Do Private Equity Managers Have Superior Information on Public Markets?

Oleg R. Gredil*

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Abstract
Using cash flows from a large sample of buyout and venture funds, I show that private equity (PE) distributions predict returns in the industries of funds' specialization. My tests distinguish timing skill from reactions to market conditions and spillover effects of PE activity. Fund managers foresee comparable public firms' earnings but sell at the industry peaks only if they have performance fees to harvest. These results have implications for manager selection and improve understanding of PE fund returns and the PE role in capital markets.

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*Gredil is with A.B. Freeman School of Business, Tulane University: ogredil@tulane.edu, phone: (504) 314-7567. The earlier version of the paper was circulated under the title *Market Timing and Agency Costs: Evidence from Private Equity*. Acknowledgments: I would like to especially thank Greg Brown for his support and guidance. Helpful comments and suggestions were provided by the anonymous referees, Francesca Cornelli, Nickolay Gantchev, Eric Ghysels, Pab Jotikasthira, Victoria Ivashina, Steven Kaplan, Arthur Korteweg, Nishad Kapadia, Cami Kuhnen, Christian Lundblad, Paige Ouimet, Urs Peyer, Robert Prilmeier, Adam Reed, Merih Sevilir, Berk Sensoy, Morten Sorensen, Geoffrey Tate, Santiago Truffa, William Waller, Yan Alperovych, Morad Zekhnini, David Robinson, and seminar participants at the 2015 Global Private Investing Conference, University of North Carolina, Arizona State University, Fordham University and Tulane University, 2015 FMA meeting, and 2016 FIRS meetings, 2018 Paris Hedge Fund and Private Equity Research Conference. I am grateful to Burgiss for data access and to Wendy Hu for providing research assistance. This research has benefited from the support of the Private Equity Research Consortium (PERC) and the UAI Foundation. All errors are my own.

I. Introduction

Although private equity (PE) funds invest in private companies, their investment outcomes depend crucially on public capital markets: a fund's entry or exit valuation is affected by comparable public market prices, regardless of whether the transaction is public. Prior research shows that PE managers (general partners [GPs]) change policies of both investee companies and the industries in which they operate (see, e.g., Bernstein et al., 2016); and that GPs vigorously respond to changes in market conditions (see, e.g., Axelson et al., 2013). Relatively little is known, however, about how informed GPs are about the valuations of public equities. Amid the growing evidence that GPs' control over PE fund cash flow schedules extracts agency benefits (see, e.g., Robinson and Sensoy, 2013), it remains poorly understood whether the fund investors also benefit from this distinctive feature of PE contracts. Since GPs oversee dozens of companies as active board members and specialize in certain types of businesses, the timing of entry and exit decisions based on this informational advantage (relative to public market prices) could create value for their fund investors.

This paper shows that GPs do appear to learn important private information about the valuation of certain public equities and that the potential gains to fund investors from delegating fund investment timing to GPs are substantial. For the typical PE fund, the contribution from timing of the industry valuation cycle to the life-time total return is as large as the contribution from holding the asset. Using the Burgiss sample of 941 US-focused buyout and venture funds incepted between 1979 and 2006, I show that an inter-quartile increase in the rate of funds' distributions to investors predicts approximately 6% lower 12-month returns for the fund's primary S&P500 sector incrementally to other predictors. I develop a simple and robust fund-level metric of a GP's timing track record that conveys valuable information about a fund's future propensity to exit close to industry highs. For tighter control of variation in exit conditions, I conduct simulations showing that this predictability vanishes outside GPs' industries of specialization and relates to the industry earnings news.

Indirect anecdotal and survey evidence is consistent with market timing ability of PE managers.[1] To date, however, there has been no direct support for superior information-based market timing by GPs. Ball et al. (2011) conclude that venture GPs simply react to market conditions; Lerner (1994), Kaplan and Strömberg (2009), and Guo et al. (2011) do not attempt to disentangle superior information-based market timing from reacting to entry/exit conditions, time-varying expected returns, and causal effects of PE activities on public company valuations. Neither do Acharya et al. (2013) and Jenkinson et al. (2018) examine this channel with deal-level samples.

