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# Polishing diamonds in the rough: The sources of syndicated venture performance ☆

Sanjiv R. Das *, Hoje Jo, Yongtae Kim

*Santa Clara University, Leavey School of Business, 500 El Camino Real, Santa Clara, CA 95053, USA*

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ABSTRACT

Using an effort-sharing framework for VC syndicates, we assess how syndication impacts investment returns, chances of successful exit, and the time taken to exit. With data from 1980 to 2003, and applying apposite econometrics for endogeneity to these different performance measures, we are able to ascribe much of the better return to selection, with the value-addition by monitoring role significantly impacting the likelihood and time of exit. While the extant literature on Venture Capital (VC) syndication is divided about the relative importance of the "selection" and "value-add" hypotheses, we find that their roles are complementary.



## 1. Introduction

Venture capitalists invested $28.3 billion in 3808 deals in 2008,[1] many of these through syndications accounting for two-thirds of all VC investment rounds, making it a significant phenomenon in this industry. Syndicated venture investment in privately held firms is hypothesized to lead to superior venture selection (Wilson, 1968; Sah and Stiglitz, 1986; Lerner, 1994; Sorenson and Stuart, 2001), to mitigate information asymmetries between the initial venture investor and other later-round potential investors (Admati and Pfleiderer, 1994; Lerner, 1994), to add value by monitoring the performance of portfolio companies (Brander et al. (2002) who test both selection and value-add, finding in favor of the latter), and to amplify the value-addition of venture capitalists (Hellmann and Puri, 2002;

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* Corresponding author.
*E-mail addresses:* srdas@scu.edu (S.R. Das), hjo@scu.edu (H. Jo), y1kim@scu.edu (Y. Kim).

[1] See http://www.pwcmoneytree.com.

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Kaplan and Stromberg, 2004; Lindsey, 2008; Hochberg, 2008). While research examining the performance of venture capital-backed firms is abundant, we do not have a complete understanding of the rationale behind VC syndication. Although theories in finance suggest that selection and value-add by monitoring should be different if capital is provided by a syndicate instead of a single VC, there has been limited scrutiny of the multivalent impact of syndication on venture firms' exit performance.

The decision to syndicate by the lead VC and entrepreneur depends on the trade-off between the likely benefits of syndication (coming from selecting better ventures or adding value to the firm) versus relinquishing some value to new syndicate members.[2] We conduct a large-scale study of the determinants of syndication and its impact on exit performance, using 98,068 financing rounds of venture firms in the Thomson Financial's Venture Economics (VentureXpert) database from 1980 to 2003. Rather than only examine returns, we focus on three different dimensions of exit performance (i.e., exit probabilities, time-to-exit, and exit multiples) and thereby reframe the debate as to whether a syndicate selects promising companies and/or adds value to portfolio firms. Employing an analytical framework of effort-sharing under which a syndicate's effort is allocated to ex-ante venture selection and post-selection value-addition activity, and controlling for endogenous treatment effects with apposite econometrics, we are able to determine the relative importance of the selection and value-addition roles in VC syndications for each of the three dimensions of venture performance.

Consider a VC syndicated project where any synergy arising from syndication is attributable to selection and/or monitoring effort. Usually, the project is sourced by a lone VC, who conducts the initial due diligence to ensure that the project has potential. This VC then approaches the syndicate to consider the project. An initial effort $e \in (0,1)$ is expended by the syndicate on project selection. Assume there are two types of projects, high quality ($H$), and low quality ($L$). The exit multiple obtained from each, respectively, will be denoted $\{Y_H, Y_L\}$. Define the relative ratio of multiples to be $\eta = Y_H/Y_L$. The more effort expended on selection increases the chances that the project chosen will be of high quality. Assuming that the efficacy of project choice is linear in effort, the expected multiple of the chosen project will be $eY_H + (1-e)Y_L$.

Total effort is normalized to unity. Therefore, post-selection effort $(1-e)$ is put into subsequent monitoring by the syndicate to add value to the project. The probability of exit per period then depends on monitoring effort. We define this probability to be $p = (1-e)$.[3]

The expected multiple on the project is the probability of exit times the expected multiple conditional on exit:

$$E(Y) = (1-e)[eY_H + (1-e)Y_L].$$

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

$$\frac{dE(Y)}{de} = Y_H - 2eY_H - 2(1-e)Y_L = 0$$

and solving for $e$ results in optimal selection effort

$$e^* = \frac{Y_H - 2Y_L}{2Y_H - 2Y_L} = \frac{\eta/2 - 1}{\eta - 1}.$$

The following comparative statics follow immediately:

$$\eta \uparrow \infty \Rightarrow e^* \uparrow 1, \quad \eta \downarrow 2 \Rightarrow e^* \downarrow 0.$$

When $\eta = Y_H/Y_L$ increases, the model predicts that more effort of the syndicate will be directed to project selection. That is, as high quality projects become relatively superior to low quality ones (i.e., as $\eta$ increases), the syndicate naturally finds that it is worth expending more effort on project

[2] In addition to selection and value-add, Lerner (1994) suggests that expected future reciprocity is also a motive for syndication, and this is empirically confirmed in Hochberg et al. (2007). See also evidence in Hochberg et al. (2010) suggesting that syndication may be used as a barrier to entry where networks of VCs aim to control market share.

[3] In 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.

choice. In other words, when firm quality dispersion is large, syndicates spend more time making sure that the chosen venture is of high quality, translating into higher multiples on exit. And, as the difference between high and low type projects declines, more effort will be directed to value-addition through monitoring, translating into more likely and timely exit. Assessing performance via multiple metrics enables us to assess the role of a syndicate in this framework.

Differential returns from investing in syndicated ventures versus non-syndicated ones may arise directly from the synergies of syndication in monitoring (the value-added hypothesis of Brander et al. (2002)), or may be the result of selection (Lerner (1994), i.e., syndicates select more promising projects. Endogeneity is posited in the model of Cumming (2001) and in the model of Casamatta and Haritchabalet (2007)). The literature is unclear about the relative importance of *selection* and *value-add*. In our framework they may be complementary in outcome, though competing for the total effort of the syndicate. Both selection and value-addition may increase expected multiples by enhancing the probability of exit, shortening the time-to-exit, and picking firms with greater prospects.

Our departure from the existing literature lies in identifying the extent to which selection and value-addition contribute separately to the *components* (multiple, probability of exit, time-to-exit) of the differential expected performance between syndicated and non-syndicated ventures. What if the benefits of syndication lie purely in selection and not in value-addition? Then, *after* correcting for endogenous selection effects (Greene, 1993), we should find no difference between syndicated and non-syndicated ventures across all three of our performance criteria. On the other hand, if value-addition has a role to play, accounting for selection effects will not suppress the statistical significance of the syndication variable. Thus, our econometric strategy delivers simultaneous benefits: apposite estimation with treatment effects and a separation of the impact of better selection versus value-add by syndicates. It is undertaken in two stages, one, a model of syndication likelihood and two, models of performance assessment across the three metrics.

In order to correct for endogeneity, we first employ an empirical model for the determinants of syndication to understand why some firms are syndicated and others are not. We use this model as a first step in the two-step procedure in estimating the impact of syndication on performance. We find that the probability of syndication is positively related to risk sharing (Wilson, 1968; Bygrave, 1987; Tian, 2009), measured by the membership in IT or biotech industries and in early stage rounds, and the VC's skill and specialty (Brander et al., 2002; Wright and Lockett, 2003; Gompers et al., 2006, 2009), measured by the industry specialist lead VC, and the number of portfolio companies the lead VC has backed. Syndication is more likely when the size of the round is large, when the lead VC has many portfolio companies, and when the lead VC is California based. 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). Location specific variables such as network density and entropy measures developed in Hochberg et al. (2010) are also associated with the likelihood of VC syndication. We find that the greater the network density and the lower the entropy of the number of investment per zip code area in the market, the higher the likelihood of syndication.

Given the model for the likelihood of a venture being syndicated, we impose endogeneity corrections in the econometric models of performance assessment. Using a probit model, we find that syndication is positively related to a higher probability of successful exit. Likewise, using a hazard model, we find that syndication significantly shortens the time-to-exit of a successful venture. Since these effects of syndication persist even after correcting for selection effects, we conclude that value-addition by the syndicate contributes to a more likely and timely outcome.

While exit multiples for syndicated ventures are significantly higher than those of non-syndicated ventures without endogeneity controls, this significant relation disappears in the second-stage regressions after we control for endogenous treatment effects. This insignificance is robust across exit by either IPO or acquisition. Therefore, value-addition effort does not statistically change the exit multiple for syndicated firms. An implication of our findings is that, conditional on successful exit, selection effort contributes to better multiples, whereas value-addition effort by syndicates materializes in higher probabilities of exit and faster exits over and above the selection effect. Hence, value-addition contributes to success and selection determines the magnitude of the outcome. We liken this to VC syndicates uncovering diamonds in the rough, and then polishing them to success.

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Our results are found to be robust irrespective of the stage of investing being considered. This complete characterization of syndication determinants and performance is presented as follows. Section 2 describes the data and sample. Section 3 presents our econometric specification covering models for all three performance metrics and treatment effects. Section 4 presents the empirical results and Section 5 concludes.

## 2. Data and sample

We obtain our data from Thomson Financial's Venture Economics (VentureXpert) database. VentureXpert reports information on private equity investments of over 6000 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.[4] 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 Thomson 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 et al. (2007) for a comprehensive examination of the latter view).

Table 1 reports the frequency of financing rounds over time and across industries. Because exit options for start-up companies are highly cyclical, 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. 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 in the internet-bubble period. Computer software, internet, 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. Deal flow decreases again in the early 2000s, because, as Giot and Schwienbacher (2007) note, market conditions dramatically change in 2001 and 2002 as the NASDAQ and other stock indices experience sharp corrections.

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

## 3. Econometric specification

We follow Gompers and Lerner (1998, 2000), Brander et al. (2002), Sorensen (2007), and Hochberg et al. (2007) in viewing a successful exit as a representation of the venture's success. Here, we extend the performance metrics to *three* distinct ones, exit probabilities, time-to-exit, and exit multiples.[5] We anticipate that the role of a 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.

### 3.1. 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 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

[4] As Venture Economic's data are somewhat unreliable before 1980, we exclude investments before 1980. See Hochberg et al. (2007) who also choose their data based on the same considerations.

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

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**Table 1**
Frequency of financing rounds.

| Industry sector | 1980 | 1981 | 1982 | 1983 | 1984 | 1985 | 1986 | 1987 | 1988 | 1989 | 1990 | 1991 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *1980–1991* | | | | | | | | | | | | | |
| 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 | 1993 | 1994 | 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | Total |
| *1992–2003* | | | | | | | | | | | | | |
| 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 | 10,894 |
| 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 | 16,531 |
| 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 | 15,245 |
| 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 | 15,292 | 10,236 | 6545 | 7673 | 98,068 |

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

$$S_{ij} = \begin{cases} 1 & \text{if } S^*_{ij} > 0 \\ 0 & \text{if } S^*_{ij} \leqslant 0, \end{cases} \tag{1}$$

where the latent variable is modeled as (subscripts suppressed)

$$S^* = \gamma' X + u, \quad u \sim N(0, \sigma_u^2), \tag{2}$$

where $X$ is a set of explanatory variables. The estimated model provides us the probability of exit for all financing rounds.

$$E(S) = E(S^* > 0) = E(u > -\gamma' X) = 1 - \Phi(-\gamma' X) = \Phi(\gamma' X), \tag{3}$$

where $\Phi(.)$ denotes the cumulative normal distribution and $\gamma$ is the vector of coefficients estimated in the Probit model, using standard likelihood methods.

### 3.2. Time-to-exit

It is widely held that the presence of a venture capitalist (Wang et al., 2002), or the "easy-money" of the internet-bubble period (Giot and Schwienbacher, 2007), shortens the time-to-exit (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 duration data (Allison, 1995). The time-to-exit starts with the round investment date and ends when the venture exits through an IPO, acquisition or other means. The hazard function is modeled as:

$$h(t, X(t)) = h(t, 0)\exp[\theta' X(t)], \tag{4}$$

where $h(t, X(t))$ is the hazard rate at time $t$ and $X(t)$ is a vector of explanatory 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 $\theta$.

### 3.3. Multiples on exit

For the firms that make a successful exit, we are able to compare the exit price with the buy-in 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 (denoted $Y$) for each firm so as to make proper comparisons across firms. For the purpose of annualization we follow the procedure outlined in Das et al. (2003), which is as follows:

$$Y_{annual} = [Y_{raw}]^{1/t}, \quad t = \mathrm{CEIL}(\mathrm{days}/365),$$

where the function CEIL rounds up to the next integer. The "*raw*" multiple $Y_{raw}$ is the ratio of exit value to buy-in value and is adjusted for the dilution effect during the financing path.[6] Further, "*days*" is the number of days to exit in the model above. We regress exit multiples on a syndication dummy and control variables.

