Business Partners, Financing, and the Commercialization of Inventions

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Abstract

This paper studies the effect of business partners on the commercialization of invention-based ventures, and it assesses the relative importance of partners' human and social capital on commercialization outcomes. 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 business partners' value added and to selection. After controlling for selection effects and observed/unobserved heterogeneity, our smallest estimate of partner value added approximately doubles the probability of commercialization and increases expected revenues by 29% at the sample mean.

1 Introduction

Business partnerships are important for the economy. Approximately 10% of all U.S. businesses are partnerships and 18% of business receipts are from partnerships. Business partners appear even more important for start-ups. For example, in the panel study of entrepreneurial dynamics, 52% of start-ups were partnerships (Ruef, Aldrich, and Carter, 2003). Reflecting conventional wisdom, the business press commonly advises entrepreneurs to partner with people in order to increase the chances to commercialize their ideas (e.g. van Osnabrugge and Robinson, 2000). However, the empirical evidence on the value of this advice is scattered.[1] More importantly, little is known about the mechanisms through which business partnerships are formed.

In this paper we estimate the relative importance of business partners by relying on a survey of Canadian individual inventors. The survey documents both the human, social, and financial capital contributions of business partners to inventive projects. Business partners are defined in the survey as those who join the original inventor to try and commercialize an invention, contributing at least one of the three aforementioned capitals. The definition is wider in scope than the legal definition of partnerships as it does not require legal co-ownership, but narrower in that it focuses on partnerships for invention commercialization.[2] The survey reveals that in approximately 21 percent of the projects the inventor was joined by business partners. 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. Human and social capital refer to complementary skills and business contacts, respectively. These partners take on substantial risk. In our sample 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), and the revenues of projects undertaken by partnerships are almost ten times as large as those run by solo-entrepreneurs. We address how much of these gross effects represents the value of obtaining human and social capital versus obtaining additional financing, while controlling for selection of projects into partnerships. Selection mechanisms likely

[1] Cressy (1996) and Astebro and Bernhard (2003) both report substantial effects on the survival of new firms of the number of owners.

[2] Business Partnerships are formally defined in the U.S. tax code as relationships between two or more persons who join to carry on a trade or business, with each person contributing money, property, labor or skill, and each expecting to share in the profits and losses of the business. Our use of the term "business partners" is similar to that in for example Ruef et al (2003) and Burton et al (2009).

lead to a positive correlation between invention quality, founder characteristics, and partnership formation.[3] Because invention quality, the prospects of ventures, and founder characteristics are typically not fully observed by the econometrician, the endogeneity of the business partnering decision likely leads to upward bias estimates of the value added of business partners on start-up ventures' success.

To address this endogeneity problem, we use several approaches. First, we control for the quality of the invention with two proxies, as well as the observed commercialization investments by the inventor and external investors in a model of the impact of partnership formation on commercialization revenues. Including realized investment levels will control for selection on the pre-investment prospects of ventures which are unobserved to the econometrician but observed by investors.[4] 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.

Our paper is related to recent work studying the potential value added of business angel groups (Kerr, Lerner, and Schoar, 2011).[5] Although business partners and angel groups both consist of individual business investors, the two types also differ on some important accounts (described in the next section). While we perform similar controls for selection on project quality as Kerr et al (2011), our additional contribution is to separate the partnership effect into the contribution of human and social capital, versus providing additional financing to reduce liquidity constrains. Our paper is also related to the rather large literature on the value added of obtaining formal venture capital (VC).[6] However, the process of finding and meeting formal VCs, and the methods of investment screening, syndication, due diligence and monitoring by formal VCs are generally quite different than those employed by business partners (see next section).

[3] The problem is similar when analyzing the potential value added of venture capital. Investors might select higher quality projects to invest in, and higher quality projects may prefer to match with investors with higher quality. Seminal work attempted matching treated and non-treated firms (Hellmann and Puri, 2000). More recently, scholars have considered structural models of the process of matching between start-ups and venture capitalists (Sorensen, 2008).

