Polishing Diamonds in the Rough: The Sources of Syndicated Venture Performance^{*}

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Abstract

Using all financing rounds for new ventures from 1980-2003, we develop a detailed empirical model to explain which portfolio companies obtain Venture Capital (VC) syndication. We then assess how syndication impacts portfolio companies' returns, their chances of successful exit, and the time taken to exit. Applying apposite econometrics for endogeneity across these different performance measures, we are able to ascribe much of the better return to selection, with the value-add role significantly impacting the likelihood and time of exit. Though the extant literature on VC syndication treats the "selection" and "value-add" hypotheses as mutually exclusive, we find that their roles are in fact complementary. To this end we propose a new "effort-sharing" model of venture syndication.

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Venture capitalists invested \$25.5 billion in 3,416 deals in 2006¹, many of these through syndications. Co-operation among venture capitalists in funding and collaborating with a potentially promising firm is effected by the joint purchase of shares by two or more venture capital companies. Lerner (1994) suggests that syndication is an important feature in venture capital practice and the decision to syndicate implies a preference for financing by a group as opposed to a single investor. The syndicated venture investment in privately held firms is hypothesized to lead to superior venture selection (Wilson (1968), Sah and Stiglitz (1986), Lerner (1994), and Stuart and Sorenson (2001)), to mitigate information asymmetries between the initial venture investor and other later-round potential investors (Admati and Pfleiderer (1994), and Lerner (1994)), to add value by better monitoring the performance of portfolio companies (Brander, Amit, and Antweiler (2002)), and to amplify the value-addition of venture capitalists through various means (Hellmann and Puri (2002)), Kaplan and Stromberg (2004), Lindsey (2005), and Hochberg (2005)). While research examining the venture capital-backed firms' performance is abundant, the impact of syndication on venture firms' exit performance is less scrutinized.

In this paper, we conduct a large-scale empirical study of the impact of syndication on portfolio company performance, based on many venture financing rounds of U.S. private firms. Specifically, we aim to contribute to the venture capital and entrepreneurial finance literature in four distinct ways. *First*, by using all the available 98,068 rounds of venture firms in the Thomson Financial's Venture Economics (VentureXpert) database from 1980 to 2003, we conduct a comprehensive examination of the determinants of the syndication decision and provide insights into why firms choose to opt for Venture Capital (VC) syndication. *Second*, by examining three different dimensions of exit performance (i.e., exit probabilities, time-to-exit, and exit multiples), we provide a more complete picture of the impact of syndication on portfolio company' exit performance. *Third*, we reframe the debate as to whether a syndicate selects promising companies or adds value to portfolio firms using three different exit-performance metrics. Our results suggest that syndication adds value over and above the selection effects in the two performance metrics, exit probabilities and time-to-exit. We interpret these results with our simple analytical model of effort-sharing under which effort is allocated to selection and value-add. *Fourth*, we control for the endogenous treatment effects that have received relatively

¹ See http://www.pwcmoneytree.com.

little attention in previous studies of VC syndication. By appropriately controlling for the endogenous treatment effects, we are able to determine the relative importance of the selection and value addition roles in VC syndications.

Without using apposite conditioning variables, or accounting for endogenous treatment effects, in which VC syndicates choose better deals to begin with, the contribution of VC syndication to firm performance will be overstated or attributed incorrectly (Greene (1993)). Differential returns from investing in syndicated ventures versus non-syndicated ones may arise directly from the synergies of syndication (the value-added hypothesis of Brander, Amit and Antweiler (2002)), or may be the result of selection (Lerner (1994)), i.e. better projects are more attractive for syndication (endogeneity is posited in the model of Cumming (2001)). We proceed in two stages - we examine the factors determining syndication extensively in the first stage, and compare syndications versus other non-syndicated ventures, in the second stage, using three performance metrics, time to exit, probability of exit, and exit multiple.

In the first-stage probit regressions, consistent with the prior literature, we find strong evidence that the likelihood of syndication is significantly associated with variables that proxy risk sharing, portfolio diversification and resources, capital constraints, and the VC's monitoring, skills, experience, and specialties. In particular, the probability of syndication is positively related to risk sharing (Wilson (1968), and Bygrave (1987)) measured by the IT or biotech industries and early stage, and the VC's experience and skills (Kaplan and Schoar (2005), and Gompers, Kovner, Lerner, and Scharfstein (2006a, b)) measured by the average age of VCs, the cumulative number of rounds the firm has participated in, the cumulative total amount it has invested, and when the lead VC is a specialist. Syndication likelihood is inversely associated with the age of the firm (less risk), the capital under management by the lead VC (fewer capital constraints), and the presence of an international lead VC (who is more likely to be already diversified).

Researchers have tended to treat the selection and value-add hypotheses as mutually exclusive; our examination across three different performance metrics finds to the contrary. In the second-stage analysis based upon the instrumental variables approach, we find that the exit probability is higher and the time-to-exit is shorter even after controlling for endogenous treatment effects. For exit multiples, however, the significant relation with syndication in the first-stage regressions disappears after we control for endogenous treatment effects, and this insignificance is robust to the exit routes of either IPO or acquisition. An implication of our findings is that the return multiple on ventures is a function of firm type, and the probability and time of exit is influenced by the efforts of the syndicate. We liken this to VC syndicates uncovering diamonds in the rough, and then polishing them to success.

The rest of the paper proceeds as follows. Section I describes the data and sample. Section II presents our econometric specification. Section III presents the empirical results, and Section IV concludes.

I. Data and Sample

We obtain our data from the Thomson Financial's Venture Economics (VentureXpert) database. VentureXpert reports information on private equity investments of over 6,000 venture capital and private equity firms. Our sample covers all venture financing rounds of U.S. private firms from 1980 to 2003, and includes 98,068 financing rounds in 43,658 unique firms.² We follow these firms until there is an exit or until the end of 2003. The information about each exit is available in the VentureXpert database, which is identified by the Thompson Financial Global New Issue database and the Mergers and Acquisitions database. We concentrate solely on U.S. private firms, observing the most disaggregated view of the data, rather than examine performance at the level of the VC fund. Our goal in this paper is to understand how syndication determines the performance of individual round investments of portfolio companies, not its impact on VC funds or their attendant relationships (see Hochberg, Ljungqvist and Lu (2007) for a comprehensive examination of the latter view).

Table I reports the frequency of financing rounds over time and across industries. The frequency of financing rounds shows cycles in private equity financing. Deal flow increases from early 1980 to the late 1980s but declines in the early 1990s. It steadily increases again from 1994 until 2000. The years 1999-2001 show the highest level of financing with an all time high in the year 2000. Deal flow decreases again in the early 2000s. The increase in the late 1990s is largely a function of increased capital commitments to the so called "new economy" firms, for example, internet, computer software, and communications business. Computer software, internet,

 $^{^{2}}$ As Venture Economic's data are somewhat unreliable before 1980, we ignore investments before 1980. See also Hochberg, Ljungqvist, and Lu (2007), who also choose their data based on the same considerations.

communications, medical/ healthcare, and consumer related industries receive a large portion of available private equity financing. These top five industry groups account for 60% of the total number of investments.

We index firms in the data set with the variable *i*, where i=1,...,N. For each firm there is a set of financing rounds, and these are indexed by variable *j*. This notation permits us flexibility in crating variables either at the firm level or at the level of each financing round.

II. Econometric Specification

The VentureXpert database does not provide return data. Absent return data, we follow Gompers and Lerner (1998a, 2000), Brander et al (2002), Sorenson (2005), and Hochberg, Ljungqvist, and Lu (2007) in viewing a succeful exit as a representation of the venture firm's success. Here, we extend this space of metrics to three distinct ones, exit probabilities, time to exit, and exit multiples. ³ We anticipate that the role of the VC syndicate in selection versus value-add might be different for each of the metrics. We believe that this is the first time in the literature that the role of the VC syndicate has been examined across different aspects of performance of the venture.

A. Probability of Exit

Not all venture-backed firms end up making a successful exit, either via an IPO, through a buyout, or by means of another exit route. By examining a large sample of firms, we can measure the probability of the firm making a successful exit. By designating successful exits as $S_{ij}=1$, and setting $S_{ij}=0$ otherwise, we fit a Probit model to the data. We define S_{ij} to be based on a latent threshold variable S_{ij}^* such that

$$S_{ij} = \begin{cases} 1 & if & S_{ij}^* > 0 \\ 0 & if & S_{ij}^* \le 0 \end{cases}$$

where the latent variable is modeled as (subscripts suppressed)

³ See Cochrane (2005) for an analysis of firm-level rate of return based on an alternative database (VentureOne).

$$S^* = \gamma' X + u, \qquad u \sim N(0, \sigma_u^2)$$

and *X* is a set of explanatory variables including a dummy variable for syndication. The fitted model provides us the probability of exit for all financing rounds.

$$E(S) = E(S^* > 0) = E(u > -\gamma' X) = 1 - \Phi(-\gamma' X) = \Phi(\gamma' X)$$

where γ is the vector of coefficients fitted in the Probit model, using standard likelihood methods. The last expression in the equation above follows from the use of normality in the Probit specification. $\Phi(.)$ denotes the cumulative normal distribution.

B. Time-to-exit

It is widely held that the presence of a venture capitalist shortens the time to exit (see Wang, Wang and Lu (2002)); Venture Economics suggests that the average time to exit is 4.2 years), but little is known about exit time differentials in syndicated versus non-syndicated ventures. We use a hazard model specification that allows modeling a duration data (Allison (1995)). The time to exit starts with its round investment date and ends when the firms exit through IPOs, acquisitions and other means. The hazard function is modeled as:

$$h(t, X(t)) = h(t, 0) \exp[\theta' X(t)]$$

where h(t, X(t)) is the hazard rate at time t and X(t) are exploratory variables, including a syndication dummy, that are potentially time varying. We use a Cox proportional hazard model with right-censoring, and time varying covariates. Time to exit is expressed in months. The vector of coefficients in this model is denoted θ .

C. Multiples on Exit

For the firms that make a successful exit, we are able to compare the exit price with the buyin price at the financing round. The ratio of exit price to buy-in price is the multiple on exit. This computation is done on a per share basis to correctly account for dilution with each succeeding financing round. Given that the time to exit varies by firm, we annualize the multiple for each firm so as to make proper comparisons across firms. For the purpose of annualization we follow the procedure outlined in Das, Jagannathan and Sarin (2003), which is as follows:

$$X_{annual} = [X_{raw}]^{1/t}, \qquad t = CEIL(days/365)$$

where the function *CEIL* rounds up to the next integer. Of course "*days*" is the number of days to exit in the model above. The "raw" multiple is just the ratio of exit value to buy in value. We regress exit multiples on the syndication dummy and control variables.

D. Endogenous Treatment Effects

Success in a syndicated venture comes from two broad sources of VC expertise. *First*, VCs are experienced in picking good projects to invest in, and syndicates are efficient vehicles for picking good firms (this is the selection hypothesis put forth by Wilson (1968), Sah and Stiglitz (1986), Lerner (1994), and Stuart and Sorenson (2001)). Amongst two projects that appear a priori similar in prospects, the fact that one of them is selected by a syndicate is evidence that the project is of better quality (ex-post to being vetted by the syndicate, but ex-ante to effort added by the VCs), since the process of syndication effectively entails getting a second opinion by the lead VC. *Second*, Syndication can also amplify the value-addition of venture capitalists by better monitoring the performance of venture firms. Venture capitalists can add value to portfolio companies in various ways including improving the business model or the management team (Kaplan and Stromberg (2004)), professionalizing company (Hellmann and Puri (2002)), facilitating strategic alliances (Lindsey (2005), and ensuring strong governance structure at the time of exit (Hochberg (2005). Syndicates may provide better monitoring as they bring a wide range of skills to the venture, and this is suggested in the value-added hypothesis of Brander, Amit and Antweiler (2002).

