have owned a business (60 percent). However, the rates of entrepreneurship are much higher for the inventor sample than for the general population sample: 72 percent of the inventor sample report current or prior self-employment, compared with 43 percent of the general population sample; 67 percent of the inventor sample report current or prior business ownership compared with 43 percent of the general population sample.²¹ Overall, the average number of businesses that have been owned is 1.20; again, the figure is much higher for the inventor sample (1.49) than for the general population sample (0.69). Note also that individuals in the more entrepreneurial inventor sample are significantly more likely to have come from an entrepreneurial family, and to have worked in more different industries and different occupations. They are also more likely to be older, and to have completed a professional degree. The two samples do not differ statistically on other comparable variables such as general education, gender, marital status, household income, managerial experience and business experience. For detailed t-statistics see Table CI.²²

²¹The large fraction of business owners in the matched sample may cause consternation. But the fraction is consistent with official statistics if one considers that: 1. We asked whether the respondent had ever been self-employed or ever been a business owner, not if the respondent is currently self-employed or business owner. 2. We matched the sample from the general population to the inventors by work experience and gender (and province); this increases the incidence of having ever been an entrepreneur since the inventor Sample is relatively mature and 90 percent male. 3. The sample is drawn from Canada. The rate of self-employment is much higher in Canada than in the U.S.A. and this explains the remaining difference compared to what would be expected in for example the U.S.A. Fairlie, Kapur, and Gates (2009) report that in the U.S.A., by age 45 approximately 17% of males have ever been a business owner, and by 55 this rises to approximately 20%, (data from Current Population Survey). However, the proportion of business owner in our Canadian general population sample is approximately double that at 43%. This difference reflects that the self-employment in the U.S.A. is less than half of that in Canada, for example 7.3% versus 15.2% in 2002 (Sources: Current Population Surveys, U.S.A. and Canada.)

²²Note that two samples were matched on sampling quotas for province in Canada, years of work experience, and gender.

Table C1: Summary Statistics: Demographic Variables for Inventors and Matched Sample from General Population

	Fractions		t-statistics
	Inventors	General population	
Male	0.91	0.91	0.00
Married	0.89	0.88	0.86
Income			
<\$30,000	0.12	0.14	-0.72
\$30,000-\$50,000	0.17	0.20	-1.04
\$50,000-\$70,000	0.21	0.16	1.62
\$70,000-\$100,000	0.23	0.23	0.16
>\$100,000	0.28	0.27	0.25
Age			
<35	0.04	0.29	-8.85
35-44	0.30	0.35	-1.39
45-54	0.36	0.18	6.06
≥55	0.29	0.18	4.14
Work experience			
<9 years	0.02	0.05	-2.76
10-19 years	0.13	0.13	0.14
≥ 20 years	0.85	0.82	1.57
Occupational fields			
1	0.11	0.16	-2.28
2 or 3	0.38	0.39	-0.44
4 or 5	0.26	0.28	-0.77
> 5	0.25	0.16	3.53
Industries worked in			
1	0.15	0.26	-3.53
2 or 3	0.40	0.41	-0.38
4 or 5	0.27	0.20	2.44
6 to 10	0.12	0.10	1.06
> 10	0.06	0.04	1.59
Education			
Did not complete high school	0.11	0.15	-1.79
High school	0.15	0.16	-0.44
Trade school	0.14	0.13	0.63
Some college	0.16	0.18	-0.70
College degree	0.18	0.14	1.57
Professional degree	0.15	0.09	2.78
Graduate studies	0.11	0.15	1.76
Arts or social science	0.51	0.45	1.04
Science or engineering	0.34	0.29	0.99
Business degree	0.16	0.20	-0.89
Business background			
Ever been self employed	0.72	0.43	8.75
Ever owned a business	0.67	0.43	7.31
No. of businesses owned	1.49	0.69	7.12
Entrepreneurial family	0.55	0.47	2.63

Note.—Two-tailed t-test with unequal group variances for differences between inventor and general population samples

Appendix D:
Regression Results Using Sample Selection and Non-Response Corrections

Table D1: Tobit Regression Analysis of Commercialization Revenues using Sample Selection and Nonresponse Corrections