[4] The 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).

[5] Business angel groups and business partners belong to the broad class of "Informal venture capital" which, by some estimates, is as large or larger than the VC sector (Shane, 2008; Sudek, Mitteness, and Baucus, 2008; and Goldfarb et al. 2009).

[6] Hall and Lerner (2010) provide a recent summary of this literature. Recent work include Hellmann and Puri (2000), Hsu (2004), Hochberg, Ljungqvist, and Lu (2007), and Sorensen (2008).

2 A Primer on Business Partners

Business Partnerships are formally defined in the U.S. tax code as relationships between two or more persons who join to carry on a trade or business, with each person contributing money, property, labor or skill, and each expecting to share in the profits and losses of the business. The approximately 3.1 million U.S. partnerships in 2007 had 18.5 million partners. Excluding limited and limited liability partnerships (popular investment vehicles in the movie, legal and construction industries), there were 852,000 U.S. partnerships with 3.9 million partners.[7] 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., ibid). Most partnerships are started by two people (Ruef et al., ibid; Burton et al., ibid).

The investment behavior of business partners is not well described in the prior literature. However, there exist some descriptive information on individual business angels, which represent a subset of all business partners.[8] Business angels typically make only a few investments at a time, tend to invest substantially smaller amounts than VCs, invest their savings on their own or in syndication with other private persons, and they more often invest in early-stage deals. They are geographically widely distributed and make most investments locally. They rely on very primitive informal networking arrangements of friends, family, and other business angels and business associates for finding deals (Prowse, 1998.) The primary criterion that angels use to screen investment proposals is whether the entrepreneur is previously known to them or to an associate they trust (Prowse, 1998.) Compared to other investors they, generally, rely less on traditional control mechanisms, such as board control, staging or contractual provisions. Instead, they typically spend time 'hands-on' in the business or exercise control through other mechanisms such as trust or social influence. For example, among Singaporian business angels, Wong and Ho (2007) report that 42% of investors are family related, and that the non-family related investors are dominated by friends/neighbors (50% of all investors.) Many are active investors who seek to contribute their experience, knowledge and contacts to the investee; they often invest in sectors where they have had previous experience, sometimes as an entrepreneur, while others are passive investors.[9] Since individual angel investors generally obtain weaker formal control rights than

[7] For official data on these, see Statistics of Income, http://www.irs.gov/taxstats/article/0,,id=175843,00.html

[8] Citing Forbes magazine Wong, Bathia, and Freeman (2009) suggest there are between 250,000 and 400,000 angel investors in the U.S. This is clearly less than the number of business partners recorded by Statistics of Income.

[9] For more details on angel investors see Harrison, Mason, and Robson (2010); Mason (2009); Van Osnabrugge and Robinson (2000); Wiltbank and Boeker (2007); Wiltbank (2009); Wong, Bathia, and Freeman (2009) and the web site http://www.angelresourceinstitute.org/.

do VCs, and since formal VC participation is generally a necessary requirement to finance larger deals, angel investors are not likely substitutes for the vast financial capital that formal VCs can provide (Goldfarb et al., 2009.)

Business angels are sometimes organized into groups. Angel groups are described by Kerr et al. (2011) as having several advantages over individual investors. Business angel groups arrange a formal process for screening ventures and typically syndicate their investments within the group. They can thus make larger investments and each investor spread risks better across multiple projects. Undertaking due diligence as a group saves on costly screening efforts. Further, the group may be more visible than an individual thus generating a better deal flow. There were approximately 300 angel groups in the U.S. The average group had 42 member angels and on average each group invested a total of $1.94 million in 7.3 deals per year in 2007.[10]

3 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 informal venture capital, 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.[11]

[10] Statistics are based on http://angelcapitalassociation.org/ (accessed November 28, 2011). See FAQ on the Importance of Angel Investors on ACA Public Policy Overview.