### 3.4. Endogenous treatment effects

A regression of venture performance measures 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 projects are simply of higher quality and deliver better performance, whether or not deals are syndicated. It is also possible that non-syndicated deals have better performance if the lead VC includes all obvious winners and there is no need for the synergies of syndication. Given that about two-thirds of all investment rounds are syndicated, despite the non-trivial cost of syndication, we claim that, on average, superior projects are more likely to be syndicated because VC syndicates can identify them better than can single VCs. In this case, the coefficient on the syndication 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 syndication dummy remains significant.

Different methodologies are used across three performance metrics for estimating endogenous treatment effects. For the exit multiple regressions, we follow the two-stage procedure based on the structural model suggested in Greene (1993). We obtain inverse Mill's ratios separately for the syndicated and non-syndicated rounds from the first stage probit for syndication choice, and include

[6] See Appendix B for a description of how we compute multiples. The approach is identical to the "cash-in, cash-out" approach.

them in the second-stage regressions. The structural two-stage model for the endogenous treatment effects may result in inconsistent parameter estimates if the second-stage specifications are non-linear such as the probit model for the exit probability, and the hazard model for the exit time. Hence, for the exit probability analyses, we estimate a bivariate probit model with two probit equations: a probit model of syndication choice and another probit model for exit probability. Like the seemingly unrelated regression model, the bivariate probit model assumes that the independent, identically distributed errors are correlated. For the exit time analysis, we use three different approaches to estimate endogenous treatment effects. Though it may generate inconsistent parameter estimates, we estimate a two-stage Cox proportional hazard model by including inverse Mill's ratios obtained from the first stage probit of syndication choice. We also estimate two alternate models: a two-stage Tobit model with right-censoring and a two-stage ordinary least squares model to confirm that the estimates from the two-stage Cox proportional hazard model are not inconsistent due to the non-linear second-stage specification.

## 4. Empirical analyses

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

Since we have three performance metrics (exit probabilities, exit times, and exit multiples), our analyses will be undertaken for each of the metrics. We use 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.

### *4.1. Descriptive performance statistics*

#### *4.1.1. Exit probabilities*

First, we examine if syndicated ventures are more likely to exit than non-syndicated ones. Three types of exit are considered here: (a) by IPO; (b) by acquisition; and (c) by LBO. The results are presented in Table 2 and show that the probability of exit is higher for syndicated firms, irrespective of the channel through which exit occurs (significant at the 1% level).

Overall, if we take all three exit routes together, the probability of a syndicated deal exiting is around 38% whereas that of a non-syndicated deal exiting 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%).

#### *4.1.2. Exit times*

Given the evidence that VC syndication increases the probability of a 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 3, which presents the mean time-to-exit (in months).

Overall, if we look at all exit routes (IPO, acquisition, or LBO), the mean time-to-exit is about 2 months 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 (more than 3 months faster, 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 1 month sooner than non-syndicated exits. This suggests that syndicates are likely to cut losses and sell off a new venture when they realize that an IPO is less likely.

#### *4.1.3. Exit multiples*

Do syndicated venture investments deliver higher multiples? We begin by examining the exit multiples for syndicated versus non-syndicated round investments using the annualized exit multiple

**Table 2**
Exit probabilities for syndicated and non-syndicated rounds.

| Variable | $N$ | Mean | Std dev. |
|---|---|---|---|
| *Panel A: Descriptive statistics* | | | |
| Non-syndicated rounds | | | |
| Exit by IPO, Acq, or LBO | 32,801 | 0.2477 | 0.4317 |
| Exit by IPO or Acq | 32,801 | 0.2367 | 0.4250 |
| Exit by Acq | 32,801 | 0.1160 | 0.3202 |
| Exit by IPO | 32,801 | 0.1207 | 0.3258 |
| Syndicated rounds | | | |
| Exit by IPO, Acq, or LBO | 63,743 | 0.3791 | 0.4852 |
| Exit by IPO or Acq | 63,743 | 0.3716 | 0.4832 |
| Exit by Acq | 63,743 | 0.2203 | 0.4145 |
| Exit by IPO | 63,743 | 0.1513 | 0.3583 |

| Variable | $t$-value | $Pr > \|t\|$ |
|---|---|---|
| *Panel B: Test for difference in means of syndicated versus non-syndicated rounds* | | |
| 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 |

*Notes*. 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. A $t$-test is used to test the difference of means between syndicated and non-syndicated rounds.

**Table 3**
Exit times for syndicated and non-syndicated rounds.

| Variable | $N$ | Mean | Std dev. |
|---|---|---|---|
| *Panel A: Descriptive statistics* | | | |
| Non-syndicated rounds | | | |
| Time-to-exit | 2770 | 43.87 | 35.69 |
| Time-to-exit by IPO | 641 | 37.52 | 32.82 |
| Time-to-exit by Acq | 1937 | 47.14 | 35.51 |
| Syndicated rounds | | | |
| Time-to-exit | 10,539 | 42.22 | 36.72 |
| Time-to-exit by IPO | 2544 | 36.64 | 32.52 |
| Time-to-exit by Acq | 7704 | 44.03 | 37.04 |

| Variable | $t$-value | $Pr > \|t\|$ |
|---|---|---|
| *Panel B: Test for difference in means of syndicated versus non-syndicated rounds* | | |
| 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 |

*Notes*. Firms can exit via three routes: by IPO, by acquisition, and by LBO. We consider all exits, and exits by IPO, or by acquisition separately. The table shows the time-to-exit (in months) of rounds exiting by means of these routes. Syndicated rounds are those that have at least one round syndicated including the current round. A $t$-test is used to test the difference of means between syndicated and non-syndicated rounds.

($Y_{annual}$) defined earlier. The cumulative distributions of annualized multiple for both syndicated and non-syndicated financing are displayed in Fig. 1. (Note also that these distributions are *conditional* ones, i.e., they represent the annualized multiples after conditioning on syndication, or the absence of syndication.) We see that the syndicated financing distribution is shifted to the right, and after a multiple level of 2, the exit multiples of syndicated deals' distribution is fatter-tailed, i.e., the likelihood of a large multiple is higher for syndicated deals than for non-syndicated ones.

Table 4 presents descriptive statistics for 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), evidence that syndicated firms yield higher exit outcomes from financing round to exit. A

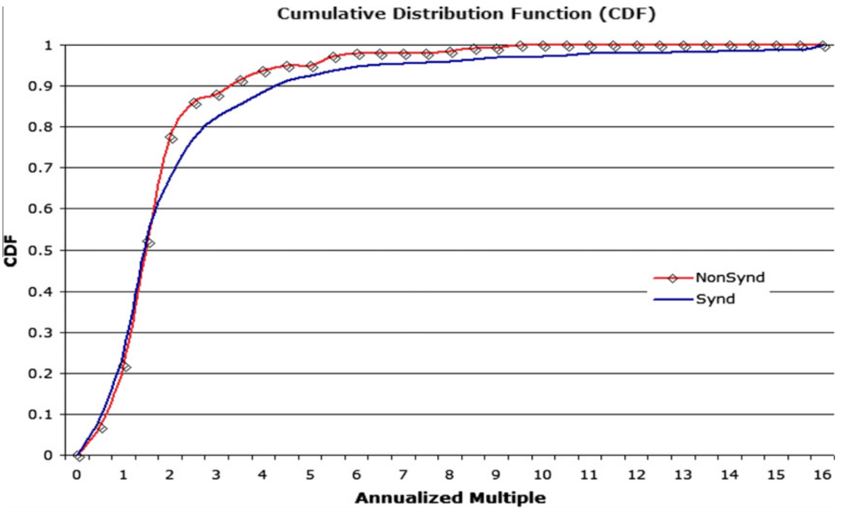


**Fig. 1.** CDFs of multiples. This figure presents the cumulative distribution function of annualized multiples for syndicated and non-syndicated firms. The plot shows that after a multiple level of 2, the syndicated firms demonstrate a much fatter tail, i.e., the likelihood of a large multiple is higher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

**Table 4**
Exit multiples of syndicated and non-syndicated rounds.

| Variable | N | Mean | Std dev. | Minimum | Maximum |
|---|---|---|---|---|---|
| *Panel A: Descriptive statistics* | | | | | |
| 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 |

| Variable | $t$-value | Pr > $\|t\|$ |
|---|---|---|
| *Panel B: Test for difference in means of syndicated versus non-syndicated rounds* | | |
| Raw multiple | 2.24 | 0.0264 |
| Annualized multiple | −2.92 | 0.0039 |

*Notes*. 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% and 99% levels. Syndicated rounds are those that have at least one round syndicated including the current round. A $t$-test is used to test the difference of means between syndicated and non-syndicated rounds.

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 longer to exit, the multiples are lower on an annualized basis. This may also be consistent with the evidence that syndicated deals are more likely to be rushed towards exit, and these results support this decision given that they provide a higher return on invested capital. The standard deviation of exit multiples is also higher for syndicated ventures, suggesting that VC syndicates may be more willing to take on riskier deals.

We transform the conditional distributions of annualized multiples into syndication probabilities using Bayes' theorem, conditional on multiples. We are interested in how the conditional probability of syndication changes as the multiple level changes. We define the probability of the multiple given that the financing was syndicated as $\Pr[Y|S=1]$. Likewise, the probability of the multiple $Y$ given the firm was not syndicated is $\Pr[Y|S=0]$. 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:

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

We plot this probability for all values of $Y$, depicted in Fig. 2. We see that the likelihood of syndication increases in the multiple, implying that when multiples 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.

### 4.2. Determinants of syndication

The decision to syndicate by the lead VC must arise from the benefits of project selection and value-add through monitoring. There are three types of information that drive this decision. First, variables relating to the risk and return of the venture itself. Second, the characteristics of the involved VCs. Third, the preferences of the entrepreneur. Our data set allows us to focus on the first two but provides relatively little information in examining the entrepreneur's motivations for syndication. Casamatta and Haritchabalet (2007) develop a detailed information-based model of the syndication decision. Their model ignores the preferences of the entrepreneur but models the information improvement (for the selection decision) by syndication as a trade-off versus the costs of VC free-riding in the implementation stage and the benefits from engaged VCs.

Our model relies on a Probit analysis of the syndication decision, as follows:

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

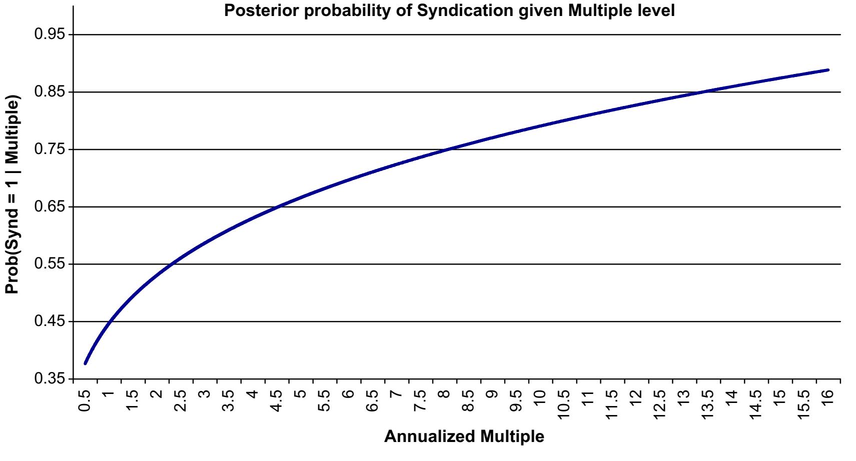


**Fig. 2.** Probability of syndication given a level of multiple. This figure shows the results of a Bayesian analysis of the distribution functions in Fig. 1 to compute the posterior probability of the venture being syndicated for each level of annualized multiple. Instead of assuming the prior probabilities 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 ($Y$) we calculated the posterior Prob(Synd|$Y$) = Prob($Y$|Synd)/[Prob($Y$|Synd) × Prob(Synd) + Prob($Y$|NoSynd) × Prob(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|$Y$) > 0.5.

where $Syn_{it}$ is a dummy variable equal to one if venture investment *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.

There are various characteristics of the firm and of the venture capitalist that lead to a venture being syndicated, and we use a large number of variables to model the probability of syndication. Based on the previous literature, we include the following variables as components of *Z*.

*4.2.1. Risk-sharing variables*

Wilson (1968) and Bygrave (1987) argue that the primary rationale behind VC syndication is risk sharing. To capture this, we use the following variables.

- *Ind*: Since the benefits and related risks 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 biotechnology industries. These two industries are known for higher levels of risk and thus we expect such firms to be syndicated more than those in other industries.
- *Erly_stg*: A dummy variable that takes the value of 1 if the firm is in an early stage or the seed round of financing. Early stage deals are more risky and more likely to be syndicated.
- *Co_age*: The age (in years) of the venture since its founding to the financing round. We would expect that firms that are older will be less risky and less likely to need syndicated financing.
- *Num_stg*: The cumulative number of stages including the current round. As a venture goes through multiple stages of financing, asymmetric information about the venture dissipates, and the venture is likely to obtain syndicated financing.