Dependent variable = log(commercialization revenues). Regressions include dummy variables controlling for industry and year. Standard errors in parenthesis. ***, ** or * mean the coefficient is significant at the 1 percent, 5 percent or 10 percent level, respectively. Missing item data are single imputed. Parameter estimates are corrected for sample selection and non-response bias.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
					Propensity Score Weighted	
	Tobit	Tobit	Tobit	Tobit	Tobit	Tobit
<hr/>						
Partnership effects						
Partnership	15.04*** (1.87)	11.84*** (1.95)	8.52*** (1.85)	8.45*** (1.81)	6.87*** (2.06)	
Partner with human/social capital						8.57*** (1.92)
Partner without human/social capital but with financing						6.52 (4.49)
<hr/>						
Control variables						
Positive evaluation		4.79*** (2.14)	2.04 (2.32)	2.02 (2.32)	3.59* (2.02)	2.00 (2.31)
R&D expenditures		1.61*** (0.34)	0.85** (0.43)	0.87** (0.43)	-0.19 (0.29)	0.86*** (0.43)
Commercialization investment			1.35*** (0.28)	0.85*** (0.33)	1.11*** (0.33)	0.86*** (0.33)
Commercialization labor				1.17*** (0.43)	1.44*** (0.48)	1.12*** (0.43)
<hr/>						
Constant	-25.04*** (3.68)	-34.27*** (4.30)	-32.59*** (4.19)	-34.27*** (4.20)	-31.03*** (5.26)	-33.90*** (4.16)
Sigma	13.87*** (1.14)	12.45*** (1.08)	11.53*** (1.00)	11.31*** (1.00)	9.84*** (0.96)	11.30*** (1.00)
<hr/>						
Pseudo R^2 (%)	0.11	0.15	0.18	0.19	0.16	0.19
N	772	772	772	772	724	772
<hr/>						

Table D2: Tobit Regression Analysis of Commercialization Revenues with Inventor's and Other's Capital using Sample Selection and Nonresponse Corrections

Dependent variable = log(commercialization revenues). Regressions include dummy variables controlling for industry and year. Standard errors in parenthesis. ***, ** or * mean the coefficient is significant at the 1 percent, 5 percent or 10 percent level, respectively. Missing item data are single imputed. Parameter estimates are corrected for sample selection and non-response bias.

	Model 2	Model 3	Model 4	Model 5	Model 6
				Propensity Score Weighted	
	Tobit	Tobit	Tobit	Tobit	Tobit
Partnership effects					
Partnership	11.82*** (2.18)	11.22*** (2.03)	10.45*** (1.96)	8.94*** (2.16)	
Partner with human/social capital					10.62*** (2.08)
Partner without human/social capital but with financing					7.25 (4.59)
Control variables					
Positive evaluation	4.57* (2.51)	4.20* (2.46)	3.87 (2.52)	7.22*** (2.12)	3.81 (2.50)
Own financing	1.40*** (0.45)	1.33*** (0.46)	0.38 (0.44)	-0.70** (0.27)	0.42 (0.43)
External financing		0.23 (0.27)	0.08 (0.26)	0.35 (0.23)	0.09 (0.26)
Commercialization labor			1.90*** (0.40)	2.34*** (0.43)	1.83*** (0.41)
Constant	-33.25*** (4.33)	-32.84*** (4.36)	-31.57*** (4.07)	-29.16*** (5.25)	-31.37*** (4.02)
Sigma	12.75*** (1.11)	12.69*** (1.10)	12.04*** (1.06)	9.63*** (0.94)	12.03*** (1.07)
Pseudo R^2 (%)	0.14	0.14	0.16	0.14	0.16
N	772	772	772	742	772

Appendix E:
Some further information on the Canadian Innovation Centre

The CIC started in 1976 at the University of Waterloo as part of its technology transfer office and formed a separate entity in 1981 to address the greater Canadian market.