A regression of venture returns on various firm characteristics and a dummy variable for syndication allows a first pass estimate of whether syndication impacts performance. However, it may be that syndicated firms are simply of higher quality and deliver better performance, whether or not deals are syndicated. Better firms are more likely to be syndicated because VC syndication tends to prefer such firms and can identify them. In this case, the coefficient on the

dummy variable might reveal a value-add from syndication, when indeed, there is none. Hence, we correct the specification for endogeneity, and then examine whether the dummy variable remains significant. The formal treatment for endogeneity is summarized in Appendix A.

III. Empirical Analyses

In this section, we assess the performance of syndicated versus non-syndicated ventures. We define the round as a syndicated round if at least one investment round including the current one is syndicated.

Since we have three performance metrics, our analyses will be undertaken for each of the metrics. We undertake different empirical specifications, from the simplest to the most complex, presented in each of the following subsections. We begin with descriptive statistics, examine the raw differences in performance, then provide an explanatory model of syndication, and finally, evaluate performance after correctly accounting for endogenous treatment effects.

A. Descriptive Performance Statistics

A.1. Exit Probabilities

First, we examine if syndicated ventures are more likely to exit successfully than nonsyndicated ones. Three types of exit are considered here: (a) by IPO, (b) by acquisition, and (c) by LBO. The results are presented in Table II. There is clear evidence that the probability of exit is higher for syndicated firms, irrespective of the channel through which exit occurs. All exit probabilities are higher for syndicated firms at the 1% level of significance.

Overall, if we take all three exit routes together, the probability of a syndicated firm exiting is around 38% whereas that of the non-syndicated firm is 25%, meaning that there is a 13% higher probability of syndication resulting in an exit. Comparing exit routes, the difference in probability is more marked for exit by acquisition (10% difference in probabilities) than for exit by IPO (3%). Increasing the likelihood of exit is thus an important function offered by the syndicate.

A.2. Exit Times

Given the evidence that VC syndication increases the chances of the firm exiting, the

interesting question is whether it enhances the speed with which firms exit as well. The answer to this question is provided in Table III, which presents the mean time to exit (in days).

Overall, if we look at all exit routes (IPO, acquisition, or LBO), the mean time to exit is 50 days faster for syndicated firms than for non-syndicated firms (significant at the 5% level). However, this result is driven mainly by firms that exit by acquisition (93 days, significant at the 1% level). For exits by IPO, there does not seem to be a statistically significant difference in exit times for syndicated and non-syndicated firms, even though syndicated exits are on average 26 days sooner than non-syndicated exits. This suggests that syndicates are more likely to cut losses and sell of a new venture when they realize that an IPO is less likely.

A.3. Exit Multiples

Do syndicated ventures deliver higher returns? We begin by examining the exit multiples for syndicated versus non-syndicated firms using the annualized exit multiple (X_{annual}) defined earlier. The return (annualized multiple) distributions for both syndicated and non-syndicated financing are displayed in Figure 1. (Note also that these return distributions are *conditional* ones, i.e. they represent the return after conditioning on syndication, or the absence of syndication). We see that the syndicated firm distribution is shifted to the right. The plot shows that after a multiple level of 2, the syndicated firms' distribution is fatter tailed, i.e. the likelihood of a large multiple is higher for syndicated firms than for non-syndicated ones.

[Figure 1 around here]

Data on exit multiples is available in lower frequency in the database compared to data on exit events, as post round valuation data should be available for exit multiple calculation. The total number of observation is 1,305 for syndicated and 142 for nonsyndicated; these comprise all available exit observations that have enough data to calculate an exit multiple from our VentureXpert database. Table IV presents the results for the annualized multiples. The annualized multiple for syndicated firms is 2.19 whereas for non-syndicated firms it is 1.79 (the difference is significant at the 1% level despite a reduced number of observations), evidence that syndicated firms yield higher exit outcomes from financing round to exit. A comparison of the raw exit multiples (not adjusted for time) reveals that non-syndicated firms provide higher

multiples (9.66 versus 6.38, significant at the 5% level). However, since these firms take much longer to exit, the returns are lower on an annualized basis. This may also be consistent with the evidence that syndicated firms are more likely to be rushed towards exit by their VCs, and these results support this decision given that they provide a higher return on invested capital.

A.4. Probability of Syndication

One of the contributions of this paper is a comprehensive empirical model of the decision to syndicate itself (the determinants of syndication are empirically examined in Table V). This empirical model (developed in subsection B below) is motivated by our finding in this subsection that the conditional probability of a firm being syndicated is increasing in returns.

We transform the conditional return distributions of the previous section into syndication probabilities using Bayes' theorem, conditional on returns. Define the probability of the return given that the financing was syndicated as Pr[R|S=1]. Likewise, the probability of the return given the firm was not syndicated is Pr[R|S=0]. Each of these may be read from the two probability density functions depicted in the previous subsection. The probability of a financing being syndicated, denoted Pr(S=1) is simply the ratio of the number of syndicated financings to total financings. We define of course, Pr(S=0)=1-Pr(S=1).

Using Bayes' theorem, the conditional probability of syndication is as follows:

$$\Pr[S=1 | R] = \frac{\Pr[R | S=1] \Pr[S=1]}{\Pr[R | S=1] \Pr[S=1] + \Pr[R | S=0] \Pr[S=0]}$$

We plot this probability for all values of R, depicted in Figure 2. We see that the likelihood of syndication increases in the return level, implying that when returns are high, there is a greater chance that the firm was financed through syndication. The extent to which this matters is also indicated by the slope of the plot. Since it is rather steep, performance is well discriminated by syndication as an explanatory factor.

[Figure 2 around here]

B. Determinants of Syndication

Here, we develop a detailed empirical model to understand the differences between venture investments that are syndicated and those that are not. To answer this question, our model relies on a Probit analysis of the syndication decision, with the following model:

$$\Pr[SYN_{it} | Z_{it}] = \Phi[B' Z_{it}]$$

Where SYN_{it} is a dummy variable equal to one if firm *i* is a syndicated venture in year *t*, and 0 otherwise. Z_{it} is a vector of firm, industry, or market characteristics at the time of firm *i*'s syndication. *B* is a vector of coefficients.

We assert that there are characteristics of the firm and of the venture capitalist that lead to a venture being syndicated, and we chose a large number of variables to model the probability of syndication. Based on the previous literature and our three chosen performance metrics, we include the following variables as components of Z:

Risk sharing variables: Wilson (1968) and Bygrave (1987) argue that the primary ratioanle behind VC syndication is risk sharing. To capture this motive, we opt for the following variables.

- *IND*: Since investment risks and benefits of syndication are likely to vary across industries, we include a dummy variable that signifies if the firm lies in the information technology (IT) or bio-technology industries. These two industries are known for higher levels of uncertainty, and thus we expect such firms to be syndicated more than those in other industries.
- *ERLY_STG*: A dummy variable that takes a value of 1 if the firm is in an early stage or the seed round of financing. Early stage investment is more risky and therefore more likely to be syndicated.
- *CO_AGE*: The age (in years) of the venture since its founding to the financing round. We expect that firms that are older will be less risky and unlikely to need syndicated financing.
- *TOT_IVT1*: The cumulative total investment by the VCs in the firm until the financing round. If the VCs' investment in the venture is large, they may seek syndication to diversify their risks.

• *NUM_STG2*: The cumulative number of stages including the current round. As a venture goes through multiple satges of financing, asymmetric information about the venture dissipates, and the firm is likely to find it easier to obtain syndicated financing.

Diversification and resouce variables: Manigart, et al (2002) and Hopp and Rieder (2006) suggest that portfolio diversification and resource-driven motives complement the risk mitigation perspective.

- *VC_INTN2*: Indicator variable with a value of 1 if the lead VC is an international VC. The lead VC is the VC whose cumulative investment including the current round investment is the greatest. The value of syndication would increase with this variable if the VC were worried about diversification. But, an international VC is likely to be already diversified in other markets, and hence the need would be less. Also, an international VC is less likely to have strong syndication relationships in the U.S. market, leading to a lower likelihood of syndication.
- *VC_IND2F*: A dummy variable with a value of 1 if the lead VC is a generalist and has no specific industry focus. A VC with a broadly diversified portfolio is less likely to seek syndication.
- *VC_PMIN2*: The lead VC's preferred minimum investment. When the lead VC's preferred minimum investment is large, the lead VC is less likely to seek syndication to diversify.

Capital constraint variables: Gompers and Lerner (1998) assert that the capital constraints of a single venture capitalist might force the venture to syndicate.

- *CAP_MGT2*: This is the capital under management in all ventures for the lead VC. We anticipate that if the total capital under management of the lead VC is small, then the current investment represents a higher proportion of his layout, and such a VC would have a greater incentive to diversify his holdings, and thus syndicate more. Hence, an increase in this variable should result in a decrease in the likelihood of syndication. Simply put, if the lead VC is not capital constrained, there is a lower chance of syndication.
- *EXVC_SZ1*: The average capital under management of all the existing VCs in the venture.

The bigger the VCs involved, the less likely they are to seek syndicated financing, as the required level of financing is not a constraint.

• *RD_IVST1*: The total amount invested in the round. If the lead VC invested too much in a certain round, the likelihood of syndication grows with the amount of investment.

VC's monitoring, skill, experience, and specialty variables: Brander, Amit and Antweiler (2002) and Wright and Lockett (2003) suggest that VC syndication provides better monitoring as they bring a wide range of skills, experience, and networks to the portfolio companies. In the VC literature, although their main focus is not on VC syndication, Gompers, Kovner, Lerner, and Scharfstein (2006b) also maintain that skill is important and show that more experienced venture capital firms identify and invest in first time entrepreneurs who are more likely to become serial entrepreneurs. Gompers, Kovner, Lerner, and Scharfstein (2007) suggest that experience is important and the most experienced VC firms – notably those with the most industry experience – are more responsive to public market signals of investment opportunities. We include Hochberg, Ljungqvist, and Lu (2007)'s proxies for experience, i.e., the age of the VC firm and the number of portfolio companies it has backed, and other variables.

- *EXVC_AG*: The average age of the existing VCs. Older VCs are more prudent and have more experience, and are thus, more likely to seek the input of outside VCs, thereby increasing the chance of a syndication. Alternatively, older VCs have more experience and thus do not need additional inputs from other VCs.
- *VC_NUMC2*: The number of companies that the lead VC has invested in. As this increases, the lead VC is more likely to have more experience and invite other experienced VCs into the syndiacte in the early stage and invite less experienced VCs in the late stages (Lerner (1994)).
- *LATE_STG*: A dummy variable that is 1 if the stage of financing is late. Syndication is less likely to occur in late stages as the set of VCs in place probably do not need additional input for selection or monitoring-related value addition.
- *VC_IND2*: This is a dummy variable that takes the value 1 if the lead VC is an industry specialist whose preferred industry is also the same industry category in which the firm resides. The lead VC may wish to obtain additional skills that are not industry specific, thereby increasing the chance of a syndication; conversely, the lead VC may not need an

another opinion given existing industry expertise.

- *IVST_BK6*: A dummy variable which is 1 if the lead VC is an investment bank, else 0. An investment bank is much more likely to want to syndicate than a pure VC, given the lack of focused expertise in the early stage. In general, however, an investment bank has skills and experience in preparing for IPO and acquisition. In addition, it is well-known that investment banks also syndicate. Hence, the likelihood of syndication should increase with this variable in either case.
- *CVC2*: A dummy variable with a value of 1 if the lead VC is a corporate VC, else the value of this variable is 0. Cumming (2001) suggests that Corporate VCs (CVCs) are more likely to seek syndication in order to get second opinions. They also syndicate to obtain additional skills. In addition, they prefer to diversify their investments, especially if the investment is in the same industry as the one in which the parent firm operates.

