Option to Abandon, Syndication and Investment Return*

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Keyword: Abandonment Option, Lumpy Projects, Syndicate Size, Return on investment, Firm performance;

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Abstract

The extant literature posits that investment reversibility and increased volatility of the option to abandon increases investment returns. We show that this result doesn't hold for lumpy project with multiple investors, and that investment irreversibility and/or decreased volatility of the option to abandon can increase ex-ante investment returns. Since increasing an investor's commitment helps to increases the likelihood of project success, such commitment exerts a positive externality on other investors' welfare. These effects imply that the optimal number of investors is either large or very small. We test this prediction using data on private equity acquisitions deals that can be executed by a single investor or syndicates of more investors. Supporting the model, we find a strong convex relationship between the investment performance and the size of the syndicate. Our model and results contribute to the debate on the consequences of the shifting allocation of assets from public to private markets.

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1 Introduction

The cost of an irreversible investment cannot be recovered once it is put to use. This constraint raises the threshold for positive NPV investments. The threshold return that justifies an irreversible investment increases with uncertainty. Irreversibility constrains the ability to redeploy capital in "bad" states, so the agent is particularly sensitive to these states when investing ex-ante.[1]

This paper studies investment returns to lumpy projects with multiple investors. Each investor's commitment to complete the project increases the likelihood of project completion and therefore exerts a positive externality on other investors' payoffs. We show that this interdependence leads to two counter-intuitive results. First, a rise in the cost of abandoning the project (or irreversibility) can increase investors' payoffs. This finding departs from the existing result that investment irreversibility (defined here as a high abandonment cost) decreases returns (see e.g., Pindyck, 1991). Second, decreased volatility of abandonment options can increase returns. This departs from the existing finding that option volatility increase returns (see e.g., Angelis, 2016; Dixit and Pindyck, 1995; Pindyck, 1988). Finally, the optimal number of investors is either very large or very small.

[1]The The role of uncertainty in delaying investment decisions was formally addressed in Bernanke (1983). McDonald and Siegel (1986) article on "The Value of Waiting to Invest" provides the first explicit valuation of investment allowing for irreversibility, incorporating option valuation (real options) into investment theory.

The intuition behind the first two results is that the option to abandon the project has two opposing effects. On one hand, each investor's abandonment option increases her payoff. On the other hand, the fact that other investors may abandon the project increases the likelihood of project failure. We show that the second effect can dominate and a rise in abandonment costs or falling option volatility can, therefore, help investors. The intuition for the third result is that, when there are only a few large investors relative to many small investors, each investor can significantly influence the project success likelihood and requires a smaller number of the remaining investors to commit to the project funding. In addition, if the project underfunded the statistical expectation sense, the law of large numbers decreases the success likelihood and it is better to increase the variance the committed investor share by decreasing the investor count.

Our model implies three empirical predictions, the first of which is directly testable. First, looking at investor base in large projects a seemingly natural expectation is that a wider investor base offers more stable funding than a narrow base (see e.g., Demirgue-Kunt and Detragiache, 2002; Petersen and Rajan, 1994). However, our model predicts a curvilinear relationship indicating that stable funding is more likely to be provided by either very small or large investor bases. Second, volatile returns to small investments can discourage large projects as investors stop trusting each other's commitments. Third, increasing the legal or regulatory costs of disinvesting (abandoning projects) can increase returns and investment levels. For example, a tax on foreign capital outflows can increase capital inflows (see e.g., Dooley, 1996).[2].

The first model implication finds a testable empirical setting in Private Equity (PE) deals that have some desirable identification properties: first, PE deals can be executed by either a single investor or by a syndicate of 2 or more allowing us to directly relate investor base and returns while controlling for investment-level characteristics. Second, investments have an inherently finite life due to the closed-end nature of financial sponsors. This implies that we can compute the complete return of an investment. Third, the investor base in PE-backed deals essentially never changes throughout the deal minimizing possible confounding effects. Our tests strongly support the model predictions and deliver two additional important contributions. First, we directly test the effect of syndication in PE deals which has remained elusive in the literature. Second we contribute to the ongoing debate about private vs public markets[3] which has been sparked by the massive shift in asset allocation, in particular from regulated institutional investors, from public to private markets. From 2012 to 2018 the growth in the share of assets managed by institutional investors and allocated to private markets has grown from 3 to over 10% and is expected to exceed 15% in the next 3 years (see Preqin (2018)). With institutional investors assets estimated at

[2]Conversely, if financial development decreases disinvestment costs it can fail to promote investment.

[3]E.g. https://www.ft.com/content/7ce1ee52-2b0e-11e9-88a4-c32129756dd8

over 70 trillion (Forum (2014)), this represents a growth from less than 2 to over 10 trillion dollars allocated to asset classes where illiquidity is allegedly compensated by higher returns. However, the realized and expected growth of the private sector assets has lead to a heightened competition for deals that often translates into syndication. A better knowledge of the effects on investment returns of different compositions of the investor base has therefore widespread normative and policy implications in the light of the social and welfare relevance of institutional investors.

Differently, identification for the second and third predictions is substantially harder. In order to test the second prediction, one would need to obtain the true ex-ante volatility of investments and the proposed composition of the investor base which are both largely not publicly available. A testing possibility could be offered by accessing the complete proposed deal flow to an investor, but unfortunately, this is private information rarely available to researchers. The third prediction would require collecting a sequence of regulatory changes affecting the cost of abandoning a project. Typically this kind of data is available in a multi-country setup which would severely affect the reliability of the tests given the much larger number of known and unknown possible covariates.

The paper is related to the classical bank run model of (see e.g., Diamond and Dybvig, 1983).[4] In both papers investors (or depositors in DD83)

[4]Henceforth, we will denote this paper as DD83.

receive independent and privately observed liquidity shocks at an intermediate date. They then decide whether to abandon the project in which they invested initially. The papers differ in four respects. First, DD83 assumes a large number of investors and can, therefore, apply the law of large numbers. This paper allows for an arbitrary number of investors. Second, the debtor in DD83 divides its funds optimally between long and short term projects. In contrast, we study an indivisible long term project. Third, we ask how changes in liquidation costs and the distribution of the investors' liquidity shocks' at the interim date affect returns. The depositors in DD83 the depositors have a zero liquidation cost and the law of large numbers makes the proportion of the high liquidity cost draws perfectly predictable. Absent a bank run, therefore, the financial intermediary can choose exactly the right reserve or short-term lending stock to service the early loan recalls and avoid liquidity problems. Fourth, DD83 focuses on how investor panics can cause a "run" on projects before they mature. In contrast, we abstract from classic investor runs by assuming that the investors coordinate on the most efficient incentive-compatible strategy profile (see e.g., Iyer and Puri, 2008).