The purpose of the CIC's invention evaluation service is to advise potential entrepreneurs on whether and how to continue efforts. CIC program evaluators assess a range of technological and economic variables. The evaluations were based on a well-established assessment process. Because assessments occurred before commercialization, and before significant R&D expenditures, they avoid problems such as methods bias (Campbell and Fiske, 1959) and hindsight bias (Fischhoff, 1975). The assessment process used a standardized preexisting method, which Baker and Albaum (1986) in a study of 86 judges and six products found to yield Cronbach (1951) alphas of 0.84 to 0.96, implying highly comparable overall ratings across CIC personnel. The CIC's evaluators were extensively trained by a chief evaluator, who ran the program consistently from 1981 through 2000, and a group meeting at the end of each review provided feedback to ensure appropriate measures for each invention. The CIC's evaluations were found, in Åstebro's (2003) study of final ratings in a prior survey, to successfully predict revenues of commercialized inventions.

The CIC was until 1999 a not-for-profit organization supported 50% by the Canadian government and 50% by service fees. Government support for the program dried up in 2000 and fees subsequently quadrupled from Canadian \$250 to \$1,000 to cover costs. The CIC assessed 11,000 inventions over the period 1976-1996, and in the late 1990s it experienced about 1,000 submissions per year from all provinces in Canada. With the increase in costs and the concomitant expansion of local "Industrial Technology Advisors" from a branch of Industry Canada, the submissions to CIC have dwindled and today the CIC assesses only a fraction of the inventions it assessed in its heyday.

Appendix F:

A model of selection into business partnerships

The economy is populated by inventors and business partners. Inventors are endowed with a unit of labor, an invention of quality Q , and assets Z .²³ The inventor can use her unit of labor to commercialize the invention. The invention quality and assets are distributed with cdf $F_{Q,Z}$ and are independent. Business partners are also endowed with a unit of time. The partner can use their unit of time to contribute complementary human and/or social capital as well as financing. The effect of the partner's human and/or social capital endowment (A) may be heterogeneous and is randomly drawn from a cdf F_A . We assume that both the inventor and partner have an inelastic supply of labor and will therefore spend their unit of time in the venture. Every inventor meets a partner with positive probability. Inventions can be commercialized by the inventor on her own or with a partner.²⁴

If the invention is commercialized by the inventor on her own, the profits are $V^S = QK^\alpha + r(Z - K)$ where K is the amount of commercialization capital invested in the business, r is the interest rate (i.e., the opportunity cost of capital), and $\alpha \in (0, 1)$. The complementarity between the commercialization capital and the invention quality implies that a higher quality of the invention will produce a higher marginal product of capital at all levels of capital. As a result some inventors may have insufficient assets to fully fund the capital investment. Following Evans and Jovanovic (1989), we consider that inventors can borrow against their assets to fund capital investment. If $Z < K$, the inventor is a net borrower, and $r(Z - K)$ is the amount he repays at the end of the period. An inventor with assets Z will be able to borrow an amount up to $(\lambda - 1)Z$ and invest up to $K \leq \lambda Z$,²⁵ where $\lambda > 1$. Whenever the optimal capital investment is higher than the inventor's borrowing capacity the inventor will be liquidity constrained.

If the invention is commercialized with a partner, the capital is leveraged by the factor A , which stands for the partner's human and/or social capital effect on revenues. The partner may also provide financing beyond what can be borrowed based on wealth to release an inventor's liquidity constraint. The joint profits then are $V^P = AQK^\alpha + r(Z - K) - \tau$.²⁶ We constrain $A \geq 1$ indicating that partners do not reduce productivity. For simplicity we hereon reduce notation to A for the partner's human and/or social capital effect on revenue. In other words, partners' human and capital contribute towards a higher level of total factor productivity, which

²³In an extended version one may separately introduce the inventor's entrepreneurial ability. Here, Q can be considered representing also the inventor's ability. In the empirical analysis we analyze the robustness of results by allowing entrepreneurial ability to vary in some specifications.

²⁴We abstract away from deciding on the number of partners; our stylized partner could therefore also be interpreted as the endowments of a set of partners. We also disregard the case where the inventor directly sells the invention. Our simplified model holds for the majority of partnerships since most partnerships are between two individuals. For example, Ruef, Aldrich, and Carter (2003) shows that in the Panel Study of Entrepreneurial Dynamics, out of 421 start-ups with partners, 74% had two members, 13% had three members, 7% four, and 5% had five or more. A slightly expanded version of our model would characterize selection of multiple partners by setting the opportunity cost to $n\tau$ where n is the number of partners.

²⁵Note that $\lambda Z = Z + (\lambda - 1)Z$.