This paper shows that, with respect to PE fund exits, 52–69% of the subsequent dip in public benchmark returns can be attributed to superior information. The remaining 31–48% is due to variation in market conditions (i.e., "pseudo timing" as per Ball et al., 2011; Schultz, 2003). However, when GPs do not stand to cash-in carried interest, they have little incentive to time the market, and PE fund distributions do not have incremental predictive power relative to publicly available (non-PE) predictors. My inference is robust to spatial dependence in calendar time and to exclusions of particularly dramatic market episodes and certain fund groups. Meanwhile, the data are inconsistent with PE exits causing lower earnings at comparable public firms or temporarily depressed valuations thereof. I find that much of the variation in fund returns due to timing derives from exits rather than entry. The entry timing is on average neutral yet also hard to distill from the constraints on GP discretion, such as investment periods' start and length.

The first contribution of this paper is, then, novel systematic evidence of successful market timing actions by PE GPs that are important for the price and allocative efficiency of capital markets (à la Asriyan et al., 2017). To identify this channel, I make use of PE contractual design. PE funds differ from other forms of delegated asset management in the near-absence of control that PE fund investors (limited partners [LPs]) have over the

[1] Anecdotes on information spillovers from investing in private companies includes examples of successful public "stock pickers" that heavily invest in private companies: Warren Buffet of Berkshire Hathaway, Charles Coleman of Tiger Global, and others. Beliefs in positive timing ability are consistent with survey responses by GPs (Gompers et al., 2016, 2020) and by PE fund investors (Da Rin and Phalippou, 2017).

timing of investments and divestments.[2] This PE contract feature allows me to disentangle GPs' superior information channel from alternative explanations, such as time-varying exit conditions and causal effects of PE on public companies. The intuition behind my tests is similar to that in the literature on private information-based self-selection in the insurance industry (Chiappori and Salanie, 2000). While my main tests assume that the shifts in GPs' personal wealth exposure do not pertain to the alternative explanations, I take advantage of PE institutional settings to scrutinize this assumption. In particular, I run placebo tests that examine industry returns following PE exits that are comparable in size and style but happen well before or after the carry cash-out date. Hence, these placebo exits do not have a "relief from exposure" effect on the GPs' wealth. I provide extensive robustness tests that include regression discontinuity with funds' to-date performance as a forcing variable.

Identifying GPs' market timing skill is one thing; whether LPs should care about this insight is another. LPs might ignore this timing altogether because their allocations to equities (and specific sectors within equities) can remain unchanged if they adjust their public equity holdings accordingly.[3] Given this argument, the literature on PE fund performance has focused on evaluating abnormal *holding period returns*—that is, in comparison to similarly-timed public market investments (see Ang et al., 2018; Kaplan and Schoar, 2005; Stafford, 2017, among others). If the valuation ratios that GPs buy [sell] at merely reflect periods of high [low] risk premia commanded by similar investments, the incrementally higher returns from these deals represent a *normal* compensation to LPs for incurring a greater disutility from risky investments. Alternatively, GPs' market timing decisions, as manifested by PE

[2] Participation in a PE fund requires LPs to provide a prespecified amount of cash over a multi-year "investment period" period (usually 5 years) on a short notice in exchange for a stream of payouts from the fund over a period of 10 to 13 years from the investment period start. LPs cede control to GPs, who determine the schedule of fund outlays and inflows (i.e., fund cash flow), which is ex ante unknown to LPs. GP also decide when to return the capital to LPs and receive fixed fees and performance fees (carry, a.k.a. carried interest), a fraction of the fund's lifetime profits. Once the investment period ends however, GPs are not allowed to reinvest proceeds from fund assets but must distribute them to the fund LPs. See, e.g., Kaplan and Strömberg (2009), Metrick and Yasuda (2010), Robinson and Sensoy (2013) for details. Internet Appendix provides more context.