Other control variables:

Strategic stage-based variable:

• *STR_STG2*: This is a dummy variable that takes a value of 1 if the stage of the financing round is the same as that of the stage preferences of the lead VC. If the stage is one that the lead VC prefers, then it is less likely that the round will be syndicated.

Geographical location variables: Stuart and Sorenson (2001) suggest that syndication makes the dissemination of information easier across geographical and industrial boundaries.

- *CO_STATE*: A dummy variable taking a value 1 if the firm is based in California. Since there is greater access to VCs in California, this makes it more likely to see a syndication of firms from that state.
- *VCSTATE2*: A dummy variable taking the value 1 if the VC is from California. The reasoning for this follows from that for the variable *CO_STATE*. We expect the same positive relationship between this variable and the probability of syndication.

Market sentiment variable:

• *HOT_MKT*: An indicator variable with a value of 1 if the year of the round belongs to 1983-1999 or 1995-2000. Syndication is less desirable in a hot market, as the lead VC

bears much less risk.

We estimated the probability of syndication using a Probit function. Four different models are attempted, and the results are presented in Table V. We estimate four different models with different sets of explanatory variables, since the data requirement of some explanatory variables reduces the sample size significantly. Progressing from Model (1) to Model (4), we eliminated some of the explanatory variables so as to include more rounds in the analysis.

Consistent with the intuition sketched above and the prior literature, from Models (1) to (4), we can see that almost all the chosen variables to measure risk sharing, diversification and resources, capital constraints, VC's monitoring, skills, and experience, and other control variables such as geographical concerns and market sentiment are highly significant in explaining the probability of syndication. The risk-sharing motive for syndication is important. Firms that are in the IT or bio-tech space are more likely to be syndicated, as are early stage firms to reduce risk. Older firms are less likely to seek syndication. The likelihood of syndication also increases with the number of stages – it is likely that the reduction in information asymmetry from being in an advanced stage helps in bringing together syndicates.

Diversification and resources matter. Syndication increases if the lead VC seeks a broadly diversified portfolio; it also increases in the number of companies the lead VC invests in. In addition, as the capital under management by the lead VC increases, there is a lower chance of syndication, since the current investment does not represent a high proportion of the lead VC's portfolio and it is less likely to seek partners to share in the venture. If the financing stage is one that the lead VC prefers then, as expected, the lead VC is less likely to want to go for a syndication.

Consistent with Kaplan and Schoar (2005) and Gompers, Kovner, Lerner, and Scharfstein (2006b, 2007) who suggest that the VC's skill and experience are important factors of firm performance, we find that these factors are also relevant in determining the likelihood of VC syndication. Syndication propensity increases with the number of companies that the firm has participated in. Moreover, the probability of syndication increases with the average age of the existing VCs and further increases if the lead VC is an industry specialist. Overall, the above results suggest that experienced VCs who have the required skills are likely to syndicate more. On the other hand, if the lead VC is a corporate one or an investment bank, they tend to

syndicate more to get additional opinions and skills, and again, the likelihood of a syndication increases.

Other control variables measuring geographical location and market sentiment are also important. Companies in California are more likely to seek and obtain syndicated financing, and VCs domiciled in California add to this impetus. The lead VC is less likely to initate a syndication in a hot venture market, preferring to retain all the gains, The presence of a VC with a preference for investing in the same industry as the venture does not appear to increase the probability of syndication. Finally, syndication is less likely if the lead VC is an international VC.

Table V shows that the results are consistent across all four Probit specifications. Given that all the explanatory variables enter the probit model with the right sign lends a level of confidence to our specification for syndication choice, and provides a solid basis for using these variables in subsequent endogeneity corrections. Because model specification (4) retains the most number of observations, we use this model in our endogeneity corrections in the second stage performance analysis regressions.

C. Instrumental Variable Methods

When the second-stage performance equation is nonlinear, traditional second-stage Heckman regressions do not provide unbiased estimates (Greene (1993)). In this case, alternative approach is to estimate probit model first, and then to set $m(\gamma'X)=\Phi(\gamma'X)$. This is known as the instrumental variables approach that Gompers, Ishii, and Metrick (2006) employ. Heckman and Robb (1985) and Moffitt (1999) suggest the instrumental variable (IV) method focusing on finding a variable (or variables) that influences the first-stage (i.e., syndication) choice but does not influence the second-stage regressions (and is thus not correlated with the random error term in the second-stage regressions).

Abadie (2000) maintains that because the instrumental variable is not correlated with the random error term, it can be used in the estimation without introducing bias even when the second-stage performance equation is nonlinear. Moffitt (1999) suggests that each IV, that is uncorrelated with the random error term in the second-stage regressions, will yield unbiased estimates. However, some IVs will yield more precise estimates. The more highly correlated is the IV with the syndication choice, the more precise will be the estimates of performance impact. Thus the challenge in IV estimation is to find an appropriate instrumental variable that is highly correlated with the first pass syndiactioan choice but uncorrelated with the second pass exit performance. Unfortunately, it is often hard to find variables that meet both these requirements, and therefore difficult to find good IVs among the many potential IVs.

Our choice of IV variables based on intuition includes an indicator variable with a value of 1 if the lead VC is an international VC (VC_intN2), a dummy variable with a value of 1 if the lead VC is a generalist and has no specific industry focus (VC_ind2f), a dummy variable with a value of 1 if the lead VC is a corporate VC, else the value of this variable is 0 (CVC2), a dummy variable taking the value 1 if the VC is from California (VCstate2), the natural log of the total amount invested in the round (LG_Rdiv1), and the natural log of the number of companies that the lead VC has invested in (LG VC_numC2). Our choice for the instrument variables turn out to work reasonably well. In particular, we check whether the partial correlation coefficients between performance variables and instrument variables are insignificant, and find that the partial correlations are all indeed insignificant for the exit multiples, although only 2-3 instrument variables have insignificant partial correlations with exit probabilities and exit time. We use the above IVs in the following second-stage exit performance regressions using the IV approach.

D. Exit Performance of Syndication

D.1. Control Variables

In examining the effect of VC syndication on exit performance, we introduce control variables to reduce misspecification from correlated omitted variables. Several studies document that VC syndication is designed for risk sharing and is a natural mechanism to reduce inherent uncertainty (Wilson (1968), Bygrave (1987); Chemmanur and Loutskina (2005) assert that the uncertainty affects firm performance in their study of IPOs). Thus, we include dummy variables for firms in the IT or bio-tech space, firms in internet-related activities, early stage firms, or the cumulative number of of stages including the current round as explanatory variables.

Brander, Amit and Antweiler (2002) and Wright and Lockett (2003) suggest that VC syndication provides additional monitoring through syndicate members' wide range of skills, experience, alliances, and networks to the portfolio companies. Many studies, such as Lerner (1995), Kaplan and Schoar (2005), and Gompers, Kovner, Lerner, and Scharfstein (2006a, b, 2007) maintain that VC's monitoring, skills, and experience are important drivers of firm performance. Kaplan, Martel, and Stromberg (2003) even suspect that the performance-enhancement of VC nertworking is simply experience. Lerner (1995) argues that VCs act as intense monitors of managers when the need for oversight is higher. Thus, in order to control for

the effect of VCs' monitoring, skills, and experience, we include the dummy variables for whether the lead VC receives monitoring fees, late stage, and dummy variables if the lead VC is an investment bank.⁴

Manigart et al (2002) suggest that diversification and resources might affect firm performance, so we include the dummy variable of whether whether the lead VC seeks a broadly diversified portfolio. Gompers and Lerner (1998b) suggest that the performance of the ventures with corporate backers are as successful as independent VCs when there are similarities between the VC firm's and portfolio company's line of business. Thus, we include a dummy variable for if the lead VC is an independent one. Additionally, we include a dummy variable for hot markets to control for the market sentiment.

D.2. Exit Probabilities

We next examine what impact syndication has on the probability of exit and the results are presented in Table VI. We examine if the higher exit probabilities of syndicated firms comes from selection or better monitoring by VC syndication by comparing the results with and without controlling for endogeous treatment effects. There are four subpanels in the table, breaking out results for exit from all routes to exit by individual routes. The evidence that syndication significantly improves exit probabilities is strong, and is not mitigated when the endogeneity correction is applied. If the higer probability of exit comes strictly from the selection, the impact of syndication on the exit probabilities should disappear after controlling for the endogenous treatment effects. We observe, however, that the impact remain intact after the endogeity correction. Hence, the likelihood that a syndicated firm will exit depends on selection, as well as on monitoring by the syndicate.

In addition, we find higher exit probabilities if firms are in the IT or bio-tech space, not in internet-related activities, are late stage firms, or are companies in California, suggesting that risk concerns, industry, and spatial location are important to the successful exit of startups. Exit probabilities are higher for firms receiving a multiple number of financing stages, and firms

⁴ We also replicate the exit-performance analyses based upon all the proxy variables of VCs' skills and experience used in the first-stage analysis and obtain qualitatively similar results. To conserve the space, we only report the selected results.

receiving financing in a hot venture market, implying a role for conditions in the financing and product markets.

Exits are more likely when the firm's lead VC is an investment bank, meaning also that the type of VC matters. However, there is an insignificant impact on exit probabilities when the lead VC seeks a broadly diversified portfolio, when the lead VC receives monitoring fees, and if the lead VC is an independent one.

For IPO, syndication and exit probability is negatively (but insignificantly) correlated without endogeneity control, but positively correlated with endogeneity control. It seems that VCs tend to select to syndicate the best deals with high probability of IPOs. While coefficients on the other control variables for IPOs and acquisitions have the same sign and similar significance, the coefficients on the early stage, monitoring fee variable (Mntrfee2), and independent lead VC (indpnVC2) are negative (positive) in IPO (acquisition), suggesting that differences in the role of the VC may lead to differential value-add outcomes.

D.3. Exit Times

We had seen in Table III that the time to exit when a venture is syndicated is less than that when it is not syndicated, and that this was primarily the case for exits by acquisition. We now examine this effect with a multi-variate analysis controlling for all other variables. We use a Cox proportional hazard model outlined earlier. We also compare the results with and without controlling for endogenous treatment effects. Results are provided in Table VII. The coefficients as well as hazard ratios are reported. A hazard ratio of an independent variable greater (less) than 1 indicates a shorter (longer) the time-to-exit. The evidence clearly shows that syndication impacts the time to exit significantly, with and without the endogeneity correction. Consistent with the results reported in Table III, where the time to exit was shorter for syndicated ventures, the hazard ratio for syndication is greater than 1, implying that after applying various controls, syndicated firms exit faster.

Firms tend to have a faster time-to-exit if they are in the IT or bio-tech space, the internet space, are late stage firms, and if the lead VC is independent, showing that type of firm and stage matter. As expected, the type of VC matters too – firms' exit take longer when the lead VC seek a broadly diversified portfolio, receives monitoring fees; all symptoms of lower engagement

levels. It is important that the VC be aligned with the industry as well. Firms also exit faster when they receive multiple financing rounds, but not necessarily in hot venture markets. Overall, an examination of the significance statistics suggests that industry and VC alignment matter most in speeding up firm exit.

Syndicated investments take a shorter time to exit through acquisitions with or without correcting for endogenous treatment effects. For exit thorugh IPOs, the impact of syndication on time-to-exit is insignificant before controlling for endogeneity but becomes significant after accounting for endogenous treatment effects. It seems that in exits through IPOs, monitoring is what reduces time-to-exit.