The paper also relates to the literature on the optimal number of creditors. However, most of these papers draw on principal-agent theory and we abstract from agency problems.[5] Most closely related, Demirgue-Kunt and

[5]For example, if having more creditors promotes free-riding or hold-outs in debt negotiations, then increasing the number of creditors should increase the cost and the managerial incentive to avoid corporate distress Berglof et al. (2002); Bolton and Scharfstein

Detragiache (2002) show that firms may prefer a wide lender base to ensure funding in case some lenders withdraw. Investors are therefore able to "step in" for each other and act as substitutes in project financing. In this paper in contrast, since each investor has limited funds, they act as complements.

The paper proceeds as follows. In Section 2 we present the model, we derive the return-maximizing solution, show that higher abandonment costs and more volatile outside options, respectively, can decrease investment returns and we determine the optimal number of creditors. In section 3 we present the empirical analysis of the testable implications. In section 4 we conclude.

2 Model

2.1 Preliminaries

There is a single lumpy project of size one with $n > 2$ potential and symmetric investors. The sequence of events is the following. First, each investor provides $1/n$ funds to finance the project. Second, investors observe the project

(1996); Padilla and Pagano (1997); Preece and Mullineaux (1996); Shleifer (2003). Alternatively, increasing the number of lenders can commit them not to form a cartel and extract the manager's rent later on, which should improve the manager's effort incentive Godlewski and Ziane (2008); Guiso and Minetti (2004); Rheinbaben and Ruckes (2004); Sharpe (1990).

return,

$$R = \begin{cases} \bar{R} + \phi & \text{w.p. } 1/2; \\ \bar{R} - \phi & \text{w.p. } 1/2. \end{cases} \tag{1}$$

where both $\bar{R}$, $\phi > 0$ and $\bar{R}$ measures the average investment return and ϕ measures investment return uncertainty.

Third, each investor privately observes a liquidity shock, which gives her an opportunity cost of funds,

$$\rho_i = \begin{cases} \rho + \sigma & \text{w.p. } 1/2; \\ \rho - \sigma & \text{w.p. } 1/2. \end{cases} \tag{2}$$

where the mean liquidity shock is ρ and σ is a mean-preserving spread.

Fourth, each investor decides whether to abandon the project at a cost of c per unit of funds invested. Midway-abandonment of projects can be costly for the investors because the project's assets are typically illiquid.[6] Investors who abandon the projects midway gets return, $\rho_i - c$. Investors who do not abandon the project get R if the project is completed, and otherwise they get nothing. We focus on symmetric equilibrium. Finally, to limit the number of cases we assume the following:

A1. $\bar{R} + \phi > \bar{\rho} + \sigma - c$;

A2. $\min[\bar{R}, \frac{\bar{R}+\phi+\bar{\rho}-c}{2}] \geqslant \bar{\rho}$;

[6]See, for example, (Shleifer and Vishny, 1992) for discussions on asset fire sale.

A3. Whenever an equilibrium with project funding exists it is accepted.

$A1$ implies that investors would like to complete good projects even with a high liquidity cost. $A2$ ensures that positive NPV projects are funded or "not bad" projects are not abandoned. $A3$ rules out investor "runs" where investors would be better off not running away from the project. We show below that there is at most one equilibrium with funding.

Finally, following Bris and Welch (2005) paper we assume that each investor has a quantity of funds f, which satisfies $1/n \leqslant f \leqslant 1/2$. This condition implies that the project can only be completed if $1/f$ or more investors commit. If $f = 0.2$, then at least five investors must commit so that the project can be undertaken. For simplicity, $1/f$ is assumed to be an integer.[7]

2.2 The Return-maximizing solution

Once the model's uncertainty has been resolved, consider any realized return R and a specific draw of liquidity costs, ρ_1, ρ_2, $\cdots$, ρ_n. Particularly, assume that m investors draw the high liquidity shock $\rho_h = \rho + \sigma$, and the rest $n - m$ investors draw the low liquidity shock, $\rho_l = \rho - \sigma$. $A1$ implies that all investors participates to fund a good project; hence, a bad project is also

[7]The assumption that the project requires at least two investors appears to be plausible in practice. Company start-ups, expansions, mergers and acquisitions, and research efforts, or instance, can be capital-intensive. In addition to the fact that each investor may have limited funds, it is also possible that, the investors may prefer a small funds commitments to diversify their portfolios due to risk-aversion or institutional restrictions (see e.g., Bris and Welch, 2005).

financed if

$$\bar{R} + \phi > \rho + \sigma - c. \tag{3}$$

If, instead, $R + \phi < \rho + \sigma - c$, then a bad project is financed if and only if

$$\max(n-m,\, {}^{1}\!/\!{}_{f})(\bar{R}-\phi)+(n-\max(n-m,\, {}^{1}\!/\!{}_{f}))(\rho_h-\phi) \geq m\,\rho_h+(n-m)\,\rho_l-c. \tag{4}$$

The left hand side of (1) is the sum of returns across investors when all low liquidity cost investors finance the project; the minimum number of high liquidity cost investors whose funds are also needed finance the project; and the remaining high liquidity cost investors pursue their outside return. The right hand side is the sum of all outside returns. Ex-ante return maximization can therefore involve that high liquidity cost investors subsidize low liquidity cost investors whenever ${}^{1}\!/\!{}_{f} > n-m$. However, this subsidy is not in the high liquidity cost investors' interest and will therefore not be paid in equilibrium.

2.3 Increasing the Liquidation Cost Can Increase Returns

Figure 1 graphs the return as a function of the liquidation cost. As long as $\bar{\rho} - \sigma - c > \bar{R} - \phi$ or $c \in [0, c_1]$ where $c_1 = (\bar{\rho} - \sigma) - (\bar{R} - \phi)$, which may be an empty range – the liquidation cost is small enough that all investors abandon bad projects. The return is, therefore,

$$\frac{\bar{R}+\phi+\bar{\rho}-c}{2} > \bar{R}+\frac{\sigma}{2}, \tag{5}$$

for all $c < c_1$.