[3] For complete irrelevance of GPs' market timing decisions however, the LP needs to reinvest from/into a comparable public stock (not just the broad index).

cash flow patterns, could create a valuable option for fund LPs, as long as GPs' decisions reflect superior information not already embedded in market prices. In other words, the literature has remained unclear on whether LPs benefit from GPs' market timing.

Revolving this lack of clarity, my second contribution is evidence that ceding cash flow rights to GPs *does* create economic value for fund LPs and constitutes an important dimension in the PE manager selection process. I show that an industry-level long-short trading strategy implemented based on the signal from PE funds distributions generates 80 basis points per quarter in the Fama-French three-factor alpha and a 0.3 higher annualized Sharpe ratios. Industry-level market timing must then create value for LPs even when total equity allocation remains constant. Therefore, some investors with PE portfolios can enhance their overall portfolio performance using the information that other investors do not have in real time.[4] These results justify using total returns to quantify variation in skill across GPs (Korteweg and Sorensen, 2017). Insofar successful market timing by GPs increases the fund total return and produces useful information, the results of this paper potentially explain the attention that LPs continue pay to GPs' ability to generate total returns (Da Rin and Phalippou, 2017) in addition to the market-adjusted performance metrics.

Finally, by demonstrating the pivotal effect of in-the-money carry for GPs' market timing decisions, this paper contributes to studies of the effects of investment manager compensation schemes on performance (see, e.g., Brown et al., 1996). In the PE context specifically, while Hüther et al. (2020) document that differences in carry rules affect fund returns *ex ante*, my results speak to the dynamic effects thereof. Market timing actions yield a good setting for examining this question, since the counterfactual outcome is relatively well observed. My analysis also highlights why LPs cannot gain much from timing their commitments to PE funds, as recently shown in Brown et al. (Forthcominig). GPs' timing of fund cash flows significantly attenuates the effect of contractual start and end times.

[4] There is a three-to-nine-month delay in the revelation of PE fund cash flows to data vendors. Thus, such a PE signal-based allocation strategy is feasible for LPs with representative enough portfolios managed by skilled GPs whose incentives can be discerned relatively well.

There is a large literature on market timing by professional managers of liquid assets (see Wermers, 2011, for a recent review). PE fund cash flows essentially indicate the times and amounts of their trades. Therefore, my empirical setup is close to studies that utilize holding-level information (see, inter alia, Agarwal, Jiang, Tang, and Yang, 2013; Copeland and Mayers, 1982; Grinblatt and Titman, 1989, 1993; Jiang, Yao, and Yu, 2007). These studies appear more likely to find evidence of successful timing than the strand of literature that examines the time series properties of portfolio returns at monthly or daily frequency (see, e.g., Ferson and Schadt, 1996; Henriksson and Merton, 1981; Jenter, 2005; Timmermann and Blake, 2005).[5] Notably, such time series statistical methods are largely inapplicable with PE fund data because GP-reported net asset values (NAVs) are smoothed (Brown et al., 2020) and prone to manipulations (Brown et al., 2019).

While my GP market timing measure is very much in spirit of the Grinblatt and Titman (1993) measure that naturally decomposes into the broad market, industry, stock specific, etc.; I zoom at the industry level. On the one hand, my data do not permit a comparable asset of a finer granularity than industry. On the other hand, the presence of market-wide timing is eclipsed by the industry timing (gross of broad market) because, as discussed above, such GP-induced changes to LP portfolios generate value even if LPs partially undo the effects by reinvesting proceeds in public equities. The preponderance of evidence suggests that, on average, GPs' broad market timing is a watered-down industry timing. Besides the long-short strategy performance results, I show that (i) the predictability is zero against the industries that comoved with the fund's focal industry the least, and (ii) the predictability in the focal industry relates to its future earnings news rather than variations in the discount factors (as per a Campbell and Shiller-like decomposition of returns).