D.4. Exit Multiples

In Table VIII, we examine if the higher annualized exit multiples by syndicated ventures shown in Table IV remain significant in the multivariate analyses and if the higher annualized exit multiples arising from syndication come from selection or from value-add by the VCs. We regress the exit multiple on various explanatory variables. We conduct this first without correcting for endogeneity, and then repeat the exercise with the correction. We find that the variable for syndication (*SYN*) is significant when no endogeneity correction is imposed, and then becomes insignificant with the correction. This finding is important. If one finds a higher exit multiple without endogeneity correction, then the exit performance is clearly overstated. This evidence also suggests that the better exit multiple comes from the selection of better projects by VC syndicates, and not from value-addition.

In Table IX, the effect of selection is examined by exit route. We compare annualized exit multiples both with and without the endogeneity correction, for exit by acquisition and IPO. Multiples for exit by acquisition are significantly related to the presence of syndication (*SYN*), but after correcting for endogeneity, the variable is insignificant, implying that higher exit multiples on acquisition come from better project choice by VC syndicates. This evidence is consistent with the finding reported in Table VIII. Multiples exit by IPO closely mirror those by acquisition, implying that VC syndicates do not impact the exit multiple for IPO after correcting for endogeneity. To the extent that our sample of annualized exit multiples, the evidence based upon the endogeneity adjustment is consistent with the selection hypothesis rather than the

value-add one.

In general, while firms tend to get higher exit multiples in a hot market, if they pay monitoring fees to VCs, and the firm's business is related to Internet, most of the other firm and industry characteristics do not affect exit multiples. The most significant determinant of exit multiples is a hot venture market. Overall, our results based on endogeneity control does not change the syndication's effect on exit probabiblities and exit time, but it removes the syndication's effect on exit multiples.

E. Re-interpreting Results with a Simple Model of Effort-Sharing

In our empirical analyses, we examine whether VC syndicates do better on account of their selection ability or on account of value-add. Rather than treat selection and value-add as mutually exclusive hypotheses, we present a simple model under which effort is allocated to these two sources of syndication value. We denote this model an ``*effort-sharing*'' model of VC syndication. Our empirical results may be viewed with this framework in mind.

Consider a VC syndicated project where an initial effort is expended on project selection and subsequent effort is put into monitoring. We assume that effort $e \in (0,1)$ is expended on project selection and effort (1-e) is put into subsequent monitoring. Thus a total effort of unit amount is allocated to selection and monitoring. After project selection is done, the probability of exit per period depends on the monitoring effort. We define this probability to be p=1-e.⁵

To keep things simple, suppose there are only two types of projects in the world, high quality (H), and low quality (L). The multiple obtained from each respectively will be denoted $\{X_H, X_L\}$. We also define the relative ratio of multiples to be $\eta = X_H/X_L$. The ex-ante expected multiple on the project is then as follows:

$$E(X) = (1-e)[eX_{H} + (1-e)X_{L}]$$

⁵In this simple model, we do not assume that good selection feeds into a higher probability of exit, only into a greater multiple on exit. Other specifications of the probability of exit are feasible, such a p=(1-e)(1+e), where the second term reflects the benefits to selection on exit probability. Note that with this modification, as effort *e* on selection increases, the probability of exit does decline, but in a slower (concave) manner, versus a fast (linear) drop as in the simpler case. Qualitatively, the results do not change.

Taking the derivative of this expression with respect to *e*, we get the first-order condition:

$$\frac{dE(X)}{de} = X_H - 2eX_H - 2(1-e)X_L = 0$$

and solving results in optimal selection effort

$$e^* = \frac{X_H - 2X_L}{2X_H - 2X_L} = \frac{\eta/2 - 1}{\eta - 1}$$

Note that the following comparative statics follow immediately:

$$\eta \downarrow 2 \Longrightarrow e^* \downarrow 0$$
$$\eta \uparrow \infty \Longrightarrow e^* \uparrow 1$$

When $\eta = X_{H}/X_{L}$ increases, one would expect that more effort will be directed on project selection. The result is fairly natural in that as the better quality projects become relatively superior to the low quality ones (i.e. as η increases), the syndicate naturally finds that it is worth expending more effort on project choice. When firm quality varies a lot, it makes sense for the VC to spend more time making sure that the chosen venture is of high quality. And, as the difference between high and low type projects declines, more effort will be directed to management of the post-project selection, i.e., monitoring. As we have seen, the exit multiple for syndicated firms is significantly higher than that for non-syndicated ones before controlling for endogenous treatment effects. After the control, it becomes insignificant, implying that greater effort will be spent on selection. Our results support the stylized model here. However, we find that effort is also required on monitoring to ensure successful exit, which in the context of our model, is a level of *e* that cannot be extreme, i.e. close to zero or unity.

IV. Conclusions

Despite the importance of the role of VC syndication in venture performance, there has been limited empirical evidence on this issue; this is changing as better and more extensive data becomes available. This paper attempts to fill this void in our knowledge by examining two questions, what the determinants of VC syndication are, and whether syndicated firms provide better exit performance. We analyze a comprehensive sample of venture firms in the United States during the 1980 to 2003 period.

Our paper complements the existing literature by making four broad contributions. *First*, we believe that this is one of the most comprehensive examinations of the determinants of VC syndication for U.S. firms, using all the available 98,068 rounds of venture firms from Thomson Financial's Venture Economics (VentureXpert) database. Consistent with the prior literature and economic intuition, risk sharing, portfolio diversification and resources, capital constraints, VC's monitoring, skills, experience, and specialty are found to be important rationales behind VC syndication. Hence, it is not just firms that matter, but also the right match of VC to firm.

Second, we complement and extend the existing literature by examining the performance of syndicated ventures not only on returns (i.e. exit multiples), but also on exit likelihood and exit times. Hence, we provide a three-way metric for assessing the benefits of syndication. Syndication is found to result in better returns, higher exit probabilities, and faster times-to-exit.

Third, we revisit the debate as to whether syndicated ventures do better because they select superior firms (Lerner (1994)) or add-value to firms post selection (as investigated by Brander, Amit and Antweiler (2002)). We reframe this debate in the light of our three distinct metrics of performance. Interestingly, we find that selection seems to matter most for return performance, but that the role of syndicates in monitoring and value-addition matters for exit likelihoods and exit times over and above the selection effect. Therefore, partitioning the metrics of performance shows that these two canonical hypotheses in the literature overlap and that the role of VC syndicates is multifaceted. We develop a theoretical model of ``effort-sharing'' by VC syndicates to explain our results.

Fourth, we undertake all tests after accounting for endogeneity by applying corrections for treatment effects. This plays two roles, in that it corrects the empirical specification, and it also allows separation between the selection and value-add hypotheses. The application of these corrections exploits the extensive empirical model we developed for the determinants of syndication. Correcting for endogenous treatment effects shows that exit multiples are no longer higher for syndicated firms on account of selection, but treatment does not negate the value-add hypothesis when considering the time to exit (using hazard analysis) and the likelihood of exit (using probit analysis).

We also note that the extant literature on syndicated venture performance has focused on Europe. By using all the available 98,068 rounds of venture firms from Thomson Financial VentureXpert database, we provide extensive evidence on the syndication of U.S. private firms.

A significant relation between VC syndication and exit probability along with time-to-exit does not necessarily imply that any participant who chooses not to syndicate is behaving irrationally. A majority manager of a private venture firm or a VC firm can rationally measure private benefits of syndication vs. related costs of syndication. Our endogeneity controlled evidence suggests that in general, syndicated ventures have higher exit probabilities, faster time-to-exit, and indifferent exit multiples. While the previous literature argues that either the selection explanation or the value-added hypothesis can explain the syndicated venture performance, our first two results are supportive of both the selection as well as the value-added hypothesis. We liken this to VC syndicates uncovering diamonds in the rough, and then polishing them to success.

References

- Abadie, Alberto, 2000, Semiparametric estimator of instrumental variable models for causal effects, Working paper, Harvard University and NBER #260.
- Admati, Anat R., and Paul Pfleiderer, 1994, Robust financial contracting and the role of venture capitalists, *Journal of Finance* 49, 371-402.
- Allison, Paul D., 1995, Survival Analysis Using the SAS System: A Practical Guide. Cary, NC: SAS Institute.
- Brander, James, Raphael Amit, and Werner Antweiler, 2002, Venture capital syndication: Improved venture selection versus the value-added hypothesis, *Journal of Economics and Management Strategy* 11, 423-452.
- Bygrave, William D., 1987, Syndicated investments by venture capital firms: A networking perspectives, *Journal of Business Venturing* 2, 139-154.
- Chemmanur, Thomas, J., and Elena Loutskina, 2005, The role of venture capital backing in initial public offerings: Certification, screening, or market power? Working paper, Boston College.
- Cochrane, John, 2005, The risk and return of venture capital, Journal of Financial Economics 75, 3-52.
- Cumming, Douglas, 2001, Is the optimality of conventional venture capital financial contracts generalizable? Working paper, University of Alberta.
- Das, Sanjiv., Murali Jagannathan, and Atulya Sarin, 2003, Private equity returns: An empirical examination of the exit of venture-backed companies, *Journal of Investment Management* 1, 152-177.
- Gompers, Paul A, Joy Ishii, and Andrew Metrick, 2006, Extreme governance: an analysis of dual-class firms in United States, Working paper, Harvard University.
- Gompers, Paul A., and Josh Lerner, 1998a, What drives venture capital fundraising? *Brookings Papers on Economic Activity: Microeconomics*, 149-192.
- Gompers, Paul A., and Josh Lerner, 1998b, The determinants of corporate venture capital success: organizational structure, incentives and complementarities, NBER Working paper 6725.
- Gompers, Paul A., and Josh Lerner, 2000, Money chasing deals? The impact of fund inflows on private equity valuations, *Journal of Financial Economics* 55, 281-325.
- Gompers, Paul A., Anna Kovner, Josh Lerner, and David Scharfstein, 2006a, Specialization and success: Evidence from venture capital, Working paper, Harvard University.

- Gompers, Paul A., Anna Kovner, Josh Lerner, and David Scharfstein, 2006b, Skill vs. luck in entrepreneurship and venture capital: Evidence from social entrepreneurs, NBER Working paper 12592.
- Gompers, Paul A., Anna Kovner, Josh Lerner, and David Scharfstein, 2007, Venture capital investment cycle: The impact of public markets, forthcoming at *Journal of Financial Economics*.
- Greene, William H., 1993, Econometric Analysis, 5th edition, Prentice-Hall.
- Heckman, James. J., 1976, The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models, *Annals of Economic and Social Measurement* 5, 475-492.
- Heckman, James, and Richard Robb, Jr., 1985, Alternative methods for evaluating the impact of interventions, Ch. 4 in *Longitudinal Analysis of Labor Market Data*, ed. By J. Heckman and B. Singer. New York: Cambridge University Press.
- Hellmann, Thomas J., and Manju Puri, 2002, Venture capital and the professionalization of start-up firms: Empirical evidence, *Journal of Finance* 57, 169–197.
- Hochberg, Yael V., 2005, Venture capital and corporate governance in the newly public firm, Working paper, Northwestern University.
- Hochberg, Yael, Alexander Ljungqvist, and Yang Lu, 2007, Whom you know matters: Venture capital networks and investment performance, *Journal of Finance* 62, 251-301.
- Hopp, Christian and Finn Rieder, 2006, What drives venture capital syndication? Working paper, University of Konstanz.
- Kaplan, Steven N., Frederic Martel, and Per Stromberg, 2003, How do legal differences and learning affect financial contracts? Working paper, University of Chicago.
- Kaplan, Steven N., and Antoinette Schoar, 2005, Private equity returns: Persistence and capital flows, *Journal of Finance* 60, 1791-1823.
- Kaplan, Steven N., and Per Stromberg, 2004, Characteristics, contracts and actions: Evidence from venture capital analyses, *Journal of Finance* 59, 2177–2210.
- Lerner, Josh, 1994, The syndication of venture capital investments, Financial Management 23, 16-27.
- Lerner, Josh, 1995, Venture capitalists and the oversight of private firms, Journal of Finance 50, 301-317.
- Lindsey, Laura A., 2005, Blurring boundaries: The role of venture capital in strategic alliances, Working paper, Arizona State University.