*4.2.2. Diversification, resource and capital constraint variables*

Manigart et al. (2002) and Hopp and Rieder (2006) suggest that portfolio diversification and resource driven motives complement the risk mitigation perspective. Gompers and Lerner (1998) assert that the capital constraints of a single venture capitalist might force the venture to syndicate. We use the following variables to address these motives.

- *VC_intN*: An indicator variable with a value of 1 if the lead VC is an international VC. The probability of syndication would increase with this variable if the VC prefers diversification. An international VC is likely to already be 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_indF*: 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.
- *Cap_mgt*: 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.
- *Rd_ivst*: The total amount invested in the round. The likelihood of syndication grows with the amount of investment, as the lead VC would want to avoid investing too much in a single round.
- *VC_numC*: The number of portfolio companies that the lead VC has invested in. As this increases, the lead VC is more likely to invite other VCs into the syndication, as this would mitigate being over-invested in any one venture.

*4.2.3. VC's skill and specialty variables*

Brander et al. (2002), Wright and Lockett (2003), and Gompers et al. (2006, 2009) suggest that VC syndication provides a wide range of skills and networks to portfolio companies.

- *Late_stg*: A dummy variable that is 1 if the stage of financing is late. After controlling for other factors, 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 value-addition.

- *VC_ind*: This is a dummy variable that takes the value of 1 if the lead VC is an industry specialist whose preferred industry is also the same industry category in which the venture 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_bk*: 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. Hence, the likelihood of syndication should increase with this variable.

#### *4.2.4. Strategic stage-based variable*

- *Str_stg*: 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.

#### *4.2.5. Corporate VC variable*

- *CVC*: 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. 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.

#### *4.2.6. Geographical location variables*

Sorenson and Stuart (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 syndicated deal in that state.
- *VCstate*: A dummy variable taking the value 1 if the VC is from California. Since there is a greater number of VCs in California, it is easier for VCs to interact. We expect a positive relation between this variable and the probability of syndication.

#### *4.2.7. Network variables*

Hochberg et al. (2010) developed network density variables to the strength of the networks among venture capitalists in local markets. In a tightly networked market, it would be easier to find syndicate partners and expected future reciprocity (Lerner, 1994) is greater and therefore the likelihood of syndication will be higher. Hochberg et al. (2010) related two measures to network density variables: the entropy of the number of investment per zip code area and the extent of the corporate VC presence in the local market. The entropy variable measures the opportunity for more frequent interaction among the VCs in the local market. The higher the entropy (disorder/dispersion), the less the likelihood of syndication. The corporate VC investment variable captures the link between the role of corporate VCs and the level of networking. We expect that the greater the proportion of corporate VC investment in the local market, the higher the likelihood of syndication. Corporate VCs have narrower expertise and are more likely to rely on other VCs. Though corporate VCs may also be less likely to syndicate if they invest only in their areas of expertise. Their diversification motive may be weaker than that of stand-alone VCs who do not have corporate hedging.

Following Hochberg et al. (2010), we define local markets based on six broad industry groups defined by Venture Economics and cross each with either states or metropolitan statistical areas (MSAs). We create four network density measures considering either “directed” or “undirected” network ties, and either states or MSAs as the market definition. We create two entropy measures considering either states or MSAs, and two CVC investment variables again considering either states or MSAs. Therefore we create the total of eight location specific network variables. Details of the calculations of these variables are available in Hochberg et al. (2010).

- *Asymden_MSA*: The proportion of all logically possible ties among incumbents that are present in the market, calculated from directed networks (i.e., conditioning on lead versus syndicate participant ties) using metropolitan statistical areas as the market definition.
- *Symden_MSA*: The proportion of all logically possible ties among incumbents that are present in the market, calculated from undirected networks using metropolitan statistical areas as the market definition.
- *Asymden_State*: The proportion of all logically possible ties among incumbents that are present in the market, calculated from directed networks using states as the market definition.
- *Symden_State*: The proportion of all logically possible ties among incumbents that are present in the market, calculated from undirected networks using states as the market definition.
- *Entropy_MSA*: The entropy of the number of investments per zip code area in the market defined based on metropolitan statistical areas. This variable measures the opportunity for more frequent interaction among the VCs in the local MSA market.
- *Entropy_State*: The entropy of the number of investments per zip code area in the market defined based on states. This variable measures the opportunity for more frequent interaction among the VCs in the local state market.
- *CVC_ivst_MSA*: The fraction of dollars invested by corporate VCs in the market defined based on metropolitan statistical areas.
- *CVC_ivst_State*: The fraction of dollars invested by corporate VCs in the market defined based on states.

We report the results with Asymden_MSA, Entropy_MSA, and CVC_ivst_MSA for the purpose of brevity. We find that the results remain unchanged when we use other network density, entropy, and CVC investment variables instead.

*4.2.8. Market sentiment variable*

- *Hot_mkt*: Based on Table 1, we assign an indicator variable with a value of 1 if the year of the round belongs to the periods 1983–1989 or 1995–2000. Syndication is less desirable in a hot market, as the lead VC bears much less risk. Furthermore, the lead VC may prefer to retain all the gains.

We estimate the probability of syndication using a Probit model. Results are presented in Table 5. We estimate three 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 (3), we eliminate some of the explanatory variables so as to include more rounds in the analysis.

From Models (1) to (3), we can see that almost all the chosen variables to measure risk sharing, diversification, resources, and capital constraints, VC's skills and other 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 biotech space are more likely to be syndicated, as are early stage financings. 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 portfolio companies the lead VC invests in. 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 firm's portfolio and therefore, it is less likely to seek partners to share in the venture. In addition, syndication is less likely if the lead VC is an international VC.

Consistent with Brander et al. (2002), Wright and Lockett (2003), and Gompers et al. (2006, 2009) who suggest that the VC's skill and specialty are important factors of firm performance, we find that these factors are relevant in determining the likelihood of VC syndication. Syndication propensity increases if the lead VC is an industry specialist. If the lead VC is an investment bank, they tend to syndicate more to get second opinions, and again, the likelihood of a syndication increases.

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**Table 5**
The determinants of syndication.

| Independent variables | Model (1) | | | Model (2) | | | Model (3) | | |
|---|---|---|---|---|---|---|---|---|---|
| | Coefficient estimates | Chi-square | Pr > Chi-square | Coefficient estimates | Chi-square | Pr > Chi-square | Coefficient estimates | Chi-square | Pr > Chi-square |
| Intercept | −2.9584 | 2308.49 | <0.0001 | −2.7979 | 3157.24 | <0.0001 | −3.2199 | 6212.38 | <0.0001 |
| Ind | 0.3904 | 504.97 | <0.0001 | 0.3170 | 435.37 | <0.0001 | 0.3757 | 903.40 | <0.0001 |
| Erly_stg | 0.1385 | 59.90 | <0.0001 | 0.1574 | 104.66 | <0.0001 | 0.1826 | 213.55 | <0.0001 |
| Ln(1 + Num_stg) | 1.9069 | 3145.27 | <0.0001 | 1.9195 | 4151.53 | <0.0001 | 2.0125 | 5802.08 | <0.0001 |
| VC_intN | −0.2816 | 169.37 | <0.0001 | −0.2884 | 216.79 | <0.0001 | −0.2615 | 252.26 | <0.0001 |
| VC_indF | −0.1281 | 39.07 | <0.0001 | −0.0700 | 22.76 | <0.0001 | −0.0547 | 18.94 | <0.0001 |
| Ln(1 + Rd_ivst) | 0.2049 | 2177.49 | <0.0001 | 0.1817 | 2555.41 | <0.0001 | 0.1926 | 3990.52 | <0.0001 |
| Ln(1 + VC_numC) | 0.1891 | 483.15 | <0.0001 | 0.0772 | 523.12 | <0.0001 | 0.0871 | 900.40 | <0.0001 |
| Late_stg | −0.0579 | 7.56 | 0.0060 | −0.0239 | 1.66 | 0.1979 | 0.0098 | 0.38 | 0.5371 |
| VC_ind | 0.0427 | 3.73 | 0.0535 | 0.0753 | 12.46 | 0.0004 | 0.0765 | 17.27 | <0.0001 |
| Ivst_bk | 0.7713 | 528.92 | <0.0001 | 0.7746 | 659.76 | <0.0001 | 0.7798 | 869.01 | <0.0001 |
| Str_stg | −0.1494 | 48.80 | <0.0001 | −0.1732 | 69.88 | <0.0001 | −0.1205 | 45.37 | <0.0001 |
| CVC | 0.0951 | 5.72 | 0.0168 | 0.1588 | 27.92 | <0.0001 | 0.1918 | 52.14 | <0.0001 |
| Co_state | 0.1895 | 92.23 | <0.0001 | 0.1119 | 45.93 | <0.0001 | 0.1369 | 89.27 | <0.0001 |
| VCstate | 0.1070 | 27.13 | <0.0001 | 0.1909 | 100.25 | <0.0001 | 0.1539 | 87.08 | <0.0001 |
| Asymden_MSA | 0.0600 | 11.08 | 0.0009 | 0.0448 | 0.01 | 0.0017 | 0.0419 | 12.61 | 0.0004 |
| Entropy_MSA | −0.0416 | 32.43 | <0.0001 | −0.0460 | 0.01 | <0.0001 | −0.0515 | 94.64 | <0.0001 |
| CVC_ivst_MSA | 0.7141 | 44.96 | <0.0001 | 0.5697 | 0.09 | <0.0001 | 0.7900 | 96.23 | <0.0001 |
| Hot_mkt | −0.1478 | 96.36 | <0.0001 | −0.1813 | 188.33 | <0.0001 | −0.1505 | 182.46 | <0.0001 |
| Ln(1 + Co_age) | −0.0224 | 8.39 | 0.0038 | −0.0179 | 7.01 | 0.0081 | | | |
| Ln(1 + Cap_mgt) | −0.0912 | 260.93 | <0.0001 | | | | | | |
| Log likelihood | | −20,815 | | | −27,404 | | | −37,614 | |
| Wald Chi-square | | 9236 | | | 11,383 | | | 16,788 | |
| Pr > Wald Chi-square | | <0.0001 | | | <0.0001 | | | <0.0001 | |
| Cox and Snell *R*-square | | 0.2382 | | | 0.2209 | | | 0.2563 | |
| Nagelkerke Max-rescaled *R*-square | | 0.3561 | | | 0.3352 | | | 0.3669 | |
| Number of observations | | 49,963 | | | 66,327 | | | 83,309 | |
| | Syndicated | 37,904 | 75.9% | Syndicated | 51,142 | 77.1% | Syndicated | 59,387 | 71.3% |
| | Non-syn. | 12,059 | 24.1% | Non-syn. | 15,185 | 22.9% | Non-syn. | 23,922 | 28.7% |

*Notes*. 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 A.

Variables measuring geographical location and market sentiment are also important. Investments in ventures based in California are more likely to be syndicated, and VCs domiciled in California add to this impetus. The lead VC is less likely to initiate a syndication in a hot venture market, preferring to retain all the gains. We also find that corporate VCs tend syndicate more. If the financing stage is one that the lead VC prefers then, as expected, the lead VC is less likely to syndicate.

The network variables are also all important determinants of syndication. We expect to find that network density, measured by asymmetric density within an MSA increases the likelihood of syndication, and indeed it does. Next, the higher the entropy (disorder/dispersion), the less the likelihood of syndication. We expect and find that the relationship of this instrument to the likelihood of syndication to be negative. Finally, we find that the greater the proportion of corporate VCs, the higher the likelihood of syndication. We expect this to be the case because corporate VCs are more likely to rely on other VCs given that they may only have niche expertise. On the other hand, it may be that corporate VCs only invest in their areas of expertise and would be less likely to syndicate. They may also need syndication less since their diversification motive may be less than that of stand-alone VCs who do not have corporate backing. Nevertheless, we find that the presence of a corporate VC increases the likelihood of syndication.

Table 5 shows that the results are consistent across all three Probit specifications. All the explanatory variables enter the probit model with the right sign which 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 our third model specification retains the most number of observations, we use this model in the endogeneity corrections in our second-stage performance analysis regressions. Use of other model specifications does not change the results reported in the following performance analysis.

Before we proceed onto the analysis of performance, we note the variables in Table 5 that are employed as instrumental variables: three network variables (network density, entropy, and CVC investment), four diversification, resource, and capital constraint variables (international VC indicator, general list VC indicator, the capital under management, total round investment, and the VC's number of portfolio companies) as well as CVC as a lead VC indicator, and California VC indicator. We included these variables in the information set $Z$ used for the syndication decision, and specifically excluded them in the information set $X$ used for assessing syndication performance, so as to satisfy the exclusion restrictions for the two-stage model employed in our syndication and performance analysis.