Why would GP market timing relate to the industry's future earnings? Ben-David et al. (2019) find that corporate executives (i.e., "insiders") earn abnormal returns in trading stocks

[5] Some exceptions include Griffin and Xu (2009), who, using 13F data, find that hedge funds exhibit no ability to pick sectors; and Chen and Liang (2007), who, using a Henriksson and Merton-like statistical model, find that self-described market timing hedge funds outperform public information-based strategies.

that belong to the industry of their employer and that this is likely due to better interpretations of public news about that industry (see also Bradley et al., 2017; Kacperczyk et al., 2005). This is one mechanism, albeit not unique to PE funds, that can explain my findings. Another (yet complementary) mechanism relates to GPs' high involvement in planning and tracking the operational performance of their investee companies.[6] It is plausible, albeit hard to corroborate with direct anecdotes, that GPs filter valuable signals from such real-time and less biased cash flow projections from the management of dozens [hundreds] of related companies they oversee [confidentially screen].

GP market timing has many scopes that my study does not pursue, however: when the new fund is launched, what strategy the fund adopts, etc. Relative to funds that invest in liquid assets, the scope and incentives for market timing are affected by the finite-life absolute returns-based contracts prevalent in PE settings. These are interesting avenues for future research facing interesting identification challenges, since the observed outcomes are more reflective of factors beyond GPs' the direct control (e.g., supply of LP capital).

Between the data description and concluding remarks, the main analysis in this paper is organized in two interconnected blocks—sections III and IV. The first block provides descriptive evidence consistent with market timing actions by GPs. The second block distinguishes the superior information channel from alternative explanations. The tests in the second block can be viewed as the conditional holdings analysis of Ferson and Khang (2002), whereas the first block features the unconditional counterpart thereof. Supportive materials are organized in Appendix A, Appendix B, and Internet Appendix, while Appendix C summarizes key variable definitions.

[6] See, for example, "What private-equity strategy planners can teach public companies," McKinsey&Company, October 2016. The attention to up-do-date projections is high in the not-for-control transaction as well—a typical term sheet requires the investee company to provide annual operating plans updated monthly even when the GPs do not receive a board seat (see, e.g., Lerner et al., 2012, p.150).

II. Data

PE data for this study are obtained from Burgiss. The dataset is sourced from approximately 300 LPs that collectively have made over 20,000 commitments to private capital funds, and it includes their complete cash flow and valuation histories. Harris, Jenkinson, and Kaplan (2014) compare several PE datasets and conclude that the Burgiss dataset is representative of the buyout and venture funds' investable universe. The dataset maintains confidentiality by removing all names (see Brown et al. 2015 for additional details).

I limit the sample to US-focused buyout and venture funds with more than 25 and 10 million in capital commitments, respectively, incepted between 1979 and 2006. The sample includes 349 (592) buyout (venture) funds, of which 126 (169) continue operations as of March 2013. For each fund, I observe: (i) the primary industry sector according to the Global Industry Classification Standards (GICS)—henceforth, *Industry*; (ii) the amount of capital committed; (iii) the strategy description; (iv) dated amounts of cash inflows and outflows as well as NAVs reported quarterly. The cash flows are net of all fees, allowing me to accurately compute returns to LPs.

I observe neither the gross-of-fees performance of fund investments, nor the fee terms. However, the only contractual term essential for my tests, the minimum rate of return to LPs above which GPs start to earn carry (henceforth Hurdle), has virtually no variation within fund type according to multiple studies (e.g., see Metrick and Yasuda, 2010) at 8 [0]% for buyout [venture] funds. The literature also documents substantial variation in schedules of fund cash flows (Robinson and Sensoy, 2013, 2016). Internet Appendix confirms the heterogeneity in cash flows for my sample and discusses the consequences of different carry waterfall contractual provisions ("deal-by-deal," "whole fund,", "catch-up,") for inference by using fund net IRR as a proxy for fund carry being in-the-money. In short, my approximation is likely to underestimate carry claims and produce more false negative than positive errors regarding whether a given fund's carry is in-the-money.

Panel A1 of Table 1 reports the basic summary statistics for buyout and venture subsamples, suggesting high within-type variation in fund life duration, size, and returns. 85% of the funds are affiliated with GPs that managed multiple funds. For each fund, I compute the chronological order (by inception date) within GP and GP×Industry. Thus, the median fund in the dataset is the second by a GP and within a given industry, while about a quarter of funds are fourth or higher in a sequence. The panel also reports Kaplan and Schoar (2005) Public Market Equivalent (PME) computed against the fund Industry.