- Manigart, Sophie, Andy Lockett, Miguel Meuleman, Hans Landstrom, and Philippe Desbrieres, 2002, The Syndication of venture capital investments in Europe: Evidence from five European countries, Working paper, Ghent University.
- Moffit, Robert, 1999, New developments in econometric methods for labor market analysis, Ch. 24 in O. Ashenfelter and D. Card, eds., *The Handbook of Labor Economics*, Volume IIIA, Amsterdam: North-Holland.
- Sah, Raj K., and Josheph E. Stiglitz, 1986, The architecture of economic systems: Hierarchies and polyarchies, *American Economic Review* 76, 716-727
- Sorenson, Morten, 2005, How smart is smart money? An empirical two-sided matching model of venture capital, Working paper, University of Chicago.
- Stuart, Toby E., and Olav Sorenson, 2001, Syndication networks and the spatial distribution of venture capital investments, *American Journal of Sociology* 106, 1546-1588.
- Tobin, James, 1958, Estimation of relationships for limited dependent variables, *Econometrica* 26, 24-36.
- Vella, Francis and MarnoVerbeek, 1999, Two-step Estimation of Panel Data Models with Censored Endogenous Variables and Selection Bias, *Journal of Econometrics* 90, 239-263.
- Wang, Kangmoo, Wang, Clement K., and Qing Lu, Q., 2002, Differences in performance of independent and finance-affiliated venture capital firms, *Journal of Financial Research* 25, 59–80.
- Wilson, Robert, 1968, The theory of syndicates, *Econometrica* 36, 119-132.
- Wright, Mike and Andy Lockett, 2003, The structure and management of alliances: syndication in the venture capital industry, *Journal of Management Studies* 40, 2073-2102.

Appendix A. Treatment for Endogeneity

Greene (1993) discusses econometric models for endogenous treatment effects. We briefly summarize the model required. The performance regression is of the form:

$$Y = \beta' X + \delta S + \varepsilon, \quad \varepsilon \sim N(0, \sigma_{\varepsilon}^2)$$

where *S* is the dummy variable taking a value of 1 if the firm is syndicated, and zero otherwise, and δ is a coefficient that determines whether performance is different on account of syndication. If it is not, then it implies that the variables *X* are sufficient to explain the differential performance across firms, or that there is no differential performance across the two types of firms.

However, since these same variables determine also, whether the firm syndicates or not, we have an endogeneity issue which is resolved by adding a correction to the model above. The error term ε is affected by censoring bias in the sub-samples of syndicated and non-syndicated firms. When *S*=1, i.e. when the firm's financing is syndicated, then the residual ε has the following expectation (see Greene (1993)):

$$E(\varepsilon \mid S=1) = E(\varepsilon \mid S^* > 0) = E(\varepsilon \mid u > -\gamma' X) = \rho \sigma_{\varepsilon} \left\lfloor \frac{\phi(\gamma' X)}{\Phi(\gamma' X)} \right\rfloor$$

where $\rho = Corr(\varepsilon, u)$, and σ_{ε} is the standard deviation of ε . This implies that

$$E(Y \mid S = 1) = \beta' X + \delta + \rho \sigma_{\varepsilon} \left[\frac{\phi(\gamma' X)}{\Phi(\gamma' X)} \right]$$

For estimation purposes, we write this as the following regression equation:

$$Y = \delta + \beta' X + \beta_m m(\gamma' X)$$

where $m(\gamma' X) = \phi(\gamma' X)/\Phi(\gamma' X)$, and $\beta_m = \rho \sigma_{\varepsilon}$. Thus, { δ, β, β_m } are the coefficients estimated in the regression. (As usual $m(\gamma' X)$ is also known as the inverse Mill's ratio.⁶)

⁶ The inverse Mills' ratio (sometimes also called 'selection hazard') is used in regression analysis to take account of a possible endogeneity bias. If a dependent variable is censored, i.e. not for all observations a positive outcome is observed, it causes a concentration of observations at zero values. This problem was first acknowledged by Tobin

Likewise, for firms that are not syndicated, we have the following result from Greene (1993):

$$E(Y \mid S = 0) = \beta' X + \rho \sigma_{\varepsilon} \left[\frac{-\phi(\gamma' X)}{1 - \Phi(\gamma' X)} \right]$$

This may also be estimated by linear cross-sectional regression.

$$Y = \beta' X + \beta_m m'(\gamma' X)$$

where $m'(\gamma'X) = -\phi(\gamma'X)/[1-\Phi(\gamma'X)]$, and $\beta_m = \rho \sigma_{\varepsilon}$.

The estimation model will take the form of a stacked linear regression comprising both equations. This forces β to be the same across all firms without necessitating additional constraints. If δ is insignificant after this endogeneity correction, then the empirical evidence supports the hypothesis that the selection role of syndication is a driver of differential performance. If the coefficients { δ , β_m } are significant, then the expected difference in performance for each syndicated financing round (*i*,*j*) is

$$\delta + \beta_m[m(\gamma_{ij}'X_{ij}) - m'(\gamma_{ij}'X_{ij})], \quad \forall i, j.$$

The method above forms one possible approach to addressing treatment effects. Another approach is to estimate a Probit model first, and then to set $m(\gamma'X)=\Phi(\gamma'X)$. This is known as the instrumental variables approach. Vella and Verbeek (1999) show that the two procedures are closely related.

^{(1958),} who showed that if this is not taken into consideration in the estimation procedure, an ordinary least square estimation (OLS) will produce biased parameter estimates. With censored dependent variables there is a violation of the Gauss-Markov assumption of zero correlation between independent variables and the error term. Heckman (1976) proposed a two-stage estimation procedure using the inverse Mills' ratio to take account of the endogeneity bias. In a first step, a regression for observing a positive outcome of the dependent variable is modeled with a probit (or logit) model. The estimated parameters are used to calculate the inverse Mills' ratio, which is then included as an additional explanatory variable in the OLS estimation.

Appendix B: Variable Definitions

Variable Definitions for Syndication Choice

syn = 1 if at least one round including the current round is syndicated, o otherwise

Ind = if the company is IT or Bio then 1, 0 otherwise

Erly_stg =1 if the company is in 'early' or 'seed' stage, 0 otherwise

 $Str_stg2 = This$ is a dummy variable that takes a value of 1 if the stage of the financing round is the same as that of the stage preferences of the lead VC.

Co_state = A dummy variable taking a value 1 if the firm is based in California.

VC_ind2 = This is a dummy variable that takes the value 1 if the lead VC is an industry

specialist whose preferred industry is also the same industry category in which the firm resides.

num_stg2 = The cumulative number of stages including the current round.

late_stg = A dummy variable that is 1 if the stage of financing is late.

Hot_mkt = An indicator variable with a value of 1 if the year of the round belongs to 1983-1999 or 1995-2000.

 $ivst_bk6 = A$ dummy variable which is 1 if the lead VC is an investment bank, else 0.

Co_age = the age (in years) of the venture since its founding to the financing round.

Tot_ivt1 =the cumulative investment by VCs in the firm until the financing round

Cap_mgt2 = This is the capital under management in all ventures for the lead VC. The lead VC

is the investor whose cumulative investment including the current round is the greatest

exVC_sz1 = The average capital under management of all the existing VCs in the venture.

exVC_ag = The average age of the existing VCs.

VC_pmin2 = The lead VC's preferred minimum investment.

Instrumental Variables

VCstate2 = A dummy variable taking the value 1 if the VC is from California.

CVC2 = A dummy variable with a value of 1 if the lead VC is a corporate VC, else the value of this variable is 0.

Rd_ivst1 = The total amount invested in the round.

 $VC_ind2f = A$ dummy variable with a value of 1 if the lead VC is a generalist and has no specific industry focus.

 $VC_numC2 =$ The number of companies that the lead VC has invested in.

 $VC_{intN2} = Indicator variable with a value of 1 if the lead VC is an international VC.$

Definitions of Variables for the Exit Performance

Exit_1 = 1 if exited through IPO, Acquisition, or LBO, 0 otherwise

 $Exit_2 = 1$ if exited through IPO or Acquisition, 0 otherwise

Exit_ACQ = 1 if exited through Acquisition, 0 otherwise

Exit_IPO = 1 if exited through IPO, 0 otherwise

syn = 1 if at least one round including the current round is syndicated, o otherwise

Ind = if the company is IT or Bio then 1, 0 otherwise

Erly_stg =1 if the company is in 'early' or 'seed' stage, 0 otherwise

 $Str_stg2 = This$ is a dummy variable that takes a value of 1 if the stage of the financing round is the same as that of the stage preferences of the lead VC.

Co_state = A dummy variable taking a value 1 if the firm is based in California.

VC_ind2 = This is a dummy variable that takes the value 1 if the lead VC is an industry specialist whose preferred industry is also the same industry category in which the firm resides.

num_stg2 = The cumulative number of distinct stages including the current round

late_stg = A dummy variable that is 1 if the stage of financing is late.

 $Hot_mkt = An$ indicator variable with a value of 1 if the year of the round belongs to 1983-1999 or 1995-2000.

 $ivst_bk6 = A$ dummy variable which is 1 if the lead VC is an investment bank, else 0.

Mntrfee2 = 1 if there exist monitoring fee or advising fee for lead VC, 0 otherwise.

IndpnVC2 = 1 if the lead VC is independent VC, 0 otherwise.