²⁶Inventors are assumed to form a partnership rather than hiring employees because it is hard to write employment contracts when commercialization efforts (while observed by the contractual parties) are not verifiable by a third party (Grossman and Hart, 1986).

increases the productivity of capital for a given level of invention quality and capital.²⁷ An additional benefit of a partnership is that business partners can contribute external financing. The parameter τ is a sunk cost to form a business partnership. We interpret it as the partner’s opportunity cost to join the partnership. For simplicity, we assume that invention quality, inventor wealth, and the partner’s human and/or social capital effect on revenue are observable by the two parties.²⁸ This assumption together with an inelastic supply of labor implies that there will be no use of convertible features in the contract between the inventor and the business partner.²⁹ In addition, we assume that partners are sufficiently financially endowed that partnerships can reach the unconstrained level of capital investment that maximizes profits. This final assumption simplifies the analysis considerably.

An inventor chooses to form a business partnership if the profit from that, V^P , is higher than the profit from a solo-entrepreneurship, V^S , assuming contracting is efficient.³⁰ Profits are evaluated at the capital investments that maximizes their respective profits subject to liquidity constraints. Efficient contracting implies that as long as forming a partnership is mutually beneficial, our results do not depend on how profits are split. If the inventor is not liquidity constrained (i.e., $Q \leq \frac{\tau}{\alpha A}(\lambda Z)^{(1-\alpha)}$)³¹, the difference between V^P and V^S represents extra profits associated with a higher productivity of capital as a result of the partner’s human and/or social capital effect on revenue. Unconstrained partnerships are formed exclusively to add human and/or social capital. If the inventor is liquidity constrained, the extra profits represent both higher productivity of capital (whenever partner’s human and/or social capital is provided) and the effect of relaxing liquidity constraints, increasing the commercialization investment to its optimal level. These partnerships may be formed to add human and/or social capital, or to obtain external financing.

The partnership optimal decisions are illustrated in Figure 1 where invention quality (Q) is plotted against partner’s human and/or social capital effect on revenues (A) for a given level of

²⁷An alternative interpretation is that partners leverage the quality of the invention. Both interpretations are possible, adopting the alternate does not change the comparative statics that follow.

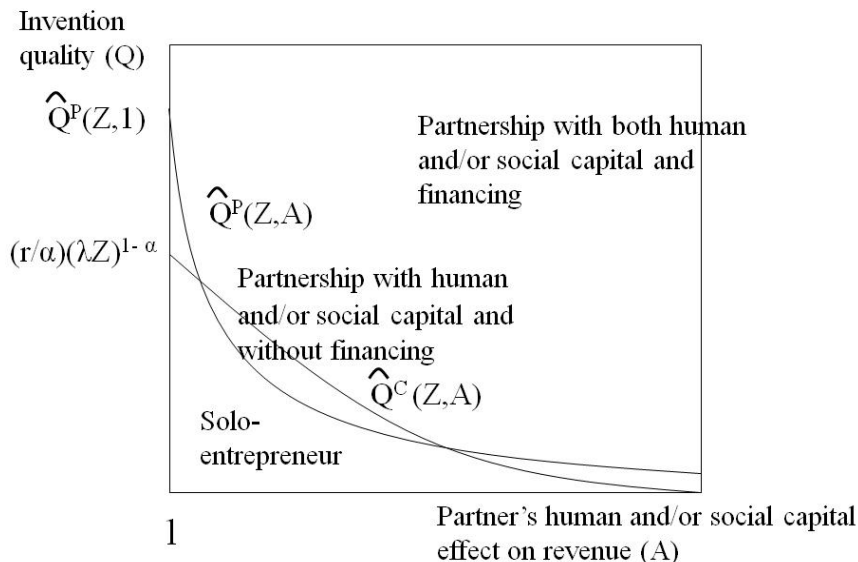
²⁸Allowing for asymmetric information in our model at the time of partnership formation will not change the qualitative results concerning selection on invention quality and demand for financing.