Next, $\bar{\rho}+\sigma-c > \bar{R}-\phi > \rho-\sigma-c$ or $c \in [c_1,\, c_2]$ where $c_2 = (\bar{\rho}+\sigma)-(\bar{R}-\phi)$ high liquidity cost investors still abandon due to the first inequality. Low liquidity cost investors abandon if and only if $q(n)(\bar{R}-\phi) < \bar{\rho}-\sigma-c$, i.e.,

$$q < q_l = \frac{\bar{\rho}-\sigma-c}{\bar{R}-\phi}, \tag{6}$$

where $q(n) = \Pr($number of low liquidity costs investors $\geqslant {}^{1}/{}_{f}-1$. As long as c remains "close" to c_1 Equation 6 always holds: the right hand side remains close to one and the left hand strictly below one. For example, since with probability 0.5^{n-1} a low liquidity cost investor will be the only such investor we have $q < 1-0.5^{n-1}$. Thus for c close to c_1, the return remains $\frac{\bar{R}+\phi+\bar{\rho}-c}{2}$.

As c increases further q_l on the right hand side of Equation 6 declines, so sooner or later Inequality 6 no longer holds. The cost level at which this switch happens is denoted as c_2 and assume for now that high liquidity cost investors still abandon, i.e., $\bar{R}-\phi < \bar{\rho}+\sigma-c$. Then, the return after c_2 is

$$\frac{R+\phi}{2}+\frac{\bar{\rho}+\sigma-c}{4}+\frac{q\,(R-\phi)}{4} \tag{7}$$

Finally, once $\bar{R} - \phi > \rho + \sigma - c$ or $c > c_3 = \bar{\rho} + \sigma - (\bar{R} - \phi)$, even high liquidity cost investors do not abandon the project. The project is now for sure to be completed, so the return is simply $\bar{R}$. The jump in the return at c_3 is therefore,

$$\bar{R} - \left(\frac{R + \phi}{2} + \frac{\bar{\rho} + \sigma - c}{4} + \frac{q\,(R - \phi)}{4} \right) = (1 - q)\frac{(R - \phi)}{4} \tag{8}$$

This jump is the paper's first key result: increasing the abandonment cost around the threshold c_3 increases returns. Intuitively, the high abandonment cost commits high liquidity cost investors not to abandon the project and therefore benefits all investors ex-ante. The upward jump does contrasts Intuitively, the high abandonment cost commits high liquidity cost investors not to abandon the project and therefore benefits all investors ex-ante. The upward jump does contrasts however with the standard result that increased investment irreversibility (higher abandonment costs) deters investment (Pindyck 1991).

Figure 1 assumes that $c_3 > c_2$, that is, there is a range over which high liquidity cost investors abandon and low liquidity cost investors commit. Assume now alternatively that $c_3 < c_2$ or $2\,\sigma(1 - q)(R - \phi)$. Then the equilibrium goes straight from all investors abandoning to all committing and the jump in the return at c_3 equals $\sigma/2$.

Insert Figure 1 here

This is drawn in Figure 2. As before, the jump at c_3 implies that investment irreversibility can increase returns.

Insert Figure 2 here

2.4 Decreasing Option Volatility Can Increase Returns

As with a higher liquidation cost, less option volatility on one hand decreases the option value to abandonment for each investor. On the other hand, it can increase other investors' commitment. If the second effect dominates then returns will rise.

Figure 2 graphs the ex-ante return as a function of option volatility σ. As long as $\bar{\rho} + \sigma - c < \bar{R} - \phi$ or $\sigma \in [0, \sigma_1]$ where $\sigma_1 = (\bar{R} - \phi) - (\bar{\rho} - c)$ volatility is small enough that high liquidity cost investors do not abandon bad projects. Note that the set $[0, \sigma_1]$ may be an empty set. The return is therefore $\bar{R}$.

Next, in the range $\bar{\rho}+\sigma-c > \bar{R}-\phi$ or $\sigma > \sigma_1$ high liquidity cost investors abandon the project. Low liquidity cost investors only abandon the investment project if Equation (8) holds for some $q(n) = \Pr(\text{number of low liquidity cost investors} \geqslant \frac{1}{f} - 1)$. For σ "close" to σ_1 again the right hand side of Equation (8) is close to one and the left hand side strictly below one. Therefore all investors abandon bad projects and the return is . This is a lower return than before since . Intuitively, if for low volatility levels all investors commit, then a small rise in volatility can decrease returns by eroding high liquidity cost investors' commitment. This gives the paper's second key result: around option volatility a fall in volatility increases returns.

As σ increases further q_l on the right hand side of Equation (3) declines, so again sooner or later the inequality is reversed. Denote the volatility level at which this happens as $\sigma_2 = (\bar{\rho}-c)-q(\bar{R}-\phi)$. Since beyond σ_2 low liquidity cost investors commit the return becomes $\frac{(R+\phi)}{2}+\frac{(\bar{\rho}+\sigma-c)}{4}+\frac{q(R-\phi)}{4}$. For $\sigma > \sigma_2$, this return exceeds $\frac{(\bar{R}+\phi+\bar{\rho}-c)}{2}$. Intuitively, all investors get $\bar{R}+\phi$ for good projects; and for bad projects high liquidity cost investors get $(\bar{\rho}+\sigma-c)$, while low liquidity cost investors ensure $\frac{q(R-\phi)}{4} > (\bar{\rho}-\sigma-c)$ by committing to fund the project.

Insert Figure 3 here

Finally if the range $\sigma \in [0,\, (\bar{R}-\phi)-(\bar{\rho}-c)]$ is empty the return is as shown in Figure 4, and does not jump.

Insert Figure 4 here

2.5 The Optimal Number of Investors

As long as all investors commit or all abandon bad projects the total number of investors, n, is irrelevant. However, if potentially only low liquidity cost investors commit then the project success probability depends on the probability of having enough low cost investors, $q(n)$. If this function is increasing, then in Figure 1 as n rises the kink at $c_2 = (\bar{\rho} - c) - q(\bar{R} - \phi)$ moves left. Moreover, the return after c_2, which is $\frac{(R+\phi)}{2} + \frac{(\bar{\rho}+\sigma-c)}{4} + \frac{q(R-\phi)}{4}$, increases. Thus having more investors tends to increase returns if and only the probability of sufficient funding increases. We consider two cases.