Internet = 1 If the company's business is internet-related, 0 otherwise

Table IFrequency of Financing Rounds

This table reports the frequency of financing rounds over time and across industries. The frequency of financing rounds shows cycles of the private equity financing.

rounds shows cycles	s of the j	private	quity II	nanemg	·								
1980-1991													
Industry sector	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	
Agr/Forestr/Fish	1	9	13	13	10	12	11	9	9	12	6	10	
Biotechnology	25	46	58	72	64	80	112	145	157	155	150	147	
Business Serv.	23	24	40	39	37	34	55	68	81	68	65	41	
Communications	52	124	150	217	260	260	273	321	274	279	243	223	
Computer Hardware	114	193	300	375	392	304	290	278	257	250	197	136	
Computer Other	1	2	3	3	4	4	3	3	7	9	9	10	
Computer Software	20	55	126	238	283	279	296	295	272	315	355	337	
Construction	5	11	3	16	10	15	18	16	24	31	19	14	
Consumer Related	54	70	118	139	137	178	214	279	388	384	301	191	
Financial Services	19	20	37	27	23	36	58	84	89	106	93	143	
Industrial/Energy	106	181	206	181	174	171	212	231	240	253	228	160	
Internet Specific	1	2	3	10	6	6	17	20	25	21	24	22	
Manufact.	16	27	67	57	65	34	64	85	116	155	99	68	
Medical/Health	50	67	102	160	202	222	224	314	278	338	317	247	
Other	3	9	17	10	7	6	7	2	5	11	7	12	
Semiconductor/Electr	82	116	129	163	231	215	208	229	210	203	179	129	
Transportation	16	13	23	20	24	23	36	45	54	51	41	33	
Utilities	1	0	1	0	1	1	1	2	5	7	6	6	
Total	589	969	1396	1740	1930	1880	2099	2426	2491	2648	2339	1929	
1992-2003													
Industry sector	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	Total
Agr/Forestr/Fish	6	11	15	17	19	22	57	21	38	35	26	31	413
Biotechnology	192	187	203	217	293	321	372	314	550	523	427	553	5363
Business Serv.	45	47	51	78	123	129	215	295	481	372	200	244	2855
Communications	315	287	314	382	562	582	753	837	1567	1140	708	771	10894
Computer Hardware	156	107	120	155	198	192	218	256	513	329	213	258	5801
Computer Other	13	8	3	7	5	10	13	17	31	33	11	20	229
Computer Software	402	345	369	523	847	1009	1238	1646	2636	1869	1351	1425	16531
Construction	10	12	18	27	52	53	71	61	88	85	47	101	807
Consumer Related	235	240	284	376	540	550	696	574	774	659	427	568	8376
Financial Services	113	134	148	170	386	252	306	268	485	525	243	353	4118
Industrial/Energy	191	153	168	215	362	335	414	347	466	419	312	476	6201
Internet Specific	36	32	62	175	428	606	943	2876	5468	2390	1143	929	15245
Manufact.	75	76	76	104	140	132	196	181	286	220	147	187	2673
Medical/Health	371	295	328	392	610	663	726	668	854	788	670	845	9731
Other	12	13	9	28	35	31	92	56	60	66	53	166	717
Semiconductor/Electr	155	139	132	175	234	276	352	374	787	594	457	562	6331
Transportation	36	36	39	63	83	98	143	123	185	167	92	157	1601
Utilities	5	6	3	6	6	10	15	10	23	22	18	27	182
Total	2368	2128	2342	3110	4923	5271	6820	8924	15292	10236	6545	7673	98068

Table II Exit Probabilities for Syndicated and Non-syndicated Rounds

We consider three types of exits: by IPO, by Acquisition or by LBO. The table shows the proportion of rounds exiting by means of these routes. Syndicated rounds are those that have at least one round syndicated including the current round. T-test is used to test the difference of means between syndicated and non-syndicated rounds.

Descriptive Statistics												
	Variable	Ν	Mean	Std Dev								
Non-syndicated Rounds	Exit by IPO, Acq, or LBO	32801	0.2477	0.4317								
	Exit by IPO or Acq	32801	0.2367	0.4250								
	Exit by Acq	32801	0.1160	0.3202								
	Exit by IPO	32801	0.1207	0.3258								
	Variable	Ν	Mean	Std Dev								
Syndicated Rounds	Exit by IPO, Acq, or LBO	63743	0.3791	0.4852								
	Exit by IPO or Acq	63743	0.3716	0.4832								
	Exit by IPO or Acq	63743	0.2203	0.4145								
	Exit by IPO	63743	0.1513	0.3583								
Test fo	r difference in means of syndicated vs no	on-syndicate	d rounds									
	Variable		t value	Pr> t								
	Exit by IPO, Acq, or LBO		-42.92	< 0.0001								
	Exit by IPO or Acq		-44.56	< 0.0001								
	Exit by Acq		-43.26	< 0.0001								
	Exit by IPO		-13.34	< 0.0001								

Table III Exit Times for Syndicated and Non-syndicated Rounds.

Firms can exit in three routes: by IPO, by Acquisition, and by LBO. We consider all exits, and exits by IPO, by Acquisition separately. The table shows the time to exit (in calendar days) of rounds exiting by means of these routes. Syndicated rounds are those that have at least one round syndicated including the current round. T-test is used to test the difference of means between syndicated and non-syndicated rounds.

Descriptive Statistics												
	Variable	Ν	Mean	Std Dev								
Non-syndicated Rounds	Time to Exit	2770	1316.14	1070.59								
	Time to Exit by IPO	641	1125.69	984.58								
	Time to Exit by Acq	1937	1414.34	1065.20								
	Variable	Ν	Mean	Std Dev								
Syndicated Rounds	Time to Exit	10539	1266.74	1101.57								
	Time to Exit by IPO	2544	1099.2	975.53								
	Time to Exit by Acq	7704	1320.97	1111.27								
Test for di	fference in means of syndica	ted vs non-syndi	icated rounds									
	Variable		t value	Pr > t								
	Time to Exit		2.15	0.0318								
	Time to Exit by IPO		0.61	0.5398								
	Time to Exit by Acq		3.42	0.0006								

Table IV Exit Multiples of Syndicated and Non-Syndicated Rounds.

This table shows the payoff to all rounds depending on whether they were syndicated or not. The statistics are presented for raw multiples as well as annualized multiples. The raw multiple is the value at exit divided by the value at investment. Annualized multiples are computed as the raw multiple taken to the n-th root, where n is the rounded up number of years from the time of investment to exit. Multiples are rounded at the 1 percent and 99 percent levels. Syndicated rounds are those that have at least one round syndicated including the current round. T-test is used to test the difference of means between syndicated and non-syndicated rounds.

Descriptive Statistics												
	Variable	Ν	Mean	Std Dev	Minimum	Maximum						
Non-syndicated Rounds	Raw multiple	142	9.66	16.97	0.01	91.38						
	Annualized Multiple	142	1.79	1.43	0.21	9.39						
Syndicated Rounds	Raw multiple	1305	6.38	12.67	0.00	91.38						
	Annualized Multiple	1289	2.19	2.48	0.09	15.82						
Test	for difference in means	of syndicat	ed vs non-s	syndicated 1	ounds							
	Variable		t value	Pr> t								
	Raw multiple		2.24	0.0264								
	Annualized Multiple		-2.92	0.0039								

Table VThe Determinants of Syndication

This table presents probit regressions to explain the likelihood of syndication. A coefficient of x for an independent variable indicates that a one-unit increase in the independent variable results in a x standard deviation increase in the predicted probit index. Multiplying the probit estimates by 1.6 gives the rough estimates of the logit slope estimates. The odds ratio in the logit model independent variable is calculated as exp(the logit slope estimates). See the definitions of variables in Appendix B.

						Dependent var	riable = syn					
		Model (1)			Model (2)			Model (3)			Model (4)	
Independent	Coefficient	Chi-	Pr > Chi-	Coefficient	Chi-	Pr > Chi-	Coefficient	Chi-	Pr > Chi-	Coefficient	Chi-	Pr > Chi-
variables	estimates	square	square	estimates	square	square	estimates	square	square	estimates	square	square
Intercept	-3.1996	633.90	<.0001	-3.0461	2761.21	<.0001	-2.8866	3747.80	<.0001	-3.3280	7508.93	<.0001
Ind	0.4926	300.44	<.0001	0.4219	615.61	<.0001	0.3458	535.54	<.0001	0.4108	1118.95	<.0001
Erly_stg	0.2340	50.64	<.0001	0.1438	64.73	<.0001	0.1629	112.39	<.0001	0.1914	235.31	<.0001
Str_stg2	-0.2480	35.89	<.0001	-0.1502	49.68	<.0001	-0.1749	71.60	<.0001	-0.1207	46.00	<.0001
Co_state	0.2177	45.11	<.0001	0.2077	114.25	<.0001	0.1292	63.58	<.0001	0.1634	132.51	<.0001
VC_ind2	0.0447	1.25	0.2639	0.0438	3.93	0.0475	0.0745	12.22	0.0005	0.0737	16.09	<.0001
Ln(1+ num_stg2)	0.8845	312.54	<.0001	1.9178	3228.08	<.0001	1.9369	4288.87	<.0001	2.0364	6051.04	<.0001
late_stg	-0.0457	1.79	0.1806	-0.0562	7.21	0.0072	-0.0191	1.07	0.3005	0.0169	1.16	0.2814
Hot_mkt	-0.0226	0.79	0.3739	-0.1454	94.83	<.0001	-0.1775	182.56	<.0001	-0.1449	171.16	<.0001
ivst_bk6	0.4525	121.78	<.0001	0.7784	547.45	<.0001	0.7807	677.99	<.0001	0.7851	895.76	<.0001
Ln(1+ Co_age)	-0.0452	8.32	0.0039	-0.0234	9.42	0.0021	-0.0190	8.07	0.0045			
Ln(1+ Cap_mgt2)	-0.1942	158.30	<.0001	-0.0935	280.85	<.0001						
Ln(1+Tot_ivt1)	0.2427	575.30	<.0001									
Ln(1+ exVC_sz1)	-0.0195	2.34	0.1258									
Ln(1+ exVC_ag)	0.0563	7.08	0.0078									
Ln(1+ VC_pmin2)	0.0024	0.08	0.7802									
Instrument veriabl												
Instrument variabl		22.00	. 0001	0.1022	04.66	. 0001	0.10(7	05.66	. 0001	0.1406	80.00	. 0001
VCstate2	0.2009	32.89	<.0001	0.1022	24.66	<.0001	0.1867	95.66	<.0001	0.1486	80.90	<.0001
CVC2	0.3111	10.84	0.0010	0.1037	6.89	0.0087	0.1713	32.80	<.0001	0.2073	61.66	<.0001
$Ln(1+Rd_ivst1)$	0.1351	348.52	<.0001	0.2031	2180.55	<.0001	0.1787	2520.48	<.0001	0.1894	3946.01	<.0001
VC_ind2f	0.0708	2.10	0.1471	-0.1176	33.06	<.0001	-0.0635	18.77	<.0001	-0.0485	14.91	0.0001
Ln(1+VC_numC2)	0.2796	223.31	<.0001	0.1917	506.97	<.0001	0.0736	479.52	<.0001	0.0829	827.22	<.0001
VC_intN2	-0.4417	116.26	<.0001	-0.3697	378.12	<.0001	-0.3747	448.83	<.0001	-0.3590	585.95	<.0001

T T 313 J		6 500			20.971			27 471			27 7 42	
Log Likelihood		-6,588			-20,871			-27,471			-37,743	
Wald Chi-square		3,061			9,164			11,296			16,636	
Pr > Wald Chi-												
square		<.0001			<.0001			<.0001			<.0001	
Cox and Snell R-												
square		0.1509			0.2365			0.2194			0.2492	
Nagelkerke Max-re	escaled R-											
square		0.3054			0.3536			0.3328			0.3784	
Total number of												
rounds	100,702			100,702			100,702			100,702		
Rounds prior to												
1980	2,634			2,634			2,634			2,634		
Rounds from												
1980	98,068	(Syndicated: 33	3.83%)	98,068	(Syndicated: 3	3.83%)	98,068	(Syndicated: 3	3.83%)	98,068	(Syndicated: 33	.83%)
OBS w missing												
values	72,643			48,105			31,741			14,759		
Number of												
observations	25,425	:		49,963			66,327			83,309		
_	Syndicated	22,696	89.3%	Syndicated	37,904	75.9%	Syndicated	51,142	77.1%	Syndicated	59,387	71.3%
	Non-syn	2,729	10.7%	Non-syn	12,059	24.1%	Non-syn	15,185	22.9%	Non-syn	23,922	28.7%

Table VI The Effect of Syndication on Exit Probabilities

In this table we present a model to explain the exit probabilities. The table contains two regressions. First, we provide the results without the endogeneity correction, and second, with the endogeneity correction. The variable "syn3" is the dummy variable for whether the venture is syndicated or not. Syn in the analysis with endogeneity control is the predicted probability of syndication estimated first stage probit. Results are provided broken down by IPO and by ACQ (acquisition) routes. See the definitions of variables in Appendix B.