Variables that proxy portfolio diversification and resource driven motives for syndication as well as variables related to VC's capital constraints are not likely related to exit performance variables and therefore these instruments are likely to satisfy the exclusion restriction. Though better-networked VCs experience significantly better fund performance (Hochberg et al., 2007), it is hard to see that the location specific density measures and entropy measures as well as corporate VC investment proportion are related to exit performance. We see wide variations of exit performance in the same local market that share the same location specific network characteristics. Therefore network density measures are also likely to satisfy the exclusion restriction.

The instruments are not weak. We conduct a log-likelihood ratio test and find that our instruments are collectively strong in all three models.

### 4.3. Syndication performance

Several studies document that VC syndication is designed for risk sharing and is a natural mechanism to reduce inherent uncertainty (Wilson (1968), Bygrave (1987), and Chemmanur and Loutskina (2009) assert that uncertainty affects firm performance in their study of IPOs). Brander et al. (2002) and Wright and Lockett (2003) suggest that VC syndication provides additional monitoring through syndicate members' wide range of skills, alliances, and networks to the portfolio companies. Many studies, such as Lerner (1995), Kaplan and Schoar (2005), and Gompers et al. (2006, 2008, 2009) maintain that VC's monitoring, skills, and experience are important drivers of firm performance. Kaplan et al. (2007) even suspect that the performance-enhancement of VC networking is simply experience. Lerner (1995) argues that VCs act as intense monitors of managers when the need for oversight is higher.

Having developed a robust model for explaining syndication choice, we now move on to an examination of the impact of syndication on performance. We control for variables that explain exit performance. Inclusion of these variables also reduces mis-specification from correlated omitted variables. All variables are summarized in Appendix A.

We include control variables that proxy for risk (Ind, Erly_Stg, Num_Stg), VC's skill and specialty (Late_stg, VC_ind, Ivst_bk), as well as monitoring (Mntrfee) which takes a value of one if the lead VC receives monitoring fees. We include a strategic stage-based variable (Str_stg), a geographical location variable (Co_state), and a market sentiment variable (Hot_mkt). Gompers and Lerner (1998) suggest that the performance of 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 an independent lead VC (IndpnVC). We also include a dummy variable if the venture's business is internet-related (Internet) to measure the impact of internet-related "easy-money" ventures on exit performance.

*4.3.1. Exit probabilities*

Syndication has a positive impact on the probability of exit. We examine whether the higher exit probabilities of syndicated ventures come from selection or better monitoring by VC syndicates, by comparing the results with and without controlling for endogenous selection. Estimation with endogeneity controls is undertaken by means of a bivariate probit, one probit for syndication choice and another for exit probability. The results are presented in Table 6. There are four sub-panels in the table, breaking out the results for exit by different routes. If higher probabilities of exit come strictly from selection, the impact of syndication on exit probabilities should disappear after controlling for endogenous treatment effects. We observe, however, that the impact remains intact after the endogeneity correction. Hence, the likelihood that a syndicated venture will exit depends on selection, as well as on monitoring by the syndicate.

Based on Table 6, we evaluated the increase in exit probability due to syndication by holding other independent variables at their mean values and looking at the impact of the syndication variable. Because the Probit model is non-linear, the increase in probability attributed to syndication versus non-syndication (i.e., the effect of the coefficient on the syndication dummy) is dependent on the values of other predictors and the starting values of other predictors. For exits by acquisition, IPO, or LBO, the increase in exit probability on account of syndication is 6.22% (we use the estimated coefficient for regressions without the Mills ratio) after controlling for the effect of other variables on exit time.

We find higher exit probabilities if ventures are in the IT or biotech space, are in California, and are not in internet-related activities, suggesting that risk concerns, industry, and spatial location are important to the successful exit of startups. Exit probabilities are higher for financings in later stages, for firms that go through a multiple number of financing stages, and for ventures receiving financing in a hot venture market, implying a role for conditions in the financing and product markets. Exits are also more likely when the lead VC is an investment bank or an independent VC, meaning that the type of VC matters.

For IPOs, syndication and exit probability are negatively (but insignificantly) correlated without endogeneity control, but positively correlated with endogeneity control. It seems that the value-add impact of syndication is greater for an IPO. While coefficients on the other explanatory variables for IPOs and acquisitions have the same sign and similar significance, the coefficients on the early stage variable, monitoring fee variable (Mntrfee), and independent lead VC (IndpnVC) variable are negative (positive) in IPOs (acquisitions), suggesting that differences in the role of the VC may lead to disparate value-add outcomes.

*4.3.2. Exit times*

As already shown in Table 3, the time-to-exit when a venture investment is syndicated is less than when it is not syndicated, primarily for exits by acquisition. We examine this effect with a multi-variate analysis controlling for all other variables. Using a Cox proportional hazard model, we also compare the results with and without controlling for endogenous treatment effects.[7] Results are provided

[7] Recently, some researchers (Earle et al., 2001; Brooks et al., 2003) have used instrumental variables analysis to evaluate alternative treatments in cancer in the hazard model context. As a robustness check, we estimate an instrumental variable model (unreported) and find the same results.

**Table 6**
The effect of syndication on exit probabilities.

| Independent variables | Without endogeneity control | | | With endogeneity control—biprobit estimation | | | Without endogeneity control | | | With endogeneity control—biprobit estimation | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Coefficient estimates | Chi-square | Pr > Chi-square | Coefficient estimates | *t*-value | Pr > *t*-value | Coefficient estimates | Chi-square | Pr > Chi-square | Coefficient estimates | *t*-value | Pr > *t*-value |
| | *Dependent variable = Exit_1 (IPO, ACQ, LBO)* | | | | | | *Dependent variable = Exit_2 (IPO, ACQ)* | | | | | |
| Intercept | −1.0946 | 2619.64 | <0.0001 | −1.1295 | −53.94 | <0.0001 | −1.1745 | 2978.75 | <0.0001 | −1.2068 | −57.23 | <0.0001 |
| Syn | 0.1707 | 226.08 | <0.0001 | 0.8124 | 30.37 | <0.0001 | 0.1636 | 205.66 | <0.0001 | 0.7830 | 28.54 | <0.0001 |
| Ind | 0.2469 | 416.35 | <0.0001 | 0.1414 | 11.11 | <0.0001 | 0.2772 | 518.32 | <0.0001 | 0.1748 | 13.58 | <0.0001 |
| Erly_stg | −0.1314 | 134.31 | <0.0001 | −0.1559 | −13.93 | <0.0001 | −0.1208 | 112.93 | <0.0001 | −0.1452 | −12.93 | <0.0001 |
| Ln(1 + Num_stg) | 0.3377 | 322.08 | <0.0001 | 0.0219 | 0.96 | 0.3355 | 0.3800 | 405.95 | <0.0001 | 0.0743 | 3.22 | 0.0013 |
| Late_stg | 0.1668 | 174.24 | <0.0001 | 0.1397 | 11.19 | <0.0001 | 0.1015 | 63.61 | <0.0001 | 0.0785 | 6.24 | <0.0001 |
| VC_ind | −0.0032 | 0.04 | 0.8391 | 0.0115 | 0.75 | 0.4543 | −0.0040 | 0.0664 | 0.7967 | 0.0102 | 0.66 | 0.5091 |
| Ivst_bk | 0.1943 | 162.54 | <0.0001 | 0.1152 | 7.46 | <0.0001 | 0.1883 | 152.06 | <0.0001 | 0.1124 | 7.25 | <0.0001 |
| Str_stg | −0.0574 | 11.17 | 0.0008 | −0.0076 | −0.45 | 0.6558 | −0.0708 | 16.71 | <0.0001 | −0.0222 | −1.29 | 0.1977 |
| Co_state | 0.1899 | 326.19 | <0.0001 | 0.1314 | 12.30 | <0.0001 | 0.1960 | 346.81 | <0.0001 | 0.1398 | 13.05 | <0.0001 |
| Hot_mkt | 0.2525 | 687.92 | <0.0001 | 0.2574 | 27.15 | <0.0001 | 0.2580 | 712.43 | <0.0001 | 0.2628 | 27.58 | <0.0001 |
| Mntrfee | −0.0312 | 5.40 | 0.0201 | −0.0189 | −1.47 | 0.1417 | −0.0405 | 8.98 | 0.0027 | −0.0287 | −2.20 | 0.0276 |
| IndpnVC | 0.0254 | 5.30 | 0.0213 | 0.0129 | 1.21 | 0.2261 | 0.0364 | 10.77 | 0.0010 | 0.0243 | 2.26 | 0.0237 |
| Internet | −0.3986 | 1484.40 | <0.0001 | −0.4003 | −40.12 | <0.0001 | −0.3999 | 1486.93 | <0.0001 | −0.4024 | −40.12 | <0.0001 |
| Number of observations | | 81,989 | | | 81,989 | | | 81,989 | | | 81,989 | |
| Log likelihood | | −50,639 | | | −87,425 | | | −50,197 | | | −87,008 | |
| Wald Chi-square | | 5132 | | | | | | 5235 | | | | |
| Pr > Wald Chi-square | | <0.0001 | | | | | | <0.0001 | | | | |
| Cox and Snell *R*-square | | 0.0632 | | | | | | 0.0646 | | | | |
| Nagelkerke Max-rescaled *R*-square | | 0.0869 | | | | | | 0.0891 | | | | |

(*continued on next page*)

**Table 6** (*continued*)

| Independent variables | Without endogeneity control | | | With endogeneity control—biprobit estimation | | | Without endogeneity control | | | With endogeneity control—biprobit estimation | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Coefficient estimates | Chi-square | Pr > Chi-square | Coefficient estimates | *t*-value | Pr > *t*-value | Coefficient estimates | Chi-square | Pr > Chi-square | Coefficient estimates | *t*-value | Pr > *t*-value |
| | *Dependent variable = Exit_ACQ* | | | | | | *Dependent variable = Exit_IPO* | | | | | |
| Intercept | −1.7747 | 5208.40 | <0.0001 | −1.7897 | −73.02 | <0.0001 | −1.1969 | 2359.56 | <0.0001 | −1.2193 | −50.21 | <0.0001 |
| Syn | 0.2390 | 330.30 | <0.0001 | 0.7560 | 22.76 | <0.0001 | −0.0018 | 0.0187 | 0.8912 | 0.4575 | 13.08 | <0.0001 |
| Ind | 0.2658 | 367.69 | <0.0001 | 0.1826 | 12.34 | <0.0001 | 0.1232 | 75.61 | <0.0001 | 0.0536 | 3.60 | 0.0003 |
| Erly_stg | 0.0443 | 12.21 | 0.0005 | 0.0207 | 1.64 | 0.1007 | −0.2437 | 317.95 | <0.0001 | −0.2609 | −19.30 | <0.0001 |
| Ln(1 + Num_stg) | 0.3571 | 299.88 | <0.0001 | 0.0991 | 3.70 | 0.0002 | 0.1445 | 43.52 | <0.0001 | −0.0830 | −2.96 | 0.0031 |
| Late_stg | 0.1076 | 58.44 | <0.0001 | 0.0922 | 6.61 | <0.0001 | 0.0349 | 5.78 | 0.0162 | 0.0189 | 1.31 | 0.1897 |
| VC_ind | −0.0344 | 3.87 | 0.0492 | −0.0225 | −1.30 | 0.1937 | 0.0326 | 3.14 | 0.0764 | 0.0427 | 2.35 | 0.0190 |
| Ivst_bk | 0.0628 | 14.38 | 0.0001 | 0.0022 | 0.13 | 0.8965 | 0.1839 | 115.65 | <0.0001 | 0.1244 | 7.04 | <0.0001 |
| Str_stg | −0.0287 | 2.17 | 0.1410 | 0.0109 | 0.56 | 0.5755 | −0.0801 | 14.52 | 0.0001 | −0.0458 | −2.18 | 0.0290 |
| Co_state | 0.1796 | 246.53 | <0.0001 | 0.1348 | 11.52 | <0.0001 | 0.0852 | 47.27 | <0.0001 | 0.0473 | 3.75 | 0.0002 |
| Hot_mkt | 0.2119 | 383.64 | <0.0001 | 0.2177 | 20.38 | <0.0001 | 0.1493 | 172.32 | <0.0001 | 0.1572 | 13.97 | <0.0001 |
| Mntrfee | 0.0261 | 3.02 | 0.0821 | 0.0345 | 2.35 | 0.0186 | −0.0915 | 32.05 | <0.0001 | −0.0815 | −5.15 | <0.0001 |
| IndpnVC | 0.0888 | 50.01 | <0.0001 | 0.0778 | 6.32 | <0.0001 | −0.0419 | 10.68 | 0.0011 | −0.0479 | −3.80 | 0.0001 |
| Internet | −0.2952 | 659.52 | <0.0001 | −0.3048 | −27.13 | <0.0001 | −0.2758 | 496.00 | <0.0001 | −0.2854 | −23.57 | <0.0001 |
| Number of observation | | 81,989 | | | 81,989 | | | 81,989 | | | 81,989 | |
| log likelihood | | −38,874 | | | −75,800 | | | −33,946 | | | −70,900 | |
| Wald Chi-square | | 3253 | | | | | | 1699 | | | | |
| Pr > Wald Chi-square | | <0.0001 | | | | | | <0.0001 | | | | |
| Cox and Snell *R*-square | | 0.0404 | | | | | | 0.0209 | | | | |
| Nagelkerke Max-rescaled *R*-square | | 0.0644 | | | | | | 0.0366 | | | | |

*Notes.* 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 results with the endogeneity correction are obtained through biprobit estimation of the syndication determination equation and the exit probability equation. The log liklihood in the biprobit estimation is the log likelihood of the system. The variable "Syn" 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 by a first stage probit. Results are provided broken down by IPO and by ACQ (acquisition) routes. See the definitions of explanatory variables in Appendix A.

in Table 7. The coefficients as well as hazard ratios are reported. A hazard ratio of an independent variable greater (less) than 1 indicates a shorter (longer) time-to-exit (the ratio is proportional to the speed of 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 3, 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 ventures are 21% more likely to exit at any given time, taken across all types, though the faster rate of exit is not significant for IPO exits without endogeneity control.