First if the number of funds per investor, $1/f$, is constant, then having more investors always promotes completion (Detragiache et al. 2000). This follows since the likelihood of drawing at least low liquidity costs in Bernoulli trials increases with the number of trials. Second, suppose instead that the total supply of potential funds is fixed. For example, households in an economy may have a fixed amount of funds they are willing to tie up in, say, infrastructure projects. The question is then whether these funds are best supplied by a few large investors (financial intermediates for households) or many small investors. Thus, assume that total funds are $n\,f = t \geqslant 1$ and each investor has $f = t/n \leqslant \frac{1}{2}$ units. The last inequality ensures that, like before, at least two investors are needed.

Each investor's cost is drawn in a Bernoulli trial with success probability $p = 1/2$ and variance $p(1-p) = 1/4$, where p is the likelihood of drawing a low liquidity cost investor. The variance of the mean success rate across investors is $1/4n$, which decreases with the number of investors. Completing the project requires $1/f = nt$ successes in n Bernoulli trials or a success rate of ${}^{n/t}/n = 1/t$. Thus, if the mean success rate exceeds the required rate, or ${}^1\!/_2 \geqslant {}^1\!/_t$, which further implies that $t \geqslant 2$, then having more investors promotes success by decreasing fluctuations around the mean. Otherwise, if $t < 2$, then the project fails in expectation and fewer investors are optimal to increase the variance of the mean. For example with $t < 1.5$ and three investors (i.e., $n = 3$), each has units of funds and at least two thirds of investors must draw a low cost. With a large number of investors only half draw a low cost and bad projects are always abandoned. However, with for example three investors each low cost investor commits if $q(R - \phi) = \left((\frac{1}{2})^3 + 3\,\frac{1}{2}\,(\frac{1}{2})^2\right)(R - \phi) = \frac{1}{2}\,(R - \phi) > (\bar{\rho} - \sigma - c)$.

3 Empirical analysis

Our model main testable implication finds an ideal empirical setting in private equity deals that can be executed by single investors or syndicates of two or more PE firms (see e.g., Lerner, 1994). Syndication is a common investment practice in the PE industry that has attracted significant scholarly attention. On the one hand, it has been argued that syndication reduces risk and improves investment selection through information aggregation and resources and expertise sharing (see e.g., Hopp and Lukas, 2014; Hopp and Rieder, 2011; Lerner, 1994). Syndication also connects VC managers with other industry players, such as financial advisors, bankers, underwriters, accountants and lawyers (see e.g., Bygrave, 1987; Hochberg et al., 2007). However, syndication may also generate adverse effects due to higher costs of the management process ((see e.g., Wright and Lockett, 2003)) and strategic behavior by syndicate members. In the light of these conflicting predictions, the causal effect of syndication and of the syndicate size on investment performance has remained elusive. Given the large economic value and welfare effects of private equity (see for a comprehensive study and review Davis et al. (2014)), fitting our model to data on granular PE deals data may both validate our model and shed light on the effects of syndication performance.

3.1 Data and empirical design

Private equity research is notoriously characterized by the lack of reliable data on transactions that are by construction opaque. In fact, unlike mutual funds, most private equity funds are not subject to the disclosure requirements of the Investment Company Act, leading to a shortage of reliable data, both at the industry and, even more so, at the individual deal level. Such lack of accurate data substantially weakens the reliability and replicability of empirical results, which are largely based on self-reported, hand-collect, or proprietary datasets.

(Kaplan and Lerner, 2017) present a comprehensive analysis of data sources and highlight the accuracy and completeness of data collected by Burgiss, a provider of data analytics to the Private Equity industry. Burgiss grants access to its data for academic purposes to "proposals" evaluated by the Private Equity Research Consortium (PERC) an academics and practitioners initiative hosted by the UNC Keglar School of Business. Proposals are evaluated on merit and data availability in the form and structure required by the investigator(s). Unfortunately, Burgiss doesn't collect data at the single deal level and therefore performance and syndicate size information is not directly available.[8]. In such cases, (Kaplan and Lerner, 2017) recommend tunring to Thomson Venture Expert as a consistent alternative. We therefore extract data from Thomson ONE, the PE backed data platform of Refinitiv, a global provider of financial markets data. To empirically test our model, we search for PE backed exit buyout deals completed over the 20 year period ranging from January 1999 to June 2019.

The database includes deals exited through different routes: IPO, secondary sale, trade sale, and write-off. Over the sample period we identify 13,799 buyout deals. Out of this initial sample we impose two additional constraints: first that information about the syndicate size is unequivocally available. Second that entry and exit values are available to compute performance. This process unfortunately severely reduces the sample size to 413 deals for which data is complete and can be utilized in our tests. This sample size is aligned with that of established studies on this topic such as

[8]We have submitted a proposal and the formal response has been that Burgiss data is collected at the Limited partner level and aggregating it to estimate deal-level statistics is not currently possible. The proposal and response are available upon request

Phalippou and Gottschalg (2009) and Bonini (2015). Table 1 provides some sample descriptive statistics.

INSERT TABLE 1 HERE

The sample distribution across time is centered around two peaks immediately before and after the financial crisis but with a non-negligible density in most years. Given the possible idiosyncratic effects of general market performance in some particular years, in all regressions we will control for time fixed-effects. Looking at the size of the investment syndicate the number of firms/funds involved in the transactions included in our sample ranges from one to a syndication of 6 with four deals done by larger syndicates of 7, 8 and 10 members.

The untabulated industry distribution of the sample companies doesn't exhibit a substantial dominance of any single macro-sector. The majority of companies, 288, belong to "non-high technology" as per the Thomson ONE classification. About 25% of the deals target companies in the information technology sector and the balance is classified as medical/health industry.

In Table 2 we provide in Panel A summary statistics of the deals, and in Panel B some key correlation statistics.