²⁹A more general framework including some elements such as persistent asymmetric information, unobserved effort, and multiple rounds of financing –albeit without selection– has been analyzed in Chemmanur and Chen (2006) and Repullo and Suarez (2004). Both papers study the double-sided moral hazard problem on the part of both the investor and the entrepreneur. The optimal contracts in both models predict the use of convertible features either to provide incentives to the entrepreneur (Repullo and Suarez, 2004) or the investor (Chemmanur and Chen, 2006). Interestingly, Chemmanur and Chen’s analysis predicts that angel financing contracts are less likely to incorporate convertible features compared to formal VC contracts.

³⁰Efficient contracting implies that we are agnostic about how the surplus is split. That is, the incentive to form a partnership for the inventor will be the same independently on how the surplus is split. There is no strictly preferred way to determine the division of surplus and, while it has sometimes been derived from an explicit bargaining game, it has been more common to assume that each party’s share of the surplus is given exogenously. For example, in one well-known model of teamwork production, Kremer (1993, p. 585) simply notes that “the division of a firm’s output among its heterogeneous workers [is] determined by a complex bargaining problem.” Our model could consider potential inefficiencies associated with moral hazard problems of partnership production (see Holmstrom, 1982), but since we have no data on partnership structure, predictions from such an extension would not be testable. Instead, we assume that all inefficiencies associated with partnerships are scaled by the parameter τ .

³¹Note that $\frac{\tau}{\alpha A}(\lambda Z)^{1-\alpha}$ is the level of invention quality such that the inventor’s commercialization investment that maximizes the profits in a partnership is equal to the inventor’s investment capacity, i.e., $(\frac{\alpha Q}{\tau})^{1/(1-\alpha)} = \lambda Z$. See appendix for more details.

Figure 1: The Decision to Partner as a function of A and Q given fixed inventor assets Z



the inventor's assets.³² The figure is divided into two main regions – solo-entrepreneurship and partnership – by the threshold $\hat{Q}^P(Z, A)$, where \hat{Q}^P is the value of Q where $V^P = V^S$. Given a partner's human and/or social capital effect on revenues and the inventor's assets, the inventor will form a partnership if and only if the invention quality is above the threshold $\hat{Q}^P(Z, A)$, which implies that $V^P > V^S$. The threshold $\hat{Q}^P(Z, A)$ decreases with the partner's human and/or social capital effect indicating that the higher the partner's human and/or social capital effect, the lower the invention quality needed for an inventor to be indifferent between commercializing the invention with or without a partner.

A prediction that follows from this model is that when invention quality increases, the probability to form a partnership increases. This is because a higher invention quality facilitates the amortization of the sunk costs to form a partnership. As a result, we should expect a positive correlation between pre-partnership invention quality and inventions commercialized in partnerships. A second prediction from the model is that the higher the human and/or social capital effect on revenues of the partner that the inventor meets the higher the probability of partnership. This implies that conditional on a partnership being formed, the average effect of the human and/or social capital of the partners that are involved in partnerships is higher than the average effect of the human and/or social capital of all potential partners. Both predictions are probabilistic because there is a probability of meeting a partner and there is ex ante uncertainty about the potential partner's human and/or social capital effect on revenues. These predictions have important implications for the estimation of the impact of business partnerships on entrepreneurship. There will be selection into partnerships based on invention quality, and there will be selection into partnerships based on the partner's human and/or social capital effect on revenues, respectively. Estimation of the marginal impact of the partner's human and/or social capital on commercial-

³²The formal proofs of the following results are in appendix G.

ization success must therefore control for the quality of the invention, and can only be interpreted as an average treatment-on-the-treated effect (Heckman, 1979).

The region with partnership formation is further divided into two areas by the threshold $\hat{Q}^C(Z, A)$ – partnerships with financing and partnerships without financing (i.e., human and/or social capital). \hat{Q}^C defines the quality level above which the inventor is liquidity constrained. The threshold \hat{Q}^C decreases with the partner’s human and/or social capital effect indicating that the higher the partner’s human and/or social capital effect the lower is the invention quality above which an inventor is liquidity constrained. Partnerships with human and/or social capital but without financing are located in the region above \hat{Q}^P and below \hat{Q}^C in Figure 1. These partnerships do not require a partner for financing reasons, but the partner’s contribution of human and/or social capital outweighs the cost of partnering. There are two characteristics about these partnerships that are worth noticing. First, partnerships with human and/or social capital provided but without financing exist only for intermediate levels of invention quality; for higher levels of invention quality there will always be external financing as the inventor’s liquidity constraint will eventually bind; and for lower levels of invention quality a partnership may only be profitable when external financing loosens liquidity constraints (inventor’s financial assets are low) and therefore partners will provide both human and/or social capital and financing. Second, for the intermediate levels of quality, decreasing invention quality further may temporarily increase the proportion of partnerships with no financing while the overall proportion of partnerships may decrease, as can be seen in Figure 1. The explanation is that the relative benefit of the contribution of partners’ human and/or social capital holds up better than the drop in the effect of external financing as invention quality diminishes.