Ventures tend to have a faster time-to-exit if they are in the IT or biotech space, the internet space, and are in the late stage, showing that type of firm and stage matter. As expected, the type of VC matters too—exits take shorter time if the lead VC is independent and take longer when the lead VC receives monitoring fees, a symptom of lower engagement levels. It is important that the VC be aligned with the industry as well. Ventures also exit faster when they receive multiple financing rounds, but not necessarily in hot venture markets.

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

To ensure that the results from the two-stage Cox proportional hazard model are not inconsistent, we also estimate a two-stage Tobit model with right-censoring, and a two-stage ordinary least squares (OLS) model. In the Tobit and OLS estimations, the signs of parameter estimates will be the opposite of those in the hazard model estimation. The negative coefficient on the syndication variable in Tobit and OLS estimations represent shorter times to exit. The results are reported in Panels B and C of Table 7, respectively, and are consistent with those from the Cox proportional hazard model estimation. Bootstrap estimation (not reported) of standard errors with 10,000 iterations also provides results consistent with those reported in Table 7. All our tests confirm that syndicated deals exit faster.

*4.3.3. Exit multiples*

In Table 8, we examine if the higher annualized exit multiples achieved by syndicated ventures shown in Table 4 remain significant after controlling for other factors, and if these high multiples come from selection or from value-add by the syndicate. We regress the exit multiple on a syndication dummy and various other explanatory variables. We conduct this first without correcting for endogeneity, and then repeat the exercise with the endogeneity correction. We find that the variable for syndication is significant (the multiple is greater by 0.72 before adjusting for industry returns and 0.50 after adjustment) when no endogeneity correction is imposed, and then becomes insignificant with the correction. This suggests that better exit multiples come from the selection of better projects by VC syndicates, and not from value-addition effort.

Exit multiples are lower for ventures with multiple stages of financing. Multiples are higher if ventures pay monitoring fees to VCs and if the venture's business is internet-related. Multiples are higher for firms in IT and biotech and during hot markets.

In order to make sure that we control for differential performance across industry sub-sectors, we expanded our assessment of performance (exit multiples) to using industry adjusted abnormal multiples. Industry adjusted abnormal multiples (abn_ann_mltp) are calculated as annualized exit multiple for a round investment minus industry average of exit multiples over the sample period. There are six different industry classifications in the Venture Economics database. The first (second, third, fourth, fifth, sixth) definition classifies firms into three (6, 10, 18, 69, 575) big industry groups. We use the fifth definition with 69 industry groups because the last classification with 575 industry groups reduces usable observations significantly. The results are also shown in Table 8 and support the results obtained from using the unadjusted multiples.

In Table 9, 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 coefficient on the syndication dummy is insignificant, implying that higher exit

**Table 7**
The effect of syndication on time-to-exit.

| Independent variables | Without endogeneity control | | | With endogeneity control | | | Without endogeneity control | | | With endogeneity control | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Hazard ratio | Chi-square | Pr > Chi-square | Hazard ratio | Chi-square | Pr > Chi-square | Hazard ratio | Chi-square | Pr > Chi-square | Hazard ratio | Chi-square | Pr > Chi-square |
| *Panel A: Hazard model analysis* | | | | | | | | | | | | |
| | *Time-to-exit through IPO, acquisition, or LBO* | | | | | | *Time-to-exit through IPO or acquisition* | | | | | |
| Syn | 1.211 | 150.97 | <0.0001 | 3.796 | 880.63 | <0.0001 | 1.207 | 141.78 | <0.0001 | 3.771 | 850.44 | <0.0001 |
| Ind | 1.360 | 380.26 | <0.0001 | 1.162 | 81.51 | <0.0001 | 1.405 | 448.27 | <0.0001 | 1.201 | 116.72 | <0.0001 |
| Erly_stg | 0.742 | 397.64 | <0.0001 | 0.704 | 541.22 | <0.0001 | 0.749 | 367.64 | <0.0001 | 0.711 | 505.25 | <0.0001 |
| Ln(1 + Num_stg) | 1.428 | 235.35 | <0.0001 | 0.873 | 21.65 | <0.0001 | 1.480 | 280.79 | <0.0001 | 0.906 | 11.07 | 0.0009 |
| Late_stg | 1.119 | 53.71 | <0.0001 | 1.102 | 39.78 | <0.0001 | 1.077 | 22.12 | <0.0001 | 1.061 | 14.22 | 0.0002 |
| VC_ind | 1.060 | 8.14 | 0.0043 | 1.069 | 10.80 | 0.0010 | 1.058 | 7.70 | 0.0055 | 1.068 | 10.25 | 0.0014 |
| Ivst_bk | 1.093 | 24.78 | <0.0001 | 0.970 | 2.74 | 0.0981 | 1.085 | 20.67 | <0.0001 | 0.965 | 3.72 | 0.0536 |
| Str_stg | 1.083 | 11.23 | 0.0008 | 1.151 | 34.96 | <0.0001 | 1.073 | 8.59 | 0.0034 | 1.142 | 30.18 | <0.0001 |
| Co_state | 1.018 | 1.94 | 0.1635 | 0.951 | 14.87 | 0.0001 | 1.024 | 3.31 | 0.0690 | 0.956 | 11.47 | 0.0007 |
| Hot_mkt | 0.975 | 3.41 | 0.0649 | 1.001 | 0.00 | 0.9492 | 0.980 | 2.12 | 0.1455 | 1.006 | 0.18 | 0.6686 |
| Mntrfee | 0.943 | 11.37 | 0.0007 | 0.958 | 5.87 | 0.0154 | 0.928 | 17.75 | <0.0001 | 0.943 | 10.86 | 0.0010 |
| IndpnVC | 1.134 | 76.48 | <0.0001 | 1.117 | 58.92 | <0.0001 | 1.149 | 91.41 | <0.0001 | 1.132 | 72.53 | <0.0001 |
| Internet | 1.947 | 2001.60 | <0.0001 | 1.886 | 1799.98 | <0.0001 | 1.960 | 2012.25 | <0.0001 | 1.899 | 1813.07 | <0.0001 |
| Lambda | | | | 0.473 | 762.62 | <0.0001 | | | | 0.474 | 740.14 | <0.0001 |
| Number of observations | | 81,716 | | | 81,716 | | | 81,716 | | | 81,716 | |
| Percent censored | | 64.65% | | | 64,65% | | | 65.26% | | | 65.26% | |
| Wald Chi-square | | 5114 | | | 5652 | | | 5270 | | | 5780 | |
| Pr > Wald Chi-square | | <0.0001 | | | <0.0001 | | | <0.0001 | | | <0.0001 | |
| | *Time-to-exit through acquisition* | | | | | | *Time-to-exit through IPO* | | | | | |
| Syn | 1.429 | 261.63 | <0.0001 | 4.401 | 554.50 | <0.0001 | 0.998 | 0.01 | 0.9427 | 3.190 | 307.10 | <0.0001 |
| Ind | 1.545 | 380.76 | <0.0001 | 1.325 | 143.57 | <0.0001 | 1.266 | 103.03 | <0.0001 | 1.078 | 9.25 | 0.0024 |
| Erly_stg | 0.914 | 20.81 | <0.0001 | 0.869 | 49.63 | <0.0001 | 0.573 | 559.94 | <0.0001 | 0.542 | 666.52 | <0.0001 |
| Ln(1 + Num_stg) | 1.706 | 296.22 | <0.0001 | 1.059 | 2.13 | 0.1442 | 1.242 | 36.80 | <0.0001 | 0.746 | 43.17 | <0.0001 |
| Late_stg | 1.131 | 33.54 | <0.0001 | 1.119 | 27.97 | <0.0001 | 1.012 | 0.25 | 0.6200 | 0.992 | 0.13 | 0.7198 |
| VC_ind | 1.004 | 0.02 | 0.8963 | 1.014 | 0.26 | 0.6134 | 1.134 | 16.65 | <0.0001 | 1.141 | 18.26 | <0.0001 |
| Ivst_bk | 1.013 | 0.28 | 0.5983 | 0.910 | 14.70 | 0.0001 | 1.187 | 40.90 | <0.0001 | 1.041 | 2.15 | 0.1424 |
| Str_stg | 1.099 | 8.88 | 0.0029 | 1.175 | 25.67 | <0.0001 | 1.042 | 1.25 | 0.2644 | 1.101 | 6.70 | 0.0096 |
| Co_state | 1.077 | 19.00 | <0.0001 | 1.007 | 0.17 | 0.6830 | 0.955 | 5.25 | 0.0220 | 0.890 | 32.15 | <0.0001 |
| Hot_mkt | 1.018 | 0.91 | 0.3393 | 1.042 | 5.11 | 0.0239 | 0.940 | 9.28 | 0.0023 | 0.967 | 2.76 | 0.0965 |
| Mntrfee | 0.989 | 0.23 | 0.6295 | 1.003 | 0.02 | 0.8950 | 0.854 | 32.98 | <0.0001 | 0.870 | 25.56 | <0.0001 |
| IndpnVC | 1.263 | 136.71 | <0.0001 | 1.244 | 119.11 | <0.0001 | 1.026 | 1.43 | 0.2314 | 1.011 | 0.27 | 0.6066 |
| Internet | 1.807 | 899.33 | <0.0001 | 1.751 | 798.68 | <0.0001 | 2.176 | 1140.97 | <0.0001 | 2.109 | 1043.39 | <0.0001 |
| Lambda | | | | 0.478 | 378.86 | <0.0001 | | | | 0.467 | 363.29 | <0.0001 |
| Number of observations | | 81,716 | | | 81,716 | | | 81,716 | | | 81,716 | |
| Percent censored | | 80.39% | | | 80.39% | | | 84.87% | | | 84.87% | |
| Wald Chi-square | | 3374 | | | 3568 | | | 2525 | | | 2845 | |
| Pr > Wald Chi-square | | <0.0001 | | | <0.0001 | | | <0.0001 | | | <0.0001 | |