[11] To summarize Appendix A, we developed a list of 6,405 inventors who had submitted ideas for IAP 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,

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 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.[12] 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 samples.[13]

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 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:

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http://www.aapor.org.

[12] The 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. Appling a correction for the probability of response reduces the incidence of survival or other bias due to survey non-response.

[13] In 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.)

"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 analysed. 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 an equity 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 had 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 white noise, i.e. 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 in favor of more noisy data. This choice will bias down the estimates of the importance of business partners for success in our analysis.

Another concern may be that entrepreneurs may embellish on their roles and downplay the roles of others if the business is succesful (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 also bias down the estimates of the value added of business partners for success in our analysis.

3.1 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 consumeroriented 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). Nevertheless, investments in these projects at the same time appears somewhat less than those undertaken by 'business angel networks'. For example, Wiltbank and Boeker (2007) report the average investment size per project (including follow-on investments) by business angel networks to be \$191,000 (median investor contribution \$50,000), while Wiltbank (2009) report an average investor contribution of £42,000. Note that the samples of projects with business angel investors are constructed conditioned on business angel investments being positive, while our sample does not have this restriction.

4 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 by partnerships? There are various reasons for this not occurring. As described in the Primer, potential partners operate locally and individually and may be hard to find by inventors. Indeed, that is probably one reason why there has been a recent proliferation of business angel groups which may have marketing advantages over business angels. Further, partnerships are formed only if the potential partner is qualified enough and/or if she releases 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.

5 The value added of partners' human/social capital

5.1 Baseline econometric model

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

$$y_i = \left\{ \begin{array}{ccc} y_i^* & \text{if} & y_i^* > 0 \\ 0 & \text{if} & y_i^* \leq 0 \end{array} \right\}$$

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 quality; 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 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 2 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.[14] 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).[15] 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 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 2 (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

[14] We 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.

[15] Consider 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 $\frac{\partial E(y|X)}{\delta x_k} \beta_k \Phi(\frac{X\beta}{\sigma})$, where x_k is a regressor of interest, $\overline{X}$ 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.

quality. To control for this possiblity we continue by including a measure of total commercialization investment. Including realized investment levels will control for selection on the pre-investment prospects of ventures which are unobserved to the econometrician but observed by investors. Rational investors will invest as a function of qualities of the project that drives commercialization performance.[16] 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 2 we analyze the effect of total commercialization investments. The third 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 3 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.[17] 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 that inventors are capital constrained. If they were not constrained the

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

[17] Unfortunately, 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).

coefficients for internal and external financing should be equal.[18] 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 2 and 3. Controlling for labor inputs, the partnership coefficient drops by 0% in Table 2 and 5% in Table 3. 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 of the partner's human/social capital, but as well to omitted variable bias. In the next two subsections we therefore attempt to further control for additional selection on inventor-invention characteristics and selection on unobservables to isolate the effect of partner human and social capital on commercialization success.

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

The control function approach used in the previous analysis should in principle account for the effects of unobserved hetereogeneity. It does so even though we have noisy measures of invention quality because we also include in the estimation the total investments. Thus, while the econometrician may not observe invention quality perfectly, we still observe the relevant investment

[18] This 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).

choices made by the parties based on their information about the invention as well as the other party. Nevertheless, there still exists the possibility that a partner's decision to join an inventor may depend on other inventor/invention characteristics that *does not* affect the observed post-partnership commercialization investment (and efforts), but *does* affect the commercialization outcomes. An example 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 know 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. Another potential source of omitted variable bias are decision biases such as optimism.

To account for the possibility that there remains inventor or invention unobserved heterogeneity and measurement error in our identified selection effects, we use a propensity-score weighted model described by Hirano, Imbens, and Ridder (2003).[19] Woolridge (2007) discuss a 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.[20] 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

[19] In 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.

[20] We 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 tehse 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.

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 2 and 3. 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 2 and 3 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, respectively. The estimate from Table 2 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 3 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.