		Dependent var	iable = Exit_1					Dependent varia	ble = Exit_2			
	withou	t Endogeneity co	ontrol	with E	Endogeneity con	trol	without	Endogeneity co	ntrol	with E	ndogeneity con	ıtrol
Independent variables	Coefficient estimates	Chi-square	Pr > Chi- square	Coefficient estimates	Chi-square	Pr > Chi- square	Coefficient estimates	Chi-square	Pr > Chi- square	Coefficient estimates	Chi-square	Pr > Chi- square
Intercept	-1.0946	2619.64	<.0001	-1.1860	2910.80	<.0001	-1.1745	2978.75	<.0001	-1.2610	3249.77	<.0001
Syn	0.1707	226.08	<.0001	0.7885	532.08	<.0001	0.1636	205.66	<.0001	0.7450	470.79	<.0001
Ind	0.2469	416.35	<.0001	0.1602	153.57	<.0001	0.2772	518.32	<.0001	0.1958	227.06	<.0001
Erly_stg	-0.1314	134.31	<.0001	-0.1587	192.07	<.0001	-0.1208	112.93	<.0001	-0.1465	162.80	<.0001
Str_stg2	-0.0574	11.17	0.0008	-0.0128	0.5414	0.4618	-0.0708	16.71	<.0001	-0.0288	2.70	0.1007
Co_state	0.1899	326.19	<.0001	0.1418	172.52	<.0001	0.1960	346.81	<.0001	0.1508	194.62	<.0001
VC_ind2	-0.0032	0.04	0.8391	0.0102	0.4249	0.5145	-0.0040	0.0664	0.7967	0.0087	0.3058	0.5803
Ln(1+ num_stg2)	0.3377	322.08	<.0001	0.0626	7.0473	0.0079	0.3800	405.95	<.0001	0.1212	26.23	<.0001
Late_stg	0.1668	174.24	<.0001	0.1464	133.27	<.0001	0.1015	63.61	<.0001	0.0825	41.78	<.0001
Hot_mkt	0.2525	687.92	<.0001	0.2656	754.89	<.0001	0.2580	712.43	<.0001	0.2703	775.39	<.0001
Ivst_bk6	0.1943	162.54	<.0001	0.1265	65.69	<.0001	0.1883	152.06	<.0001	0.1247	63.60	<.0001
Mntrfee2	-0.0312	5.40	0.0201	-0.0233	2.98	0.0845	-0.0405	8.98	0.0027	-0.0332	6.01	0.0142
IndpnVC2	0.0254	5.30	0.0213	0.0187	2.85	0.0914	0.0364	10.77	0.0010	0.0305	7.54	0.0060
internet	-0.3986	1484.40	<.0001	-0.4244	1650.88	<.0001	-0.3999	1486.93	<.0001	-0.4242	1641.59	<.0001
Number of obse	ervations	81,989			81,989			81,989			81,989	
Log Likelihood Wald Chi-		-50,639			-50,486			-50,197			-50,063	
square		5,132			5,408			5,235			5,472	
Pr > Wald Chi-s	square	<.0001			<.0001			<.0001			<.0001	
Cox and Snell F	1	0.0632			0.0668			0.0646			0.0676	
Nagelkerke Ma: square	x-rescaled K-	0.0869			0.0918			0.0891			0.0932	

		Dependent var	iable = Exit_A	CQ				Dependent vari	able = Exit_IPO			
	withou	t Endogeneity co	ontrol	with E	Endogeneity con	trol	withou	ut Endogeneity co	ontrol	with E	Endogeneity cor	ntrol
Independent variables	Coefficient estimates	Chi-square	Pr > Chi- square	Coefficient estimates	Chi-square	Pr > Chi- square	Coefficient estimates	Chi-square	Pr > Chi- square	Coefficient estimates	Chi-square	Pr > Chi- square
Intercept	-1.7747	5208.40	<.0001	-1.8563	5305.63	<.0001	-1.1969	2359.56	<.0001	-1.2569	2436.87	<.0001
Syn	0.2390	330.30	<.0001	0.7335	349.43	<.0001	-0.0018	0.0187	0.8912	0.4086	103.22	<.0001
Ind	0.2658	367.69	<.0001	0.1973	179.21	<.0001	0.1232	75.61	<.0001	0.0664	19.32	<.0001
Erly_stg	0.0443	12.21	0.0005	0.0247	3.74	0.0533	-0.2437	317.95	<.0001	-0.2633	364.60	<.0001
Str_stg2	-0.0287	2.17	0.1410	0.0071	0.1282	0.7203	-0.0801	14.52	0.0001	0.0520	5.98	0.0145
Co_state	0.1796	246.53	<.0001	0.1416	145.68	<.0001	0.0852	47.27	<.0001	0.0548	18.62	<.0001
VC_ind2 Ln(1+	-0.0344	3.87	0.0492	-0.0255	2.11	0.1467	0.0326	3.14	0.0764	0.0416	5.08	0.0242
num_stg2)	0.3571	299.88	<.0001	0.1403	29.10	<.0001	0.1445	43.52	<.0001	-0.0357	1.69	0.1931
Late_stg	0.1076	58.44	<.0001	0.0942	44.56	<.0001	0.0349	5.78	0.0162	0.0214	2.16	0.1420
Hot_mkt	0.2119	383.64	<.0001	0.2221	418.97	<.0001	0.1493	172.32	<.0001	0.1577	190.90	<.0001
Ivst_bk6	0.0628	14.38	0.0001	0.0134	0.63	0.4284	0.1839	115.65	<.0001	0.1383	62.21	<.0001
Mntrfee2	0.0261	3.02	0.0821	0.0310	4.23	0.0397	-0.0915	32.05	<.0001	-0.0849	27.47	<.0001
IndpnVC2	0.0888	50.01	<.0001	0.0891	50.23	<.0001	-0.0419	10.68	0.0011	-0.0520	16.37	<.0001
internet	-0.2952	659.52	<.0001	-0.3167	746.05	<.0001	-0.2758	496.00	<.0001	-0.2912	544.00	<.0001
Number of obse	ervations	81,989			81,989			81,989			81,989	
Log Likelihood Wald Chi-	l	-38,874			-38,868			-33,946			-33,892	
square		3,253			3,256			1,699			1,791	
Pr > Wald Chi-	square	<.0001			<.0001			<.0001			<.0001	
Cox and Snell H Nagelkerke Ma		0.0404			0.0406			0.0209			0.0222	
square		0.0644			0.0646			0.0366			0.0388	

Table VII The Effect of Syndication on Time-to-exit - Hazard Model Analysis

Effect of syndication on exit times by exit route. In this table we present a model to explain the exit times The table contains two regressions. First, we provide the results without the endogeneity correction, and second, with the endogeneity correction. The variable "syn" is the dummy variable for whether the venture is syndicated or not. Syn3 in the analysis with endogeneity control is the predicted probability of syndication estimated first stage probit. Results are provided broken down by IPO and by ACQ (acquisition) routes. See the definitions of explanatory variables in Appendix B.

		Time-to-Exit th	nrough IPO, Ac	equisition, or I	LBO		Time-to-Exit through IPO or Acquisition					
	witho	out Endogeneity	control	with	n Endogeneity c	ontrol	withc	out Endogeneity	control	wit	th Endogeneity of	control
Independent	Hazard	Chi-square	Pr > Chi-	Hazard	Chi-square	Pr > Chi-	Hazard	Chi-square	Pr > Chi-	Hazard	Chi-square	Pr > Chi-
variables	ratio		square	ratio		square	ratio		square	ratio		square
Syn	1.211	150.97	<.0001	5.178	1082.29	<.0001	1.207	141.78	<.0001	5.156	1048.25	<.0001
Ind	1.360	380.26	<.0001	1.116	42.52	<.0001	1.405	448.27	<.0001	1.153	69.02	<.0001
Erly_stg	0.742	397.64	<.0001	0.696	574.81	<.0001	0.749	367.64	<.0001	0.703	537.99	<.0001
Str_stg2	1.083	11.23	0.0008	1.173	45.21	<.0001	1.073	8.59	0.0034	1.165	39.83	<.0001
Co_state	1.018	1.94	0.1635	0.928	31.50	<.0001	1.024	3.31	0.0690	0.934	26.46	<.0001
VC_ind2	1.060	8.14	0.0043	1.072	11.61	0.0007	1.058	7.70	0.0055	1.070	11.04	0.0009
Ln(1+ num_stg2)	1.428	235.35	<.0001	0.759	80.25	<.0001	1.480	280.79	<.0001	0.788	58.88	<.0001
Late_stg	1.119	53.71	<.0001	1.097	36.46	<.0001	1.077	22.12	<.0001	1.057	12.37	0.0004
Hot_mkt	0.975	3.41	0.0649	1.004	0.08	0.7740	0.980	2.12	0.1455	1.009	0.41	0.5200
Ivst_bk6	1.093	24.78	<.0001	0.939	11.99	0.0005	1.085	20.67	<.0001	0.934	13.82	0.0002
Mntrfee2	0.943	11.37	0.0007	0.962	4.95	0.0261	0.928	17.75	<.0001	0.946	9.66	0.0019
IndpnVC2	1.134	76.48	<.0001	1.108	51.00	<.0001	1.149	91.41	<.0001	1.123	63.82	<.0001
internet	1.947	2001.60	<.0001	1.850	1680.07	<.0001	1.960	2012.25	<.0001	1.862	1693.63	<.0001
Number of observations		81,716			81,716			81,716			81,716	
Percent censored		64.65%			64,65%			65.26%			65.26%	
Wald Chi-square		5,114			5,788			5,270			6,193	
Pr > Wald Chi-square		<.0001			<.0001			<.0001			<.0001	

	Time-to-Exit through Acquisition							Time-to-Exit t	hrough IPO			
	with	out Endogeneity	control	with	n Endogeneity c	ontrol	withc	out Endogeneity	control	wit	h Endogeneity c	control
Independent	Hazard	Chi-square	Pr > Chi-	Hazard	Chi-square	Pr > Chi-	Hazard	Chi-square	Pr > Chi-	Hazard	Chi-square	Pr > Chi-
variables	ratio		square	ratio		square	ratio		square	ratio		square
Syn	1.429	261.63	<.0001	6.043	675.36	<.0001	0.998	0.01	0.9427	4.318	384.91	<.0001
Ind	1.545	380.76	<.0001	1.267	98.94	<.0001	1.266	103.03	<.0001	1.0040	2.51	0.1134
Erly_stg	0.914	20.81	<.0001	0.860	57.07	<.0001	0.573	559.94	<.0001	0.534	695.59	<.0001
Str_stg2	1.099	8.88	0.0029	1.200	32.49	<.0001	1.042	1.25	0.2644	1.124	9.90	0.0017
Co_state	1.077	19.00	<.0001	0.983	0.93	0.3342	0.955	5.25	0.0220	0.869	46.62	<.0001
VC_ind2	1.004	0.02	0.8963	1.016	0.34	0.5620	1.134	16.65	<.0001	1.147	19.75	<.0001
Ln(1+ num_stg2)	1.706	296.22	<.0001	0.914	4.71	0.0300	1.242	36.80	<.0001	0.650	84.12	<.0001
Late_stg	1.131	33.54	<.0001	1.116	26.70	<.0001	1.012	0.25	0.6200	0.985	0.41	0.5215
Hot_mkt	1.018	0.91	0.3393	1.051	7.21	0.0072	0.940	9.28	0.0023	0.962	3.67	0.0554
Ivst_bk6	1.013	0.28	0.5983	0.880	26.92	<.0001	1.187	40.90	<.0001	1.008	0.08	0.7830
Mntrfee2	0.989	0.23	0.6295	1.003	0.01	0.9061	0.854	32.98	<.0001	0.876	22.99	<.0001
IndpnVC2	1.263	136.71	<.0001	1.243	118.15	<.0001	1.026	1.43	0.2314	0.995	0.07	0.7979
internet	1.807	899.33	<.0001	1.710	728.29	<.0001	2.176	1140.97	<.0001	2.081	1000.07	<.0001
		01.71.6			01.51.6			01 71 6			01 71 4	
Number of observations Percent censored		81,716 80.39%			81,716 80.39%			81,716 84.87%			81,716 84.87%	
Wald Chi-square		3,374			3,606			2,525			2,940	
Pr > Wald Chi-square		<.0001			<.0001			<.0001			<.0001	

Table VIII The Effect of Syndication on Exit Multiples

In this table we present a model to explain the annualized multiple from exit, to assess if syndication adds value. The table contains two regressions. First, we provide the results without the endogeneity correction, and second, with the endogeneity correction. The variable "syn3" is the dummy variable for whether the venture is syndicated or not. Syn in the analysis with endogeneity control is the predicted probability of syndication estimated first stage probit. Dependent variable is ann_mltp that is annualized exit multiples. See the definitions of explanatory variables in Appendix B.