| Independent variables | Without endogeneity control | | | With endogeneity control | | | Without endogeneity control | | | With endogeneity control | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Estimate | Chi-square | Pr > Chi-square | Estimate | Chi-square | Pr > Chi-square | Estimate | Chi-square | Pr > Chi-square | Estimate | Chi-square | Pr > Chi-square |
| *Panel B: Tobit analysis* | | | | | | | | | | | | |
| | *Time-to-exit through IPO, acquisition, or LBO* | | | | | | *Time-to-exit through IPO or acquisition* | | | | | |
| Intercept | 5.5838 | 51060.00 | <0.0001 | 5.7329 | 50754.70 | <0.0001 | 5.6544 | 51643.30 | <0.0001 | 5.8024 | 51255.30 | <0.0001 |
| Syn | −0.1682 | 163.85 | <0.0001 | −1.1103 | 873.62 | <0.0001 | −0.1632 | 152.81 | <0.0001 | −1.0974 | 844.86 | <0.0001 |
| Ind | −0.2653 | 371.82 | <0.0001 | −0.1347 | 86.25 | <0.0001 | −0.2943 | 451.61 | <0.0001 | −0.1648 | 127.54 | <0.0001 |
| Erly_stg | 0.2964 | 518.39 | <0.0001 | 0.3414 | 679.82 | <0.0001 | 0.2874 | 487.75 | <0.0001 | 0.3322 | 643.81 | <0.0001 |
| Ln(1 + Num_stg) | −0.2965 | 200.66 | <0.0001 | 0.1160 | 20.28 | <0.0001 | −0.3283 | 244.86 | <0.0001 | 0.0810 | 9.83 | 0.0017 |
| Late_stg | −0.1221 | 75.58 | <0.0001 | −0.0967 | 47.71 | <0.0001 | −0.0782 | 30.52 | <0.0001 | −0.0538 | 14.52 | 0.0001 |
| VC_ind | −0.0509 | 8.20 | 0.0042 | −0.0666 | 14.11 | 0.0002 | −0.0489 | 7.56 | 0.0060 | −0.0650 | 13.42 | 0.0002 |
| Ivst_bk | −0.1036 | 39.07 | <0.0001 | −0.0031 | 0.03 | 0.8521 | −0.0977 | 34.51 | <0.0001 | 0.0011 | 0.00 | 0.9472 |
| Str_stg | −0.0266 | 1.75 | 0.1865 | −0.0840 | 17.23 | <0.0001 | −0.0176 | 0.76 | 0.3837 | −0.0747 | 13.45 | 0.0002 |
| Co_state | −0.0514 | 19.24 | <0.0001 | 0.0132 | 1.24 | 0.2652 | −0.0556 | 22.57 | <0.0001 | 0.0082 | 0.48 | 0.4874 |
| Hot_mkt | 0.1848 | 272.62 | <0.0001 | 0.1657 | 219.89 | <0.0001 | 0.1776 | 250.16 | <0.0001 | 0.1590 | 201.16 | <0.0001 |
| Mntrfee | 0.0410 | 7.12 | 0.0076 | 0.0266 | 3.01 | 0.0829 | 0.0529 | 11.66 | 0.0006 | 0.0388 | 6.32 | 0.0120 |
| IndpnVC | −0.0491 | 15.29 | <0.0001 | −0.0380 | 9.17 | 0.0025 | −0.0613 | 23.52 | <0.0001 | −0.0505 | 16.10 | <0.0001 |
| Internet | −0.3796 | 1032.70 | <0.0001 | −0.3482 | 865.66 | <0.0001 | −0.3811 | 1040.16 | <0.0001 | −0.3501 | 874.31 | <0.0001 |
| Lambda | | | | 0.6217 | 723.87 | <0.0001 | | | | 0.6163 | 704.58 | <0.0001 |
| Number of observations | | 81,716 | | | 81,716 | | | 81,716 | | | 81,716 | |
| Percent censored | | 64.65% | | | 64.65% | | | 65.26% | | | 65.26% | |
| Log likelihood | | −65,861 | | | −65,497 | | | −65,874 | | | −65,520 | |
| | *Time-to-exit through acquisition* | | | | | | *Time-to-exit through IPO* | | | | | |
| Intercept | 6.7201 | 35025.50 | <0.0001 | 6.8826 | 34096.00 | <0.0001 | 5.9521 | 29334.90 | <0.0001 | 6.0825 | 29072.40 | <0.0001 |
| Syn | −0.2854 | 247.22 | <0.0001 | −1.2712 | 576.28 | <0.0001 | −0.0113 | 0.38 | 0.5391 | −0.9059 | 305.99 | <0.0001 |
| Ind | −0.3686 | 373.28 | <0.0001 | −0.2334 | 134.94 | <0.0001 | −0.2060 | 116.80 | <0.0001 | −0.0814 | 16.48 | <0.0001 |
| Erly_stg | 0.1203 | 48.36 | <0.0001 | 0.1632 | 88.11 | <0.0001 | 0.4816 | 651.23 | <0.0001 | 0.5277 | 771.73 | <0.0001 |
| Ln(1 + Num_stg) | −0.4399 | 247.37 | <0.0001 | −0.0138 | 0.16 | 0.6929 | −0.1694 | 32.51 | <0.0001 | 0.2273 | 39.08 | <0.0001 |
| Late_stg | −0.1054 | 30.36 | <0.0001 | −0.0858 | 20.28 | <0.0001 | −0.0408 | 4.32 | 0.0376 | −0.0145 | 0.55 | 0.4575 |
| VC_ind | −0.0339 | 2.04 | 0.1529 | −0.0489 | 4.26 | 0.0390 | −0.0672 | 6.96 | 0.0083 | −0.0827 | 10.64 | 0.0011 |
| Ivst_bk | −0.0069 | 0.09 | 0.7580 | 0.0892 | 15.57 | <0.0001 | −0.1831 | 62.90 | <0.0001 | −0.0815 | 12.04 | 0.0005 |
| Str_stg | −0.0569 | 4.46 | 0.0346 | −0.1193 | 19.38 | <0.0001 | 0.0238 | 0.66 | 0.4183 | −0.0258 | 0.76 | 0.3828 |
| Co_state | −0.0940 | 37.24 | <0.0001 | −0.0278 | 3.18 | 0.0746 | 0.0079 | 0.22 | 0.6393 | 0.0681 | 16.01 | <0.0001 |
| Hot_mkt | 0.1267 | 70.61 | <0.0001 | 0.1102 | 53.64 | <0.0001 | 0.2111 | 177.00 | <0.0001 | 0.1896 | 143.30 | <0.0001 |
| Mntrfee | −0.0181 | 0.78 | 0.3771 | −0.0341 | 2.77 | 0.0958 | 0.1389 | 38.69 | <0.0001 | 0.1259 | 32.01 | <0.0001 |
| IndpnVC | −0.1554 | 81.16 | <0.0001 | −0.1443 | 70.30 | <0.0001 | 0.0397 | 5.11 | 0.0238 | 0.0501 | 8.20 | 0.0042 |
| Internet | −0.4459 | 808.01 | <0.0001 | −0.4123 | 685.89 | <0.0001 | −0.3498 | 414.51 | <0.0001 | −0.3205 | 347.96 | <0.0001 |
| Lambda | | | | 0.6477 | 400.14 | <0.0001 | | | | 0.5909 | 344.60 | <0.0001 |
| Number of observations | | 81,716 | | | 81,716 | | | 81,716 | | | 81,716 | |
| Percent censored | | 80.39% | | | 80.39% | | | 84.87% | | | 84.87% | |
| Log likelihood | | −46,205 | | | −46,004 | | | −37,269 | | | −37,096 | |

(*continued on next page*)

**Table 7** (*continued*)

| Independent variables | Without endogeneity control | | | With endogeneity control | | | Without endogeneity control | | | With endogeneity control | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Estimate | *t*-value | Pr > *t*-value | Estimate | *t*-value | Pr > *t*-value | Estimate | *t*-value | Pr > *t*-value | Estimate | *t*-value | Pr > *t*-value |
| Panel C: OLS with treatment effects | | | | | | | | | | | | |
| | *Time-to-exit through IPO, acquisition, or LBO* | | | *Time-to-exit through IPO or acquisition* | | | *Time-to-exit through acquisition* | | | *Time-to-exit through IPO* | | |
| Intercept | 4.3240 | 154.59 | <0.0001 | 4.3647 | 154.31 | <0.0001 | 4.4435 | 109.27 | <0.0001 | 4.2173 | 107.07 | <0.0001 |
| Syn | −0.4940 | −11.44 | <0.0001 | −0.4899 | −11.21 | <0.0001 | −0.4317 | −6.76 | <0.0001 | −0.4828 | −8.10 | <0.0001 |
| Ind | 0.0473 | 2.87 | 0.0040 | 0.0283 | 1.70 | 0.0895 | 0.0324 | 1.40 | 0.1615 | 0.0201 | 0.85 | 0.3967 |
| Erly_stg | 0.2546 | 17.00 | <0.0001 | 0.2517 | 16.78 | <0.0001 | 0.2328 | 11.97 | <0.0001 | 0.3246 | 13.88 | <0.0001 |
| Ln(1 + Num_stg) | 0.0974 | 3.49 | 0.0005 | 0.0847 | 3.01 | 0.0027 | 0.0308 | 0.81 | 0.4199 | 0.1408 | 3.40 | 0.0007 |
| Late_stg | −0.0281 | −1.86 | 0.0631 | −0.0102 | −0.67 | 0.5056 | −0.0058 | −0.28 | 0.7793 | −0.0410 | −1.80 | 0.0714 |
| VC_ind | −0.0460 | −2.34 | 0.0194 | −0.0438 | −2.22 | 0.0266 | −0.1049 | −4.01 | <0.0001 | 0.0244 | 0.82 | 0.4109 |
| Ivst_bk | 0.0617 | 3.50 | 0.0005 | 0.0627 | 3.53 | 0.0004 | 0.0819 | 3.48 | 0.0005 | 0.0170 | 0.64 | 0.5231 |
| Str_stg | −0.0595 | −2.57 | 0.0103 | −0.0514 | −2.19 | 0.0288 | −0.0968 | −3.16 | 0.0016 | 0.0302 | 0.84 | 0.4015 |
| Co_state | 0.0739 | 5.72 | <0.0001 | 0.0733 | 5.66 | <0.0001 | 0.0816 | 4.89 | <0.0001 | 0.0649 | 3.22 | 0.0013 |
| Hot_mkt | 0.1894 | 15.24 | <0.0001 | 0.1798 | 14.37 | <0.0001 | 0.1585 | 9.60 | <0.0001 | 0.2071 | 11.01 | <0.0001 |
| Mntrfee | 0.0350 | 2.04 | 0.0410 | 0.0409 | 2.36 | 0.0183 | 0.0126 | 0.56 | 0.5737 | 0.0961 | 3.59 | 0.0003 |
| IndpnVC | −0.0289 | −2.05 | 0.0402 | −0.0362 | −2.55 | 0.0108 | −0.1002 | −5.21 | <0.0001 | 0.0434 | 2.09 | 0.0367 |
| Internet | −0.6401 | −47.96 | <0.0001 | −0.6444 | −48.11 | <0.0001 | −0.8375 | −47.77 | <0.0001 | −0.3781 | −18.52 | <0.0001 |
| Lambda | 0.3149 | 11.92 | <0.0001 | 0.3139 | 11.76 | <0.0001 | 0.2940 | 7.56 | <0.0001 | 0.3111 | 8.54 | <0.0001 |
| Number of observations | | 28,887 | | | 28,388 | | | 16,026 | | | 12,362 | |
| *F*-value | | 234.04 | | | 234.15 | | | 208.18 | | | 62.02 | |
| Pr > *F* | | <0.0001 | | | <0.0001 | | | <0.0001 | | | <0.0001 | |
| Adjusted *R*-square | | 0.1015 | | | 0.1031 | | | 0.1533 | | | 0.0646 | |

*Notes*. In this table we present a model to explain 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. “Syn” in the analysis with endogeneity control is the predicted probability of syndication estimated by a first stage probit. Results are provided broken down by IPO and by ACQ (acquisition) routes. See the definitions of explanatory variables in Appendix A.

**Table 8**
The effect of syndication on exit multiples.

| Independent variables | Without endogeneity control | | | With endogeneity control | | | Without endogeneity control | | | With endogeneity control | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Coefficient estimates | *t*-value | Pr > *t* | Coefficient estimates | *t*-value | Pr > *t* | Coefficient estimates | *t*-value | Pr > *t* | Coefficient estimates | *t*-value | Pr > *t* |
| | *Dependent variable=ann_mltp* | | | | | | *Dependent variable=abn_ann_mltp* | | | | | |
| Intercept | 0.6255 | 1.53 | 0.1259 | 0.6979 | 1.34 | 0.1790 | −0.5105 | −1.32 | 0.1860 | −0.3498 | −0.71 | 0.4757 |
| Syn | 0.7164 | 3.26 | 0.0012 | 0.5503 | 0.72 | 0.4731 | 0.4952 | 2.38 | 0.0173 | 0.1264 | 0.17 | 0.8615 |
| Ind | 0.5107 | 1.95 | 0.0518 | 0.5299 | 1.92 | 0.0549 | 0.0199 | 0.08 | 0.9361 | 0.0625 | 0.24 | 0.8105 |
| Erly_stg | 0.2407 | 1.43 | 0.1521 | 0.2422 | 1.44 | 0.1501 | 0.2177 | 1.37 | 0.1704 | 0.2209 | 1.39 | 0.1645 |
| Ln(1 + Num_stg) | −0.6981 | −2.63 | 0.0086 | −0.6492 | −1.90 | 0.0581 | −0.5335 | −2.13 | 0.0336 | −0.4250 | −1.31 | 0.1889 |
| Late_stg | 0.0836 | 0.50 | 0.6156 | 0.0812 | 0.49 | 0.6266 | 0.0013 | 0.01 | 0.9932 | −0.0040 | −0.03 | 0.9800 |
| VC_ind | −0.4815 | −2.35 | 0.0189 | −0.4824 | −2.35 | 0.0188 | −0.6435 | −3.32 | 0.0009 | −0.6454 | −3.33 | 0.0009 |
| Ivst_bk | −0.0964 | −0.54 | 0.5859 | −0.0858 | −0.47 | 0.6397 | −0.0384 | −0.23 | 0.8183 | −0.0148 | −0.09 | 0.9321 |
| Str_stg | 0.4774 | 1.62 | 0.1045 | 0.4723 | 1.60 | 0.1095 | 0.3143 | 1.13 | 0.2578 | 0.3028 | 1.09 | 0.2772 |
| Co_state | 0.2263 | 1.76 | 0.0779 | 0.2318 | 1.77 | 0.0761 | 0.0701 | 0.58 | 0.5633 | 0.0822 | 0.67 | 0.5051 |
| Hot_mkt | 0.8240 | 5.17 | <0.0001 | 0.8224 | 5.15 | <0.0001 | 0.6046 | 4.02 | <0.0001 | 0.6008 | 3.98 | <0.0001 |
| Mntrfee | 0.3898 | 1.80 | 0.0716 | 0.3860 | 1.78 | 0.0753 | 0.3615 | 1.77 | 0.0769 | 0.3532 | 1.72 | 0.0849 |
| IndpnVC | 0.1544 | 0.91 | 0.3630 | 0.1555 | 0.92 | 0.3600 | 0.0961 | 0.60 | 0.5489 | 0.0986 | 0.61 | 0.5391 |
| Internet | 0.3013 | 2.36 | 0.0184 | 0.3030 | 2.37 | 0.0180 | −0.0576 | −0.48 | 0.6329 | −0.0538 | −0.45 | 0.6561 |
| Lambda | | | | 0.0971 | 0.23 | 0.8211 | | | | 0.2155 | 0.53 | 0.5951 |
| Number of observations | | 1407 | | | 1407 | | | 1407 | | | 1407 | |
| *F*-value | | 6.83 | | | 6.35 | | | 3.95 | | | 3.68 | |
| Pr < *F* | | <0.0001 | | | <0.0001 | | | <0.0001 | | | <0.0001 | |
| Adjusted *R*-square | | 0.0512 | | | 0.0505 | | | 0.0265 | | | 0.0260 | |

*Notes*. 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. "Syn" in the analysis with endogeneity control is the predicted probability of syndication estimated via a first stage probit. The dependent variables are the annualized exit multiple (ann_mltp) and industry-mean-adjusted abnormal multiples (abn_ann_mltp). See the definitions of explanatory variables in Appendix A.