INSERT TABLE 2 HERE

Entry values range from about 8 million for the bottom decile to over 900 million for the top decile with a mean of about 321 million which hints at the sample being possibly slightly skewed towards somewhat bigger deals. Similarly the average exit value about 640 million USD, spanning from 1.6 million for the bottom decile (which reflects the presence of several write-offs) to over 1.4 billion for the top decile. The average holding period for the deals in our sample is 4.93 years with top/bottom decile figures at 8approximately 8 and 3 respectively. These figures are aligned with the evidence in Braun et al. (2017) on a sample of over 13,000 transactions which provides additional validation to our sample. It's worth noting that Braun et al. (2017) report figures for a large sample of deals for the purpose of computing fund level performance. While their data allow the estimation of aggregate summary statistics they lack the deal level granularity required to test our model predictions. The main dependent variable in our analyses is deal-level performance that we compute as the Money-On-Money Multiplier (henceforth MoM), i.e. the ratio between Exit and Entry Enterprise Values, adjusted where possible for interim cash flows such as dividends, dividend recapitalizations and additional capital contributions. While we strived to identify all possible cash flows as accurately as possible, we reckon that Thomson data may fail to capture some intermediate distributions/contributions. We acknowledge this as a possible factor in our data collection exercise but we argue that the effects on performance should be relatively minor. Lastly we present figures for the performance metric. The Money on Money multiple average is above 8 with a bottom decile at 0 - consistent with the frequency of write-offs in the sample - and a top decile above 10. The relatively high average values if compared with the top decile threshold is indicative of the presence of a few outliers that may add skewness to the raw data. We alleviate this problem in our tests by adopting a common logarithmic transformation of the main dependent variable of the form $logMom = ln(MoM + 1)$. Taking logs helps also dealing with the fact that the main independent variable is a integers only, discrete one with gaps, that exhibits limited variation as it ranges from 1 to 10.

In panel B we present correlation statistics for the key explanatory variable and deal size and holding period and for deal size and performance. A possible concern in fact, could be that larger deals require the deployment of more capital and are more lengthy to manage thus being inherently more likely to be syndicated. This could potentially be the main driver of performance. Results show that there only exist a small, positive correlation of .19 that explains just about 3.7% of the variation, while there is no statistically significant correlation with the holding period. The raw correlation of performance with syndicate size is negative but insignificant. Given that we have identified a possible skewness we also present correlation statistics of size with a modified performance multiple that we obtain by right-winsorizing at the 1% level the original variable. The results are larger in magnitude and turn mildly significant. This result is consistent with Phalippou (2013) that highlight a marginally lower performance for larger deals. However the magnitude of the correlation is small and explains just about 1% of the total variation fro the winsorized variable. This evidence therefore largely mitigates possible model mis-specification concerns.

3.2 Empirical results

We test our main hypothesis by running a set of regressions of the buyout performance on the size of the syndicate. Our main dependent variable is the MoM multiplier described in the previous section and the main explanatory variable is the size of the investor syndicate measured as the number of different investors that jointly execute the buyout providing equity financing. Since our model predicts a U-shaped curvilinear relationship we construct a quadratic term of the size of the investor pool. In Figure 5 we plot the relationship between the MoM multiplier and the syndicate size [9].

INSERT FIGURE 5 HERE

The relationship between the investment performance and the size of the syndicate visually confirms the main empirical implications of our model showing that performance monotonically decreases with syndicate size reaching a minimum at 4 syndicate members but then inverts becoming increasing in the number of investors.

[9] Given that the observations with 7,8 and 10 syndicate members are singleton, for representation purposes we exclude them from the figure. All regressions however are run with the complete set of observations

In order to robustly confirm the graphical evidence we turn to more formal regression analyses where we also control for several possible covariates. It's worth noting that the MoM multiplier by construction is lower bound at 0 as a complete write-off would exhibit a zero exit value against a positive acquisition price. This is a classical case of data censoring that is best addressed by a Tobit model (Tobin (1958) rather than a standard OLS because the latter may lead to biased and inconsistent estimates (Wooldridge (2002)). We therefore estimate the following functional form:

$y^* = \alpha + \beta_1 N + \beta_2 N^2 + B\,\Xi + \epsilon$

where:

$y = y^*$ if $y^* \geq 0,\ y = 0$ if $y^* < 0$

N = number of syndicate members

N^2 = number of syndicate members squared

Ξ = a vector of controls

ϵ = error term $N(0, \sigma^2)$

Results are presented in Table 3.

INSERT TABLE 3 HERE

Panel A presents regressions including only positive realized exits, i.e. trade sales, secondary buyouts and IPOs. The first specification of the model includes the main explanatory variable, syndicate size, and its quadratic term and controls for time invariant effects. Parameters estimates are large and significant at the 1% level for the linear term and at the 5% level for the quadratic term confirming the model prediction. The computed vertex of the estimated equation is around 6 syndicate members and the effects are fully absorbed at a size of about 10, reflecting the diminishing value of the option to abandon when the pool of co-investors becomes large enough. In Models 2 and 3 we sequentially add the investment duration and the type of exit as covariates. Results are qualitatively unchanged.

Complete write-offs are relatively less common in later stage private equity backed buyouts than in Venture Capital deals. However, as documented by Degeorge et al. (2016) they still represent a non-negligible fraction of the outcomes for private equity funds with an average of about 13% of all investments. In Panel B we present regressions where we include in the sample write-offs for which an entry value is available. The parameter estimates are not surprisingly smaller but strongly significant. In models (2) and (3) we control for investment duration and the type of exit but similarly to previous results the effect of the former is insignificant while and the latter, while adding explanatory power, does not absorb the main effect. Phalippou (2013) and a recent white paper by Canterbury Advisory (CanterburyConsulting (2019)) a leading investment advisory firm have shown that deal size affects performance with larger deals generally offering lower but less volatile returns. Given that larger deals are more likely to be syndicated, our results may capture a size effect. In model (4) we control for deal size by adding size deciles dummies. The magnitude of the parameters estimates is only marginally smaller but significance is even stronger for both linear and quadratic terms. Inspection of the (unreported) parameters for the size bins is consistent with the results in Phalippou (2013). In Figure 6 we summarize these results plotting the marginal effects of the syndicate size on performance for models 1 and 3 in Panel A and 1 and 4 in Panel B. The model prediction of a U-shaped relationship is strikingly captured by the plots. Models estimated without write-offs exhibit a deeper trough but this is due to the fact that write-offs are uncorrelated with size and therefore somewhat smooth the estimates across all size bins.

As discussed in the previous section size might have an effect on performance. In Table 2 Panel B we have shown negative but limited correlation of performance with deal values which has motivated adding size controls in regression analyses. Given the potential importance of this concern we perform a further robustness test by running regressions on tercile sub-samples. If size is only mildly affecting performance then our regressions should exhibit diminishing magnitudes but preserve the overall explanatory power. Results presented in Table 4 support our conjectures with parameter estimates for syndicate size showing the same signs and, as expected, decreasing magnitudes, but significance qualitatively unchanged. These results allow confidence in our model specification and lend conclusive support to our theoretical model predictions.