Partnerships with both human and/or social capital and financing are characterized by inventions that range from high to low levels of invention quality. The partnerships with higher level of invention quality involve external financing because the inventor’s liquidity constraints are more likely to bind. Instead, partnerships of low invention quality may only be profitable when inventor’s assets are low and therefore partners must provide both human and/or social capital and financing. If the demand for external financing originates from these lower quality inventions, the selection effect on demand for financing will be less. These results suggest that to assess the importance of selection on demand for financing we may compare the mean invention quality in partnerships with both human and/or social capital and financing against partnerships with human and/or social capital but without financing. If the mean quality in partnerships with both human and/or social capital and financing is lower than the quality in partnerships with human and/or social capital but without financing, then the proportion of inventors with sufficiently low financial assets in the economy will be large and the selection on demand for financing will be less.

Finally, it is possible that if invention quality is sufficiently high a partner with neither human nor social capital may join simply to release credit constraints. Partnerships that provide only financing are located at the top left corner of Figure 1.

To summarize this discussion, there will be three types of partnerships; those where partners only bring financing, those where partners provide both human and/or social capital and financing, and those where partners only provide human and/or social capital. A first testable prediction of the model was that when invention quality increases, the probability to form a part-

nership increases. This implies selection on quality. The second prediction was that the higher is the partner's human and/or social capital effect of revenues that the inventor meets the higher the probability of partnership. This implies selection on the partner's human and social capital effect on revenues. A third prediction was that the probability to form a partnership to obtain financing increases with invention quality. This prediction implies selection on demand for financing. However, we also showed that the mean invention quality in partnerships with both human partner social capital and financing may be lower than for partnerships with human and/or social capital and without financing. This could happen if the proportion of inventors with sufficiently low financial assets in the economy is large and would imply that selection on demand for financing would be less.³³

³³If we for the moment assume uniform distributions of assets and invention quality in the inventor population, and a uniform distribution of partner ability, the most likely type of partnership is that where partners bring both financing and abilities. However, skew or bimodal distributions of quality, assets or ability in the economy may temper this prediction. An additional conclusion from the model is that the pool of solo-entrepreneurs will consist of two types; those with low quality inventions which are not liquidity constrained and those with higher quality which are liquidity constrained but which did not find a suitable partner. The fraction of liquidity constrained solo-entrepreneurs as well as the fraction of partnerships varies across economies as a function of the preponderance of potential partners (with financing and abilities) in the economy, and the distribution of invention quality and assets in the inventor population.

Appendix G:

Proofs: A model of selection into business partnerships

Proposition 1. There exist two cut-off rules, $\widehat{Q}^P(Z, A)$ and $\widehat{Q}^C(Z, A)$, that describes three potential choices that an inventor (Z, Q) that meets a potential partner with human and/or social capital effect on revenues A can make: no partnership; partnership with financing; and partnership with no financing.

Proof. We start by showing that there exist a level of Q such that for a fixed Z an inventor is liquidity constrained. Consider two cases: the inventor meets a partner, or she does not. If the inventor does not meet a partner, the constrained investment level is $K^* = \lambda Z$ for $Q > \frac{r}{\alpha}(\lambda Z)^{1-\alpha} = \widehat{Q}^C(Z, p)$. Note that $\widehat{Q}^C(Z, p)$ is quality level such that the solo-entrepreneur capital investments that maximizes profits are equal to the inventor's maximum investment capacity λZ . If the inventor meets a partner, we have $K^* = \lambda Z$ for $Q > \frac{r}{\alpha A}(\lambda Z)^{1-\alpha} = \widehat{Q}^C(Z, A)$, where A is the partner's human and/or social capital effect on revenue.