**Table 9**
The effect of syndication on exit multiples by exit route.

| Independent variables | Without endogeneity control | | | With endogeneity control | | | Without endogeneity control | | | With endogeneity control | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Coefficient estimates | *t*-value | Pr > *t* | Coefficient estimates | *t*-value | Pr > *t* | Coefficient estimates | *t*-value | Pr > *t* | Coefficient estimates | *t*-value | Pr > *t* |
| | *Dependent variable = ann_mltp for acquisition* | | | | | | *Dependent variable = abn_ ann_mltp for acquisition* | | | | | |
| Intercept | 0.1361 | 0.19 | 0.8510 | 0.3334 | 0.38 | 0.7027 | −1.1217 | −1.64 | 0.1017 | −0.7490 | −0.91 | 0.3639 |
| Syn | 0.9858 | 2.37 | 0.0181 | 0.4525 | 0.33 | 0.7431 | 0.7728 | 1.97 | 0.0496 | −0.2347 | −0.18 | 0.8571 |
| Ind | 0.3861 | 0.75 | 0.4516 | 0.4753 | 0.85 | 0.3948 | −0.2665 | −0.55 | 0.5821 | −0.0980 | −0.19 | 0.8525 |
| Erly_stg | 0.6881 | 2.42 | 0.0158 | 0.6925 | 2.43 | 0.0153 | 0.5833 | 2.17 | 0.0302 | 0.5916 | 2.20 | 0.0281 |
| Ln(1 + Num_stg) | −0.4811 | −1.06 | 0.2896 | −0.3223 | −0.54 | 0.5913 | −0.2875 | −0.67 | 0.5026 | 0.0125 | 0.02 | 0.9824 |
| Late_stg | −0.1594 | −0.52 | 0.6015 | −0.1659 | −0.54 | 0.5874 | −0.1649 | −0.57 | 0.5671 | −0.1773 | −0.61 | 0.5391 |
| VC_ind | −0.4496 | −1.31 | 0.1896 | −0.4493 | −1.31 | 0.1902 | −0.6609 | −2.04 | 0.0414 | −0.6603 | −2.04 | 0.0416 |
| Ivst_bk | −0.1307 | −0.41 | 0.6810 | −0.0893 | −0.27 | 0.7893 | −0.1542 | −0.51 | 0.6075 | −0.0760 | −0.24 | 0.8097 |
| Str_stg | 0.3753 | 0.82 | 0.4123 | 0.3543 | 0.77 | 0.4422 | 0.1414 | 0.33 | 0.7435 | 0.1017 | 0.23 | 0.8152 |
| Co_state | 0.2234 | 1.01 | 0.3119 | 0.2403 | 1.07 | 0.2856 | 0.1811 | 0.87 | 0.3854 | 0.2129 | 1.00 | 0.3161 |
| Hot_mkt | 1.1365 | 4.34 | <0.0001 | 1.1301 | 4.30 | <0.0001 | 0.9316 | 3.76 | 0.0002 | 0.9196 | 3.71 | 0.0002 |
| Mntrfee | 0.1923 | 0.59 | 0.5525 | 0.1761 | 0.54 | 0.5898 | 0.2163 | 0.71 | 0.4795 | 0.1854 | 0.60 | 0.5475 |
| IndpnVC | 0.2533 | 0.78 | 0.4329 | 0.2581 | 0.80 | 0.4249 | 0.3076 | 1.01 | 0.3133 | 0.3166 | 1.04 | 0.2997 |
| Internet | −0.2106 | −0.96 | 0.3396 | −0.2037 | −0.92 | 0.3574 | −0.3713 | −1.78 | 0.0749 | −0.3583 | −1.72 | 0.0866 |
| Lambda | | | | 0.3400 | 0.41 | 0.6854 | | | | 0.6423 | 0.81 | 0.4176 |
| Number of observations | | 610 | | | 610 | | | 610 | | | 610 | |
| *F*-value | | 3.93 | | | 3.66 | | | 3.19 | | | 3.01 | |
| Pr > *F* | | <0.0001 | | | <0.0001 | | | 0.0001 | | | 0.0002 | |
| Adjusted *R*-square | | 0.0589 | | | 0.0576 | | | 0.0447 | | | 0.0441 | |
| | *Dependent variable = ann_mltp for IPO* | | | | | | *Dependent variable = abn_ ann_mltp for IPO* | | | | | |
| Intercept | 1.2525 | 2.65 | 0.0083 | 1.3645 | 2.18 | 0.0294 | 0.1293 | 0.29 | 0.7737 | 0.2446 | 0.41 | 0.6807 |
| Syn | 0.4488 | 1.83 | 0.0671 | 0.2096 | 0.23 | 0.8171 | 0.2522 | 1.08 | 0.2786 | 0.0060 | 0.01 | 0.9944 |
| Ind | 0.4836 | 1.70 | 0.0902 | 0.5054 | 1.71 | 0.0883 | 0.1224 | 0.45 | 0.6515 | 0.1449 | 0.51 | 0.6068 |
| Erly_stg | −0.1565 | −0.78 | 0.4346 | −0.1560 | −0.78 | 0.4363 | −0.0937 | −0.49 | 0.6225 | −0.0932 | −0.49 | 0.6245 |
| Ln(1 + Num_stg) | −0.7843 | −2.48 | 0.0133 | −0.7151 | −1.77 | 0.0775 | −0.6497 | −2.16 | 0.0309 | −0.5785 | −1.50 | 0.1329 |
| Late_stg | 0.1235 | 0.66 | 0.5093 | 0.1198 | 0.64 | 0.5235 | 0.0229 | 0.13 | 0.8977 | 0.0190 | 0.11 | 0.9151 |
| VC_ind | −0.4254 | −1.72 | 0.0850 | −0.4279 | −1.73 | 0.0836 | −0.5728 | −2.44 | 0.0148 | −0.5754 | −2.45 | 0.0144 |
| Ivst_bk | −0.0384 | −0.19 | 0.8505 | −0.0254 | −0.12 | 0.9032 | 0.0734 | 0.38 | 0.7046 | 0.0867 | 0.44 | 0.6627 |
| Str_stg | 0.4546 | 1.20 | 0.2308 | 0.4497 | 1.18 | 0.2367 | 0.3926 | 1.09 | 0.2761 | 0.3876 | 1.07 | 0.2832 |
| Co_state | 0.1478 | 0.97 | 0.3314 | 0.1554 | 1.00 | 0.3153 | −0.0871 | −0.60 | 0.5469 | −0.0793 | −0.54 | 0.5897 |
| Hot_mkt | 0.4152 | 2.12 | 0.0340 | 0.4132 | 2.11 | 0.0351 | 0.2227 | 1.20 | 0.2311 | 0.2206 | 1.19 | 0.2361 |
| Mntrfee | 0.7657 | 2.55 | 0.0108 | 0.7664 | 2.55 | 0.0108 | 0.6618 | 2.32 | 0.0204 | 0.6625 | 2.32 | 0.0204 |
| IndpnVC | 0.0803 | 0.43 | 0.6670 | 0.0825 | 0.44 | 0.6589 | −0.0488 | −0.28 | 0.7833 | −0.0465 | −0.26 | 0.7935 |
| Internet | 0.7737 | 5.08 | <0.0001 | 0.7755 | 5.09 | <0.0001 | 0.2765 | 1.91 | 0.0562 | 0.2784 | 1.92 | 0.0550 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Lambda | | 0.1330 | 0.27 | 0.7840 | | 0.1369 | 0.30 | 0.7665 |
| Number of observations | 797 | | 797 | | 797 | | 797 | |
| $F$-value | 5.32 | | 4.94 | | 2.10 | | 1.95 | |
| Pr > $F$ | <0.0001 | | <0.0001 | | 0.0124 | | 0.0188 | |
| Adjusted $R$-square | 0.0659 | | 0.0648 | | 0.0176 | | 0.0165 | |

*Notes*. 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. "Syn" in the analysis with endogeneity control is the predicted probability of syndication estimated by a first stage probit. The dependent variables are the annualized exit multiple (ann_mltp) and industry-mean-adjusted abnormal multiples (abn_ann_mltp). See the definitions of explanatory variables in Appendix A. Results are provided broken down by IPO and by ACQ (acquisition) routes.



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multiples on acquisition come from better project choice by VC syndicates and not from value-added after selection. This evidence is consistent with the finding reported in Table 8. Multiples for exit by IPO closely mirror those by acquisition, implying that VC syndicates do not impact the exit multiple for IPOs after correcting for endogeneity. This evidence also is consistent with the finding reported in Table 8. To the extent that our sample of annualized exit multiples from the VentureXpert database properly represents the entire population of exit multiples, the evidence based upon the endogeneity adjustment is consistent with the selection hypothesis rather than the value-add one.

To gauge the representativeness of our sample, we conduct out-of-sample forecasts of exit multiples. We use out-of-sample data for firms that did not report exit valuations, but for which the fact of syndication or non-syndication is reported. We applied the estimated models to the variables of these firms to see whether the expected (forecast) annualized multiples of these firms is higher for ventures that were syndicated relative to those that were not. The results shown in Table 10 imply that syndicated firms have a forecast multiple that is much higher. The mean annualized multiple is 1.98 versus 1.35 for non-syndicated firms, and the difference is highly significant.

### *4.4. Robustness test*

As a robustness check we examine the same questions as we asked before, but restrict the sample to first round financings. We rerun the probit analysis for the determinants of syndication to see if the coefficients on the explanatory variables that we used change with the first round only sub-sample in comparison to the full sample containing all financing rounds. In the first round only sub-sample analysis, Erly_stg, Late_stg, and Num_stg are not included. Since no investment bank is a lead VC for the first-round investment, Ivst_bk is also not included in the first-round analysis. The result is reported in Table 11, Panel A, and correspond to the Model (3) estimated in Table 5. We can see that the selection model is a robust specification that applies to first-round financings. Though positive, we find that the coefficient on the network density is insignificant. The coefficient on entropy and corporate VC investment proportions are significant with the same signs as in Table 5.

Next, we also evaluate the models for syndication performance for first rounds, redoing the analyses for all three performance metrics, i.e., exit probability, time-to-exit, and exit multiple. Table 11, Panel B presents the signs of the coefficients on the syndication dummy for these analyses, that relate to the models estimated in Tables 6–9. The results are consistent irrespective of whether we estimate the models for all rounds, or the first round only. Insignificant coefficients in the exit multiples regressions with industry adjusted abnormal multiples are most likely on account of the smaller sample sizes.

## 5. Conclusions

Using an effort-sharing framework, we undertake a comprehensive examination of 98,068 financing rounds of U.S. venture firms from Thomson Financial's Venture Economics (VentureXpert) database (1980–2003). Risk sharing, portfolio diversification, resources, capital constraints, and VC's skills, and specialty are found to be important rationales behind VC syndication. We complement and extend the existing literature by analyzing the performance of syndicated ventures not only using returns (i.e., exit multiples), but also using exit likelihood and the speed of exit. Hence, we provide a three-way metric for assessing the benefits of syndication. Our results attribute improved multiples to the selection efforts of the syndicate, and more likely and timely exit to value-addition along with selection effort. Therefore, using multiple metrics of performance shows that the two canonical hypotheses in the literature overlap and that the role of VC syndicates is multifaceted.