INSERT TABLE 4 HERE

4 Conclusion

We analyze a project too large for a single investor, such as large acquisition or a scale expanding real investment. Since each investor's commitment to complete the project increases the likelihood of project completion it exerts a positive externality on other investors' return. Due to this fundamental interdependence we find that improving investors' value of the option to abandon the project, as well as including more investors at the outset, can either increase or decrease their payoffs. The model implies, first, that greater abandonment costs can increases investors' returns, which contrasts with existing results that higher degree of irreversibility decreases investment returns. Second, in contrast to prior literature which show that volatility raises option values and therefore returns to risk-neutral investors, we find that volatility can decrease returns by eroding each interdependent investor's project commitment. Third, either a few or large number of investors can be optimal depending on the project as well as the investors' characteristics. Model implications are strongly supported by empirical findings. Our main testable implication finds a near-perfect empirical setting in private equity deals that can be executed by a single investor or a syndicate of investors. We find that the relationship between the performance of a project and the size of the syndicate monotonically decreases with syndicate size, reaches a minimum but then inverts again becoming an increasing function in the number of investors. Our empirical results are further relevant also in two additional ways: first we provide for the first time a direct test of the effect of syndication in PE deals which has been largely overlooked in the literature. Second we contribute to the ongoing debate on the consequences of the staggering shift in asset allocation from public to private market that has determined a growth in assets under management by private equity funds to over 3 trillion dollars at the end of 2018[10], the majority of which contributed by regulated institutional investors such as pension and insurance funds. In the light of the substantial welfare effects of a contraction in returns for such investors, a better knowledge of the relationship between investment returns and the syndicate base has therefore widespread normative and policy implications.

[10] According to data in Preqin (2018)

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Figures

Figure 1: Return as a function of the liquidation cost if $c_3 > c_2$.

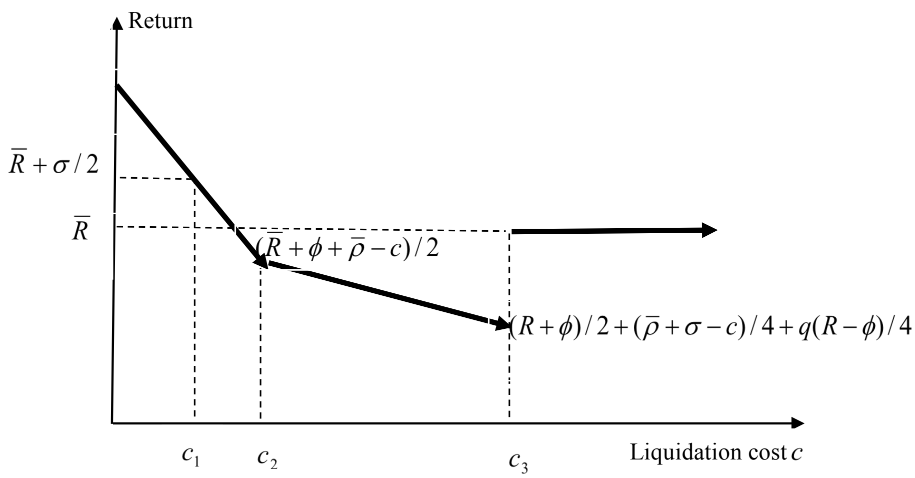

Figure 2: Return as a function of the liquidation cost if $c_3 \leqslant c_2$.

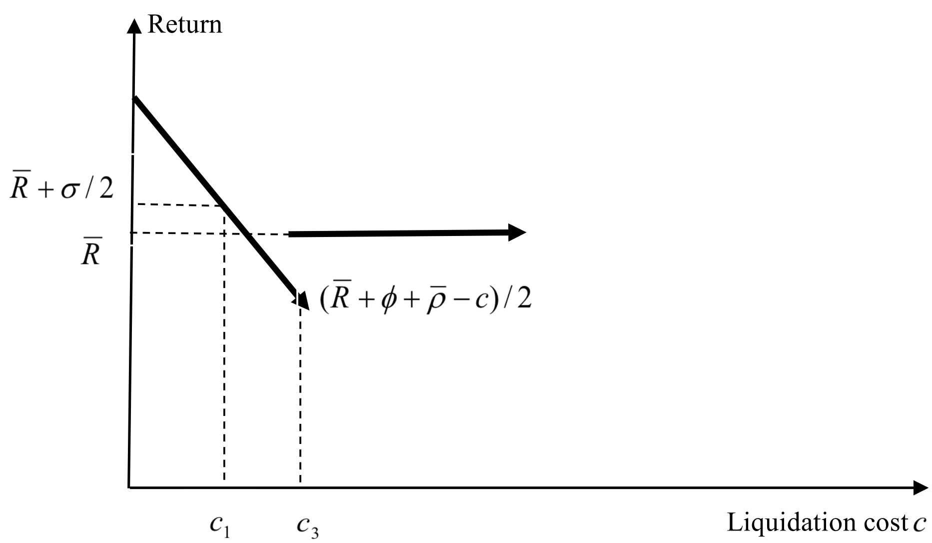

Figure 3: Return as a function of option volatility.

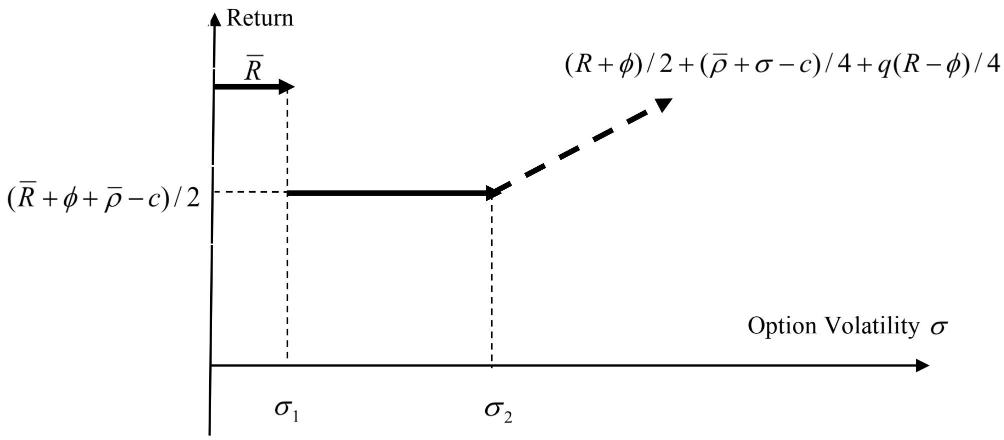

Figure 4: Return as a function of option volatility if $\sigma \in [0,\, (\bar{R}-\phi)-(\bar{\rho}-c)]$ is empty.