The second cutoff rule $\widehat{Q}^P(Z, A)$ is the level of invention quality that makes an inventor indifferent between forming a partnership and commercializing the invention solo. Let $V(Q, Z, A) = \max\{V^P(Q, Z, A), V^S(Q, Z, A)\}$ be the value of an invention. $\widehat{Q}^P(Z, A)$ is the invention quality such that $V^P(\widehat{Q}^P, Z, A(\beta)) = V^S(\widehat{Q}^P, Z, A(\beta))$. There exists a unique cutoff $\widehat{Q}^P(Z, A)$. For that to follow, it must be the case that $\widetilde{V}(Q) = V^P(Q, Z, p) - V^S(Q, Z, p)$ is strictly increasing with Q and that the value of $\widetilde{V}(Q)$ is positive for some Q (e.g., a Q sufficiently high) and negative for another Q (e.g., $Q = 0$). We will then focus our analysis on showing that $\widetilde{V}(Q)$ is increasing in Q . Let us first consider a Q such that the inventor is liquidity constrained, i.e., $K = \lambda Z$. Then, as Q increases, the value of V^P increases at a faster pace than V^S . Next consider the inventor not liquidity constrained. Here V^P increases at a faster pace than V^S with Q because a marginal change in Q in a partnership is amplified through the partner's effect of human and/or social capital A . This is because A and Q enters multiplicatively in the revenue of an innovation. Therefore, we can conclude that, for a fixed Z and A , there exist an invention quality level $\widehat{Q}^P(Z, A)$ that makes an inventor indifferent between forming a partnership or working solo.

Proposition 2. For a fixed wealth Z , the cutoff rule $\widehat{Q}^P(Z, A(\beta))$ is decreasing with the partner's human and/or social capital effect on revenue $A(\beta)$. Therefore, the probability of forming a partnership increases with the quality of the invention Q .

Proof: We would like to show that the liquidity cutoff $\widehat{Q}^C(Z, A)$ and the partnership cutoff $\widehat{Q}^P(Z, A)$ are decreasing functions with the partner's human and/or social capital effect A . That $\widehat{Q}^C(Z, A)$ is decreasing with A for a fixed Z is straightforward because $\widehat{Q}^C(Z, A) = \frac{r}{\alpha A}(\lambda Z)^{1-\alpha}$. Showing that $\widehat{Q}^P(Z, A(\beta))$ decreases with A is somewhat more involved. For a fixed Q , the higher A is, the higher is the the capital investment, and so is the value of partnership V^P . The value of solo-entrepreneurship V^S does not change with A , so the difference between partnership and entrepreneurship increases with $A(\beta)$. Now we have to show that the higher Q is, the lower is the different between V^P and V^S . For a fixed A , the lower Q is, the lower is the capital investment and so is the value of partnership and the value of solo-entrepreneurship. However, because A and Q enter multiplicatively in the revenue function, the value of partnership will drop more than

the value of solo-entrepreneurship. Therefore, we conclude that the higher is the partner's human and/or social capital effect A , the lower is the cutoff $\widehat{Q}^P(Z, A)$.

Proposition 3. Inventors who are liquidity constrained are more likely than unconstrained inventors to form partnerships.

Proof: To prove this result we must show that for a fixed inventor's wealth Z , the probability to form a partnership is higher for an invention with quality $Q > \widehat{Q}^C(Z, A)$ than for the rest of the inventions $Q \leq \widehat{Q}^C(Z, A)$. The probability to form a partnership is the probability to meet a partner with human and/or social capital effect A such that $Q > \widehat{Q}^P(Z, A)$. Let us start with inventions where an inventor is not liquidity constrained, i.e., the quality level is such that $Q \leq \widehat{Q}^C(Z, A)$. Here the benefit of partnership is exclusively given by the partner's human and/or social capital effect A and partnerships will only be formed for inventions with invention quality above $\widehat{Q}^P(Z, p)$ (see proposition 2). This implies that when $Q \leq \widehat{Q}^C(Z, A(\beta))$ the probability of partnership will tend to be low. Alternatively, if an inventor is liquidity constrained (i.e., $Q > \widehat{Q}^C(Z, A)$), the benefit to form a partnership is due to both the partner's human and/or social capital effect A as well as the increase in the level of capital investment from the constrained level λZ to the unconstrained $K^* = \left(\frac{\alpha A Q}{r}\right)^{1/(1-\alpha)}$. The two effects together are associated with a lower cutoff to form a partnership $\widehat{Q}^P(Z, A)$ than for inventions held by inventors that were not liquidity constrained, i.e., $Q \leq \widehat{Q}^C(Z, A)$. Therefore, the probability to form a partnership is higher when the inventor is liquidity constrained than for the rest of inventions.