One caveat is that a significant relation between syndication and our performance metrics does not necessarily imply that any VC 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 versus related costs of syndication. A future study with better data may be able to examine the choice against syndication.

**Table 10**
Out-of-sample forecasts of exit multiples for syndicated and non-syndicated firms.

| Variable | *N* | Mean | Median | Std dev. | 25th Pctl | 75th Pctl | *t*-value | Pr > \|*t*\| | *t*-test *t*-value syn = 0 versus 1 | *t*-test *p*-value syn = 0 versus 1 |
|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Expected annualized multiples calculated with parameter estimates obtained from regressions without treatment effect control* | | | | | | | | | | |
| Non-syndicated | 23,782 | 1.3472 | 1.3608 | 0.6370 | 0.9206 | 1.8571 | 326.16 | <0.0001 | −129.14 | <0.0001 |
| Syndicated | 58,120 | 1.9781 | 1.9902 | 0.6338 | 1.5232 | 2.4348 | 752.46 | <0.0001 | | |
| *Panel B: Expected annualized multiples calculated with parameter estimates obtained from treatment effect controlled regressions* | | | | | | | | | | |
| Non-syndicated | 23,782 | 1.3822 | 1.4048 | 0.6386 | 0.9517 | 1.8776 | 333.76 | <0.0001 | −123.01 | <0.0001 |
| Syndicated | 58,120 | 1.9859 | 2.0009 | 0.6350 | 1.5322 | 2.4476 | 753.94 | <0.0001 | | |

*Notes*. We applied our estimated model for exit multiples to firms for which we did not have exit multiples, but for whom we had knowledge of whether they were syndicated or not. Since we have already established that firms with syndication generate higher annualized (return) multiples, we expect that the expected multiples from our model should be higher for syndicated firms that we did not use in the original model. We verified these results for models with and without endogeneity corrections.

**Table 11**
First round only results.

| Independent variables | Coefficient estimates | Chi-square | Pr > Chi-square |
|---|---|---|---|
| *Panel A: Determinants of syndication* | | | |
| Intercept | −2.3042 | 2427.13 | <0.0001 |
| Ind | 0.3980 | 597.72 | <0.0001 |
| VC_intN | −0.2319 | 118.23 | <0.0001 |
| VC_indf | −0.0140 | 0.68 | 0.4104 |
| Ln(1 + Rd_ivst) | 0.2436 | 2953.96 | <0.0001 |
| Ln(1 + VC_numC) | 0.0772 | 402.48 | <0.0001 |
| VC_ind | 0.0643 | 6.50 | 0.0108 |
| Str_stg | −0.0772 | 11.83 | 0.0006 |
| CVC | 0.1538 | 19.03 | <0.0001 |
| Co_state | 0.1347 | 43.95 | <0.0001 |
| VCstate | 0.1696 | 53.30 | <0.0001 |
| Asymden_MSA | 0.0093 | 0.51 | 0.4732 |
| Entropy_MSA | −0.0518 | 50.01 | <0.0001 |
| CVC_ivst_MSA | 0.8603 | 66.02 | <0.0001 |
| Hot_mkt | −0.0973 | 38.92 | <0.0001 |
| Log likelihood | | −20,723 | |
| Wald Chi-square | | 5301 | |
| Pr > Wald Chi-square | | <0.0001 | |
| Cox and Snell *R*-square | | 0.1616 | |
| Nagelkerke Max-rescaled *R*-square | | 0.2155 | |
| Number of observations | | 34,267 | |
| *Panel B: Coefficient on "Syn" in performance analyses* | | | |
| Exit probability | | | |
| Exit_1 | Without endogeneity control | | + |
| | Biprobit | | + |
| Exit_2 | Without endogeneity control | | + |
| | Biprobit | | + |
| ACQ | Without endogeneity control | | + |
| | Biprobit | | + |
| IPO | Without endogeneity control | | Insignificant |
| | Biprobit | | + |
| Time-to-exit | | | |
| *Hazard model analysis* | | | |
| Exit_1 | Without endogeneity control | | >1 |
| | With endogeneity control | | >1 |
| Exit_2 | Without endogeneity control | | >1 |
| | With endogeneity control | | >1 |
| ACQ | Without endogeneity control | | >1 |
| | With endogeneity control | | >1 |
| IPO | Without endogeneity control | | >1 |
| | With endogeneity control | | >1 |
| *Tobit analysis* | | | |
| Exit_1 | Without endogeneity control | | – |
| | With endogeneity control | | – |
| Exit_2 | Without endogeneity control | | – |
| | With endogeneity control | | – |
| ACQ | Without endogeneity control | | – |
| | With endogeneity control | | – |
| IPO | Without endogeneity control | | – |
| | With endogeneity control | | – |
| *OLS analysis* | | | |
| Exit_1 | With endogeneity control | | – |
| Exit_2 | With endogeneity control | | – |
| ACQ | With endogeneity control | | – |

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**Table 11** (*continued*)

| *Panel B: Coefficient on "Syn" in performance analyses* | | |
|---|---|---|
| IPO | With endogeneity control | – |
| Exit multiples | | |
| *ann_mltp as a dependent variable* | | |
| All | Without endogeneity control | + |
| | With endogeneity control | Insignificant |
| ACQ | Without endogeneity control | + |
| | With endogeneity control | Insignificant |
| IPO | Without endogeneity control | + |
| | With endogeneity control | Insignificant |
| *abn_ann_mltp as a dependent variable* | | |
| All | Without endogeneity control | + |
| | With endogeneity control | Insignificant |
| ACQ | Without endogeneity control | Insignificant |
| | With endogeneity control | Insignificant |
| IPO | Without endogeneity control | Insignificant |
| | With endogeneity control | Insignificant |

*Notes*. In order to assess the robustness of our results, we rerun all the empirical analyses with first-round venture investment only. We report results for the first pass of the regression in which the determinants of syndication are established in Panel A, and results for the second pass, wherein performance metrics for (a) exit multiples, (b) time-to-exit, and (c) probability of exit are assessed, in Panel B. For compactness of exposition in Panel B, we report the signs of the coefficients on Syn, so that ease of comparison across models is also enhanced. Panel A relates to the empirical results in Table 5. Panel B relates to the results in Tables 6–9. In the first round only analyses, Erly_stg, Late_stg, and Num_stg are not included. Ivst_bk is also not included because no investment bank is a lead VC for the first-round investment.

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 is not definite about the relative importance of the selection explanation or the value-added hypothesis in explaining syndicated venture performance, our results show that selection contributes to the magnitude of exit multiples and value-add after selection contributes to the probability and speed of success. We liken this to VC syndicates uncovering diamonds in the rough, and then polishing them to success.

## Appendix A. Variable definitions

We present here the variables used in all the analyses in the paper, so as to make referencing the Tables easier.

- ann_mltp = annualized multiples.
- Cap_mgt = The lead VC's capital under management in all ventures.
- Co_age = The age (in years) of the venture since its founding to the financing round.
- Co_state = A dummy variable taking a value of 1 if the firm is based in California, and 0 otherwise.
- CVC = A dummy variable taking a value of 1 if the lead VC is a corporate VC, and 0 otherwise.
- Erly_stg = A dummy variable taking a value of 1 if the company is in 'early' or 'seed' stage, and 0 otherwise.
- Exit_1 = A dummy variable taking a value of 1 if exited through IPO, Acquisition, or LBO, and 0 otherwise.
- Exit_2 = A dummy variable taking a value of 1 if exited through IPO or Acquisition, and 0 otherwise.
- Exit_ACQ = A dummy variable taking a value of 1 if exited through Acquisition, and 0 otherwise.
- Exit_IPO = A dummy variable taking a value of 1 if exited through IPO, 0 otherwise.
- Hot_mkt = A dummy variable taking a value of 1 if the year of the financing round belongs to 1983–1999 or 1995–2000, and 0 otherwise.

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- Ind = A dummy variable taking a value of 1 if the company is in information technology or biotech industry, and 0 otherwise.
- IndpnVC = A dummy variable taking a value of 1 if the lead VC is independent VC, 0 otherwise.
- Internet = A dummy variable taking a value of 1 If the venture's business is internet-related, 0 otherwise.
- Ivst_bk = A dummy variable taking a value of 1 if the lead VC is an investment bank, and 0 otherwise.
- lambda = inverse Mill's ratio estimated from the first stage probit model of syndication choice, separately for syndicated and non-syndicated rounds.
- Late_stg = A dummy variable taking a value of 1 if the stage of financing is late stage, 0 otherwise.
- Mntrfee = A dummy variable taking a value of 1 if there exist monitoring fee or advising fee for lead VC, 0 otherwise.
- Num_stg = The cumulative number of stages including the current round.
- Rd_ivst = The total amount invested in the round.
- Str_stg = A dummy variable taking a value of 1 if the stage of the financing round is the same as that of the stage preferences of the lead VC, and 0 otherwise.
- Syn = A dummy variable taking a value of 1 if at least one round including the current round is syndicated, and 0 otherwise.
- VC_ind = A dummy variable taking a value of 1 if the lead VC is an industry specialist whose preferred industry is also the same industry category in which the firm resides, and 0 otherwise. The lead VC is the investor whose cumulative investment including the current round is the greatest.
- VC_indf = A dummy variable taking a value of 1 if the lead VC is a generalist and has no specific industry focus, and 0 otherwise.
- VC_intN = A dummy variable taking a value of 1 if the lead VC is an international VC, and 0 otherwise.
- VC_numC = The number of companies that the lead VC has invested in.
- VCstate = A dummy variable taking the value of 1 if the VC is from California, and 0 otherwise.
- *Asymden_MSA*: The proportion of all logically possible ties among incumbents that are present in the market, calculated from directed networks (i.e., conditioning on lead versus syndicate participant ties) using metropolitan statistical areas as the market definition.
- *Symden_MSA*: The proportion of all logically possible ties among incumbents that are present in the market, calculated from undirected networks using metropolitan statistical areas as the market definition.
- *Asymden_State*: The proportion of all logically possible ties among incumbents that are present in the market, calculated from directed networks using states as the market definition.
- *Symden_State*: The proportion of all logically possible ties among incumbents that are present in the market, calculated from undirected networks using states as the market definition.
- *Entropy_MSA*: The entropy of the number of investments per zip code area in the market defined based on metropolitan statistical areas. This variable measures the opportunity for more frequent interaction among the VCs in the local MSA market.
- *Entropy_State*: The entropy of the number of investments per zip code area in the market defined based on states. This variable measures the opportunity for more frequent interaction among the VCs in the local state market.
- *CVC_ivst_MSA*: The fraction of dollars invested by corporate VCs in the market defined based on metropolitan statistical areas.
- *CVC_ivst_State*: The fraction of dollars invested by corporate VCs in the market defined based on states.

## Appendix B. Calculating multiples

Our approach to calculating multiples is best explained with a simple example. We assume that the first-round investors start the firm with an investment of 10. Then there is a second round where the new investment is 20, with an ex-post valuation of 50. And finally, there is an IPO round at which new money of 30 is invested and the valuation at IPO is 120. The sequence of rounds is depicted in the following table:

| Round | New investment | Post-money valuation | Investor in round 1 | Investor in round 2 | Investor in round 3 |
|---|---|---|---|---|---|
| First | 10 | 10 | 100% | – | – |
| Second | 20 | 50 | 60% | 40% | – |
| Third/IPO | 30 | 120 | 45% | 30% | 25% |
| Cash-in | | | 10 | 20 | 30 |
| Cash-out | | | 54 | 36 | 30 |
| Multiple | | | 5.4 | 1.8 | 1.0 |

1. The first-round investment is 10, and so, the first-round investors own 100% of the company at the end of the first round.
2. The second-round financing is 20 with a post-money valuation of 50. The second-round investors paid in 20 and their stake is $20/50 = 40\%$. Therefore, the shares of ownership at the second round are 60% (first-round investors) and 40% (second-round investors).
3. At IPO, the company raised extra capital of 30 from third-round investors. The IPO is sold at 120. Therefore, the third-round investors own $30/120 = 25\%$ of the company. The remaining 75% of the firm is shared by the first-round and second-round investors in the ratio of 60:40, respectively. Hence, the share of the first-round investors at IPO is $60\% \times 75\% = 45\%$. The share of the second-round investors is $40\% \times 75\% = 30\%$. The total shares of investors in the first, second and IPO rounds is 45%, 30%, and 25%, respectively. In cash terms, their shares are 54, 36, and 30, respectively.
4. Finally, the multiples may be computed on a "cash-in, cash-out" basis, i.e., divide the cash-out amount for each investor by the amount invested. This is shown in the table above and leads to multiples of 5.4, 1.8, and 1.0, respectively, for the three rounds of investors.

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