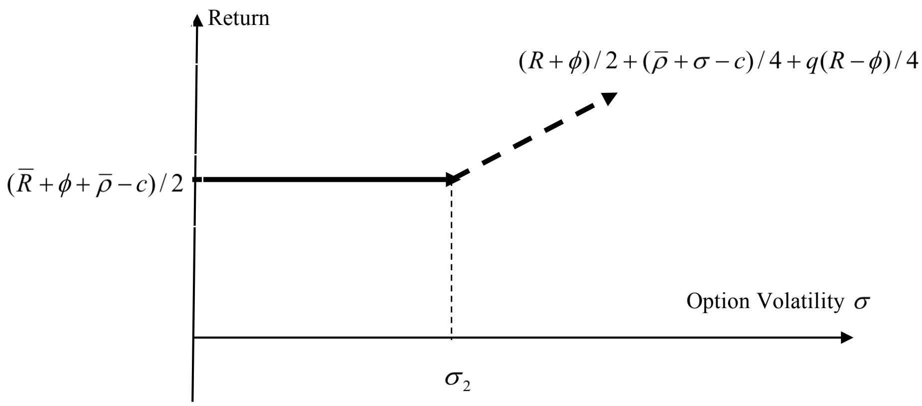

Figure 5: Private Equity backed Buyout Returns and Syndicate size

In this figure we plot the average log returns of the deals in our sample over the acquiror syndicate size

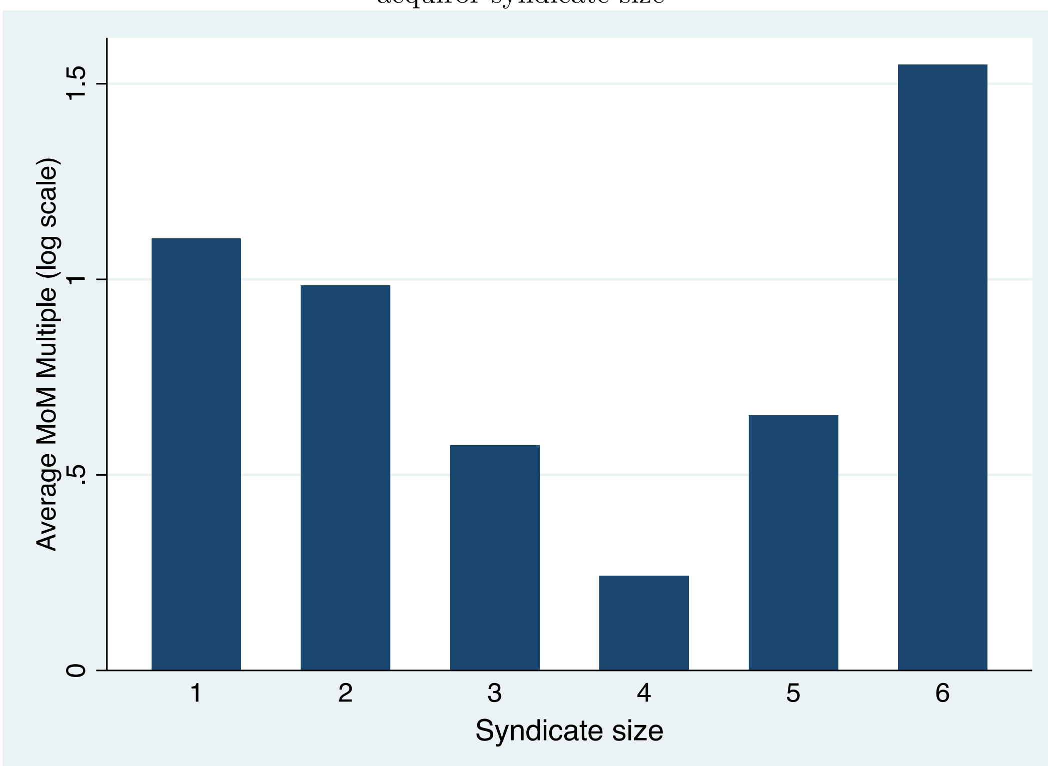

Figure 6: Estimated Marginal effects

In this figure we plot the estimated marginal effects of the syndicate size on performance measured as the Money-on-Money multiplier of the transaction in logarithm. Estimates are obtained from the models reported in Table 3, Panels A and B