5.3 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 [$P(a)$] + partner without human/social capital but with financing [$P(not\_a\_fin)$]. 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 $P(not\_a\_fin)$ should be zero ($\gamma = 0$). If the estimated coefficient for $P(not\_a\_fin)$ is zero, $\widehat{\gamma} = 0$, then the coefficient for $P(a)$ (label this $\widehat{\beta}$) should represent the partner's estimated value added. Alternatively, if $\widehat{\gamma}$ is positive, then there will likely be selection on unobservables and therefore $\widehat{\beta}$ may have an upward bias.

Model 6 in Tables 2 (3) replaces Partnership with dummies for $P(a)$ and $P(not\_a\_fin)$. In Table 2 we find that $\widehat{\beta} = 7.09$ ($p < 0.01$), and $\widehat{\gamma} = 6.52$ ($p = 0.08$). Results in Table 3 are similar. Therefore, it appears that $\widehat{\beta}$ 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 $\widehat{\beta}$. The effect of selection on unobservables may differ between partners who provide abilities 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. Åstebro and Serrano (2011) derived 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.[21] This implies that the ventures where partners did not contribute value added in the form of human and 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 $cov(P(a), Q) < cov(P(not\_a\_fin), Q)$. The sign of this inequality allows us to calculate a lower bound of the partner's human/social capital: $\beta^L = \widehat{\beta} - 0.224\widehat{\gamma}$.[22] Evaluating the right hand side of the bound at the estimated $\widehat{\beta}$ and $\widehat{\gamma}$, 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 2 and Table 3, respectively. Because we can safely assume that an upper bound for β is $\widehat{\beta}$, 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 2, 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 value added, and the effect on expected revenues is a 38% increase. As the lower bound estimate is higher for results in Table 3 we refrain from reporting those details. Note that this method returns estimates quite similar to those from the method controlling for observed heterogeneity.

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

[22] Define $bias(\widehat{\beta}) = \frac{cov(P(a),Q)}{Var(P(a))}$ and $bias(\widehat{\gamma}) = \frac{cov(P(not\_a\_fin),Q)}{Var(P(not\_a\_fin))}$. $bias(\widehat{\gamma}) = \widehat{\gamma}$ since our theoretical model implies that the true value of γ is 0, while $bias(\widehat{\beta}) = \widehat{\beta} - \beta$. Rearranging and using that $Cov(P(a), Q) < Cov(P(not\_a\_fin), Q)$, the lower bound β^L for $\widehat{\beta}$, is $\beta^L = \widehat{\beta} - (\frac{Var(P(not\_a\_fin))}{Var(P(a))})\widehat{\gamma} = \widehat{\beta} - 0.224\widehat{\gamma}$. We have replaced $Var(P(a))$ and $Var(P(a\_not\_a\_fin))$ with their sample counterparts.

As stated in the methods 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 DI and DII in Appendix D. These results are qualitatively similar to those reported in the text where weights are not applied (Table 2 and 3). This indicates that while there were trace and response sampling biases, these did not covary strongly with the correlations in the model.

6 Conclusion

Business partners are an important feature of the economy, and in particular appear frequently among start-ups. 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, and they have mean revenues approximately ten times greater than projects run by solo-entrepreneurs. 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.

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 in Kerr at al (2011). At the same time our sample does not contain many projects that receive formal VC funding and our results may reflect this fact.[23] Our data exhibited some limitations, such as not providing information on the number of partners, the division of equity in the venture, and the

[23] The fraction which received VC financing was 0.8%, too small to be analyzeable in our study.

characteristics of partners. These limitations provide opportunities for future research to further examine the value added of business partners.

Our work contributes to the literature in several ways. To our knowledge this is the first paper to examine the performance consequences when an inventor obtains business partners. The paper echoes previous concerns about selection into financial agreements potentially contaminating estimates of the value of such agreements for early stage businesses. We suggest some alternate and slightly novel approaches to solving this contamination issue. Business partners operate differently than business angel groups and much differently than formal venture capital and the merits of business partners as financial intermediaries should be studied in more detail. Nevertheless, our results provide complementary evidence to the many other studies of both formal and informal venture capital which show that there are real perfomance consequences associated with non-financial assets provided to early-stage ventures.