I	Dependent va	riable = ann	_mltp		
without En	dogeneity co	ntrol	with End	rol	
Coefficient estimates	t-value	Pr > t	Coefficient estimates	t-value	Pr > t
0.6255	1.53	0.1259	0.6602	1.24	0.2145
0.7164	3.26	0.0012	0.8113	0.96	0.3355
0.5107	1.95	0.0518	0.4230	1.51	0.1321
0.2407	1.43	0.1521	0.2370	1.41	0.1601
0.4774	1.62	0.1045	0.5194	1.75	0.0799
0.2263	1.76	0.0779	0.1897	1.44	0.1488
-0.4815	-2.35	0.0189	-0.4597	-2.24	0.0254
-0.6981	-2.63	0.0086	-0.7304	-2.02	0.0432
0.0836	0.50	0.6156	0.0986	0.69	0.5558
0.8240	5.17	<.0001	0.8137	5.09	<.0001
-0.0964	-0.54	0.5859	-0.1169	-0.63	0.5257
0.3898	1.80	0.0716	0.3872	1.78	0.0750
0.1544	0.91	0.3630	0.1864	1.10	0.2732
0.3013	2.36	0.0184	0.3172	2.47	0.0136
	1 407			1 407	
	<i>,</i>			,	
	without En Coefficient estimates 0.6255 0.7164 0.5107 0.2407 0.4774 0.2263 -0.4815 -0.6981 0.0836 0.8240 -0.0964 0.3898 0.1544	without Endogeneity correct Coefficient t-value estimates 0.6255 1.53 0.7164 3.26 0.5107 1.95 0.2407 1.43 0.4774 1.62 0.2263 1.76 -0.4815 -2.35 -0.6981 -2.63 0.8240 5.17 -0.0964 -0.54 0.3898 1.80 0.1544 0.91	without Endogeneity control Coefficient t-value $Pr > t$ estimates 0.6255 1.53 0.1259 0.7164 3.26 0.0012 0.5107 1.95 0.0518 0.2407 1.43 0.1521 0.4774 1.62 0.1045 0.2263 1.76 0.0779 -0.4815 -2.35 0.0189 -0.6981 -2.63 0.0086 0.0836 0.50 0.6156 0.8240 5.17 <.0001	$\begin{tabular}{ c c c c c c c c c c c c c c c c c c c$	without Endogeneity control with Endogeneity control Coefficient t-value Pr > t Coefficient t-value 0.6255 1.53 0.1259 0.6602 1.24 0.7164 3.26 0.0012 0.8113 0.96 0.5107 1.95 0.0518 0.4230 1.51 0.2407 1.43 0.1521 0.2370 1.41 0.4774 1.62 0.1045 0.5194 1.75 0.2263 1.76 0.0779 0.1897 1.44 -0.4815 -2.35 0.0189 -0.4597 -2.24 -0.6981 -2.63 0.0086 -0.7304 -2.02 0.0836 0.50 0.6156 0.0986 0.69 0.8240 5.17<<<0001

Table IX The Effect of Syndication on Exit Multiples by Exit Route

In this table we present a model to explain the annualized multiple from exit, to assess if syndication adds value. The table contains two regressions. First, we provide the results without the endogeneity correction, and second, with the endogeneity correction. The variable "syn" is the dummy variable for whether the venture is syndicated or not. Syn3 in the analysis with endogeneity control is the predicted probability of syndication estimated first stage probit. Dependent variable is ann_mltp that is annualized exit multiples. See the definitions of explanatory variables in Appendix B. Results are provided broken down by IPO and by ACQ (acquisition) routes.

	I	Dependent var	iable = ann_i	mltp for Acquisitior	1		Dependent variable = ann_mltp for IPO							
	E	without Endogeneity control			with Endogeneity control		I	without Endogeneity control		with Endogeneity control				
Independent	Coefficient	t-value	$\Pr > t$	Coefficient	t-value	$\Pr > t$	Coefficient	t-value	$\Pr > t$	Coefficient	t-value	Pr > t		
variables	estimates			estimates			estimates			estimates				
Intercept	0.1361	0.19	0.8510	0.3384	0.38	0.7024	1.2525	2.65	0.0083	1.2299	1.91	0.0560		
Syn	0.9858	2.37	0.0181	0.8213	0.57	0.5708	0.4488	1.83	0.0671	0.5589	0.56	0.5767		
Ind	0.3861	0.75	0.4516	0.3096	0.55	0.5830	0.4836	1.70	0.0902	0.4229	1.41	0.1597		
Erly_stg	0.6881	2.42	0.0158	0.7162	2.51	0.0124	-0.1565	-0.78	0.4346	-0.1664	-0.83	0.4070		
Str_stg2	0.3753	0.82	0.4123	0.4462	0.97	0.3346	0.4546	1.20	0.2308	0.4601	1.21	0.2274		
Co_state	0.2234	1.01	0.3119	0.2243	0.99	0.3203	0.1478	0.97	0.3314	0.1105	0.71	0.4788		
VC_ind2	-0.4496	-1.31	0.1896	-0.4143	-1.21	0.2284	-0.4254	-1.72	0.0850	-0.4137	-1.67	0.0946		
Ln(1+ num_stg2)	-0.4811	-1.06	0.2896	-0.4609	-0.74	0.4589	-0.7843	-2.48	0.0133	-0.8008	-1.89	0.0598		
Late_stg	-0.1594	-0.52	0.6015	-0.1335	-0.43	0.6639	0.1235	0.66	0.5093	0.1310	0.70	0.4853		
Hot_mkt	1.1365	4.34	<.0001	1.1186	4.25	<.0001	0.4152	2.12	0.0340	0.4092	2.09	0.0371		
Ivst_bk6	-0.1307	-0.41	0.6810	-0.1357	-0.40	0.6867	-0.0384	-0.19	0.8505	-0.0533	-0.25	0.7992		
Mntrfee2	0.1923	0.59	0.5525	0.1267	0.39	0.6985	0.7657	2.55	0.0108	0.7937	2.65	0.0083		
IndpnVC2	0.2533	0.78	0.4329	0.2870	0.89	0.3764	0.0803	0.43	0.6670	0.1000	0.54	0.5924		
internet	-0.2106	-0.96	0.3396	-0.1881	-0.85	0.3964	0.7737	5.08	<.0001	0.7868	5.15	<.0001		
Number of observation	ons	610			610			797			797			
F-value		3.93			3.50			5.32			5.06			
Pr > F		<.0001			<.0001			<.0001			<.0001			
Adjusted R-square		0.0589			0.0506			0.0659			0.0623			
Aujusieu K-squale		0.0569			0.0500			0.0039			0.0023			

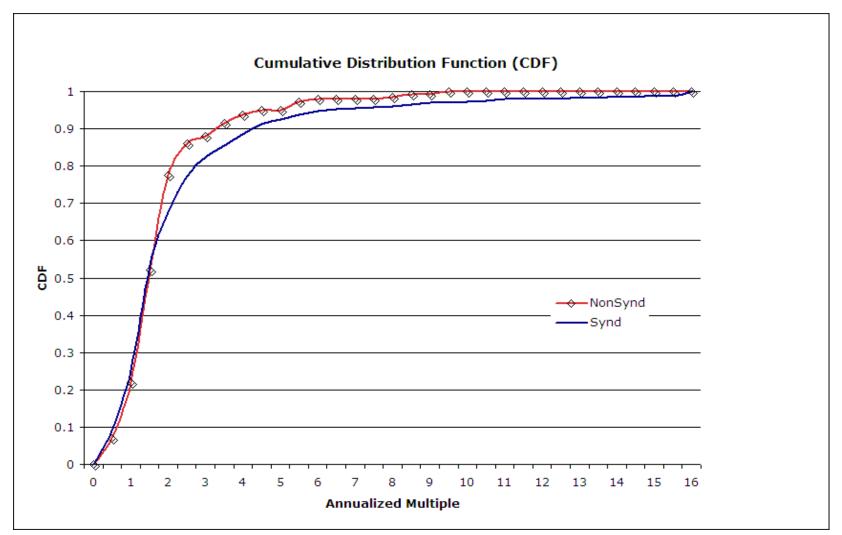


Figure 1: CDFs of multiples. This figure presents the cumulative distribution function of annualized multiples for syndicated and non-syndicated firms. The plot shows that after a multiple level of 2, the syndicated firms demonstrate a much fatter tail, i.e. the likelihood of a large multiple is higher for syndicated firms than for non-syndicated ones.

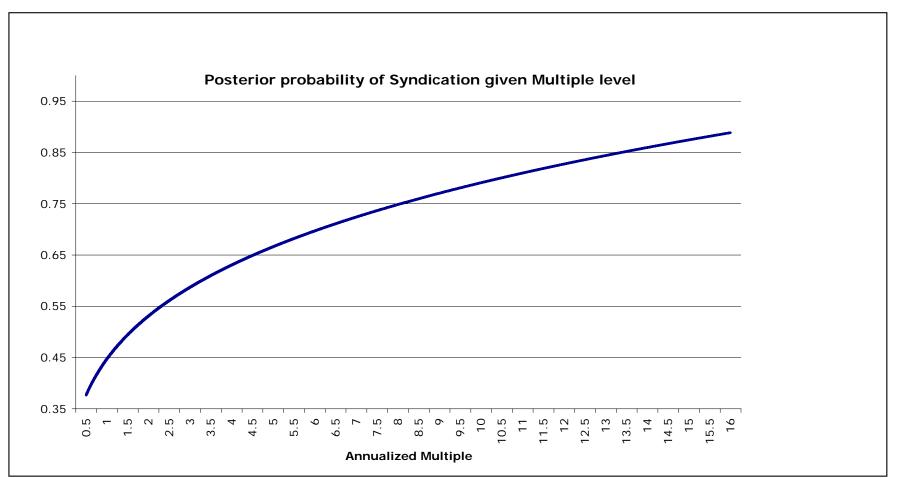


Figure 2: Probability of syndication given a level of return. This figure shows the results of a Bayesian analysis of the distribution functions in Figure 1 to Compute the posterior probability of the venture being syndicated for each level of annualized multiple (return). Instead of assuming the prior probabilities of syndication to be the actual proportions in the data, we assumed them to be diffuse, i.e. half each. For each level of multiple (R) we calculated Prob(Synd|R) = Prob(R|Synd)/[Prob(R|Synd)xProb(Synd)+Prob(R|NoSynd)]. We then smoothed this probability function and plotted it as above. We can see that the posterior probability of the venture being syndicated rises as the multiple increases. When the annualized multiple is greater than 2, the Prob(Synd|R)=0.5.