Proposition 4. Conditional on a partnership being formed, the average human and social capital effect on revenues of a partner is strictly higher than the human and social capital effect on revenues of the average potential partner (unconditional on a partnership formed).

Proof: Recall that A is the realization of a stochastic random variable that determines the partner's human and social capital effect on revenues. Before meeting a partner, the effect of human and/social capital of a potential partner is $E[A]$. For a fixed invention quality Q and inventor's wealth Z , the probability of partnership is the probability a partner with A meets an inventor with $Q > \widehat{Q}^P(Z, A)$. Since the function $\widehat{Q}^P(Z, A)$ is strictly monotone with A , for a fixed invention quality Q , we can define the probability of partnership $\Pr(A > \widehat{Q}^{P[-1]}(Z, Q))$, where $\widehat{Q}^{P[-1]}$ is the inverse function of \widehat{Q}^P . We want to show that conditional on a partnership being formed, the average partner human and/or social capital effect on revenues is higher than the expected partner's human and social capital effect (unconditional on a partnership formed), i.e., $E[A|A \geq \widehat{Q}^{P[-1]}(Z, Q)] > E[A]$. This inequality holds for all Q in a partnership because $A \geq 1$. Therefore, the human and/or social capital effect on revenue of the average partner that formed a partnership is higher than the one of the average potential partner's human and social capital effect on revenue.

Proposition 5. For a fixed human and/or social capital effect on revenues A , (a) the cutoff rule $\widehat{Q}^C(Z, A)$ is increasing with the inventor's financial assets Z ; and (b) the cutoff rule $\widehat{Q}^P(Z, A)$ is increasing with the inventor's financial assets Z up to a level of inventor's assets where $\widehat{Q}^P(Z, A)$ is independent of Z .

Proof: First, we show that cutoff rule $\widehat{Q}^C(Z, A)$ is increasing with the inventor's assets Z . Let us consider a level of invention quality Q such that for a fixed Z an inventor is liquidity

constrained. There are two cases to analyze. (1) If the inventor does not meet a partner, the constrained investment level is $K^* = \lambda Z$ for $Q > \frac{r}{\alpha}(\lambda Z)^{1-\alpha} = \widehat{Q}^C(Z, A)$. It is easy to see that the function $\widehat{Q}^C(Z, A)$ is increasing in Z because $\alpha \in (0, 1)$. (2) If the inventor meets a partner, we have $K^* = \lambda Z$ for $Q > \frac{r}{\alpha A}(\lambda Z)^{1-\alpha} = \widehat{Q}^P(Z, A)$. Again, it is easy to see that the function $\widehat{Q}^C(Z, A)$ is increasing in Z because $\alpha \in (0, 1)$. Second, we show that $\widehat{Q}^P(Z, A)$ is increasing with the inventor's assets Z up to a level of inventor's assets where $\widehat{Q}^P(Z, A)$ is independent of Z . Let us consider a sufficiently high level of invention quality Q and partner's human and/or social capital effect A such that a partnership can be profitable. Note that for a given Q and A , there exists a level of inventor's assets $\bar{Z}(Q, A)$ above which the inventor is not liquidity constrained. Above this level of the inventor financial assets, the cutoff rule $\widehat{Q}^P(Z, A)$ will be independent of Z because the partner does not provide any positive impact in the business through the channel of relaxing liquidity constraints. Below the level of assets $\bar{Z}(Q, A)$, the inventor is liquidity constrained and thus the partner provides an impact on the business through relaxing the liquidity constraint. Note that the higher the assets of the inventor, the lower the potential benefits of partnership and thus the higher is the cutoff $\widehat{Q}^P(Z, A)$.