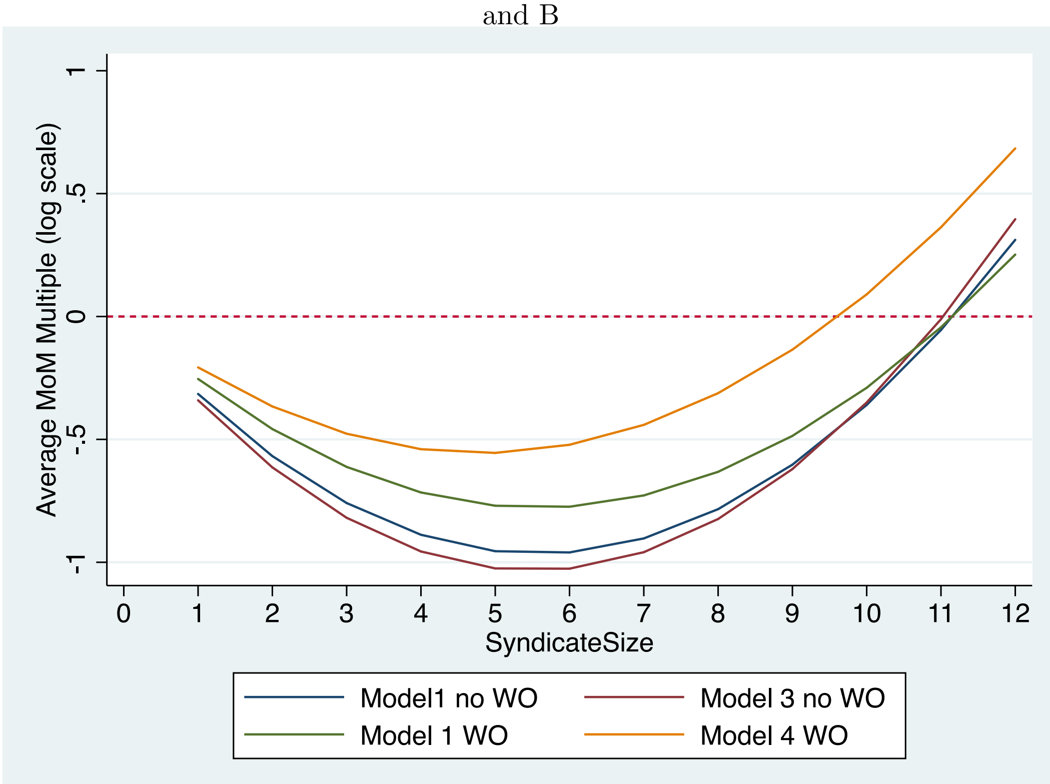

Table 1

Sample descriptive statistics

This table presents summary statistics for a sample of 413 completed buyouts during the period 1999-2019

PANEL A - Year distribution

Deal Completion Year	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	
No. of deals	1	2	3	5	8	26	41	65	41	14	
Percent	0.24%	0.48%	0.73%	1.21%	1.94%	6.30%	9.93%	15.74%	9.93%	3.39%	
	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Total
No. of deals	31	39	36	22	24	21	14	10	7	3	413
Percent	7.51%	9.44%	8.72%	5.33%	5.81%	5.08%	3.39%	2.42%	1.69%	0.73%	100%

PANEL B - Syndicate size

	No. of funds at investment date									
Exit Type	1	2	3	4	5	6	7	8	10	Total
IPO	0	0	1	0	0	0	0	0	0	1
Secondary Sale	175	113	51	21	6	3	1	2	1	373
Trade Sale	1	0	0	0	0	0	0	0	0	1
Write Off	15	13	6	2	1	1	0	0	0	38
Total	191	126	58	23	7	4	1	2	1	413

Table 2

Sample Summary Statistics

This table presents summary statistics for the main independent variables in the sample. Time to exit is the holding period calculated in years from the acquisition completion to exit; Entry and Exit Values are the deal Enterprise Values at acquisition and divestment in million of dollars; Money-on-Money Multiplier is the raw return computed as the ratio between Exit and Entry values and adjusted for interim dividends whenever possible

PANEL A - Summary statistics

	Mean	St.dev.	10%	90%
Entry Value	321.32	681.94	7.71	913.00
Exit Value	640.51	2013.04	1.60	1400.00
Time to exit	4.93	2.67	1.90	8.10
Money on Money multiplier	8.34	36.75	0.00	9.96

PANEL B - Correlations

Syndicate Size	ρ	p	R^2
Entry Value	0.193	0.001	0.037
Time to exit	0.078	0.113	0.006
Deal Size			
Money on Money multiplier	-0.04	0.405	0.002
Money on Money multiplier (1% right-winsorized)	-0.089	0.069	0.008

Table 3

Buyout performance and Syndicate size

This table presents results for a set of Tobit regressions of the performance of buyout deals. The dependent variable is the natural logarithm of the Money on Money Multiple, i.e. the ratio of the exit equity value over the entry equity value. The main independent variable is the size of the buying syndicate. Regressions control for investment duration, exit type and time invariant fixed-effects. Panel A presents regressions including only realized exits, i.e. trade sales, secondary buyouts and IPOs; Panel B includes write-offs for which an entry value was available and in Model (4) controls also for deal size deciles. Standard error are clustered at the year level and are reported in parentheses. Significance at 10%, 5% and 1% level is denoted by by *, ** and *** respectively

PANEL A - POSITIVE EXITS ONLY

	Money Multiplier		
	(1)	(2)	(3)
Syndicate size	-0.346***	-0.366***	-0.375***
	(0.118)	(0.116)	(0.115)
Syndicate Size Squared	0.031**	0.033**	0.034**
	(0.014)	(0.015)	(0.015)
Investment duration		-0.001	-0.001
		(0.002)	(0.002)
Constant	1.451***	3.510***	3.358***
	(0.235)	(0.109)	(0.183)
YEAR F.E.	YES	YES	YES
Exit Type F.E.	NO	NO	YES
Pseudo-R^2	0.01	0.02	0.04
Obs.	375	375	375

PANEL B - INCLUDING WRITE-OFFS

	Money Multiplier			
	(1)	(2)	(3)	(4)
Syndicate size	-0.279***	-0.265**	-0.244**	-0.231***
	(0.095)	(0.105)	(0.096)	(0.083)
Syndicate Size Squared	0.025**	0.024**	0.021**	0.026***
	(0.011)	(0.013)	(0.011)	(0.010)
Investment duration		-0.000	-0.001	0.000
		(0.001)	(0.002)	(0.001)
Constant	1.665***	3.420***	3.100***	3.374***
	(0.199)	(0.109)	(0.152)	(0.189)
YEAR F.E.	YES	YES	YES	YES
Exit Type F.E.	NO	NO	YES	YES
Size Bins (1-10)	NO	NO	NO	YES
Pseudo-R^2	0.01	0.04	0.15	0.24
Obs.	413	413	413	413

Table 4

Deal size robustness test

This table presents results for a set of Tobit regressions of the performance of buyout deals. The dependent variable is the natural logarithm of the Money on Money Multiple, i.e. the ratio of the exit equity value over the entry equity value. The main independent variable is the size of the buying syndicate. Regressions are run separately for three deal size tercile subsamples. Regressions control for investment duration, exit type, within-tercile deal size and time invariant fixed-effects. Standard error are clustered at the year level and are reported in parentheses. Significance at 10%, 5% and 1% level is denoted by by *, ** and *** respectively

	Tercile		
	(1)	(2)	(3)
Syndicate size	-0.716**	-0.312*	-0.149***
	(0.301)	(0.164)	(0.057)
Syndicate Size Squared	0.110***	0.057**	0.019**
	(0.014)	(0.015)	(0.015)
Investment duration	-0.001	0.002	-0.001
	(0.004)	(0.002)	(0.001)
Constant	1.573***	0.323***	0.161***
	(0.242)	(0.048)	(0.046)
YEAR F.E.	YES	YES	YES
Exit Type F.E.	YES	YES	YES
Size Bins (1-10)	YES	YES	YES
Pseudo-R^2	0.19	0.31	0.54
Obs.	137	138	138