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.

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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

	All	Partnership	Solo-entrepreneur
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: Tobit Regression Analysis of Commercialization Revenues

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 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
	Tobit	Tobit	Tobit	Tobit	Propensity Score Weighted Tobit	Tobit
Partnership effects						
Partnership	15.25***	11.68***	7.54***	7.54***	7.06***	
	(2.38)	(2.14)	(1.94)	(1.92)	(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***	3.02	3.05	2.19	3.11
		(2.15)	(1.98)	(1.98)	(1.94)	(1.98)
R&D expenditures		1.57***	0.54*	0.48	-0.30	0.49
		(0.35)	(0.33)	(0.33)	(0.29)	(0.33)
Commercialization investment			1.61***	1.14***	1.00***	1.19***
			(0.28)	(0.31)	(0.31)	(0.32)
Commercialization labor				1.05**	1.32***	1.01**
				(0.44)	(0.48)	(0.44)
Constant	-25.07***	-34.22***	-31.78***	-32.71***	-25.76***	-32.17***
	(4.70)	(5.43)	(4.98)	(5.05)	(4.49)	(4.98)
Sigma	14.88***	13.37***	11.97***	11.81***	9.51***	11.87***
	(1.44)	(1.28)	(1.13)	(1.11)	(0.91)	(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 3: Tobit Regression Analysis of Commercialization Revenues with Inventor's and Other's Capital

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 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
	Tobit	Tobit	Tobit	Propensity Score Weighted Tobit	Tobit
Partnership effects					
Partnership	10.28***	9.26***	8.83***	7.98***	
	(2.08)	(2.08)	(2.02)	(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***	4.30**	4.29**	4.02**	4.31**
	(2.06)	(2.05)	(2.02)	(2.05)	(2.03)
Own financing	1.90***	1.74***	0.81**	-0.56*	0.86**
	(0.36)	(0.36)	(0.37)	(0.28)	(0.37)
External financing		0.43**	0.22	0.40*	0.25
		(0.22)	(0.21)	(0.22)	(0.22)
Commercialization labor			1.73***	2.13***	1.70***
			(0.44)	(0.46)	(0.44)
Constant	-36.38***	-35.37***	-33.67***	-24.01***	-33.22***
	(5.54)	(5.42)	(5.17)	(4.50)	(5.12)
Sigma	13.02***	12.83***	12.31	9.22***	12.39***
	(1.24)	(1.22)	(1.17)	(0.88)	(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 $X_1,\ldots, X_N$ for year $1,\ldots N$, 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 $X_l,\ldots,X_N$ 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 $X_l,\ldots,X_{E(N)}$ 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 $X_l,\ldots,X_{E(N)}$ 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.[24] 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.[25]

[24] The 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.)

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

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
	Tobit	Tobit	Tobit	Propensity Score Weighted Tobit	Tobit
Partnership effects					
Partnership	11.82***	11.22***	10.45***	8.94***	
	(2.18)	(2.03)	(1.96)	(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*	4.20*	3.87	7.22***	3.81
	(2.51)	(2.46)	(2.52)	(2.12)	(2.50)
Own financing	1.40***	1.33***	0.38	-0.70**	0.42
	(0.45)	(0.46)	(0.44)	(0.27)	(0.43)
External financing		0.23	0.08	0.35	0.09
		(0.27)	(0.26)	(0.23)	(0.26)
Commercialization labor			1.90***	2.34***	1.83***
			(0.40)	(0.43)	(0.41)
Constant	-33.25***	-32.84***	-31.57***	-29.16***	-31.37***
	(4.33)	(4.36)	(4.07)	(5.25)	(4.02)
Sigma	12.75***	12.69***	12.04***	9.63***	12.03***
	(1.11)	(1.10)	(1.06)	(0.94)	(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.