[Place Table 1 here]

For public equity returns, I utilize S&P500 Global Industry Classification Sectors (GICS) subindexes, which map directly to the classification in the Burgiss data and represent widely followed benchmarks by practitioners. Burgiss reports GICS for 881 out of 942 in my sample. For the unclassified funds (most of which are buyout funds), I assign "Industrials" as Industry focus. Results are similar if I use S&P600 subindexes, the small capitalization stocks.

Panel A2 of Table 1 reports the distribution of my fund sample by GICS and vintage year group. Panel B reports the summary statistics for monthly returns, price-earnings, and book-to-market ratios from January 1989 through September 2014 for respective S&P500 subindexes. Additionally, for each fund, I observe a dummy (but not the underlying scores) indicating whether the declared industry comprises more than 50% by value of the actual investments made by the fund. Only 59% of my sample funds portfolios have such concentrated portfolios (untabulated). It does not imply, however, that the remainder of funds have investments spread over more than 2–3 industries.

Summary statistics for other variables of interest are reported in Panel C of Table 1. These include equity return *Predictive covariates* (see Appendix C). The panel also reports summary statistics for IndEPSsurprise and IndForwardMultΔ, which denote, respectively, the industry aggregate difference in reported earnings from the analyst forecast and the change in price-to-'forecasted earnings' ratio. Both variables are computed from the median 12-month analyst forecasts of EPS for the S&P500 GICS subindex as computed by Bloomberg.

III. Suggestive Evidence

This section outlines the ways that GPs' market timing decisions can manifest in PE fund data. It proposes a simple metric that unambiguously captures one of these timing effects on fund performance based on readily observable fund cash flow data.

The pieces of information that a GP obtains through the investment cycle and public markets valuations are closely related (see Internet Appendix for a discussion of the institutional background). Public market prices reflect cash flow expectations and investor preferences, while also affecting the fund's investment entry and exit prices, regardless of the deal sourcing and exit route. As an example, consider an exit through a sale to a public corporation, which might be a stronger indication of a GP's negative outlook because IPOs feature lockups and represent merely a "beginning of exit." Bargaining over price would normally revolve around an assortment of valuation ratios of comparable publicly traded firms as indications of a fair value, even if their business characteristics might not exactly match those of the target company. Hence, GPs have incentives to act on their superior information about the industry trends even when their portfolio companies have relatively small exposures to these trends.

GPs' ability to act on company-specific information is likely to be limited by adverse selection concerns from the prospective buyers. A need to make concessions regarding company-specific valuation is consistent with buyout- and venture-backed IPOs' outperformance against characteristics-matched portfolios (Cao and Lerner, 2009; Harford and Kolasinski, 2013). However, the adverse selection is a less relevant concern with respect to the company's industry-wide valuation, since those who typically trade with PE funds are more concerned about the relative performance of the asset rather than *absolute* performance of the asset. In contrast, PE GPs stand to receive a fraction of the fund's finite lifetime absolute profits (see, e.g., Metrick and Yasuda, 2010; Robinson and Sensoy, 2013).

Given the institutional settings, the scope for market timing by GPs can be very broad. In this paper, I study GPs' arguably more discretionary decisions—when to deploy and release the committed capital over a fund's contractual life. I abstract away from the analysis of decisions concerning when to launch a fund and what strategy to adopt as its mandate.

Specifically, I define (the effect of GPs') market timing as the excess return that an outside investor would attain if she bought and sold an *identical company* at the *same times* as the fund GPs made capital calls and distributions. The tightest definition of an *identical company* that my data allow is the portfolio of public firms in the same industry. To the extent that GPs' informational advantage dissipates beyond the area of fund specialty, a poor match of industry (as the *identical company* proxy) will act against finding robust results. Conversely, finding results to be stronger with benchmarks less related to the funds' areas of expertise would point to explanations other than private information flow in PE.

A. Market Timing Metric

Consistent with the above definition of market timing, I propose a measure of gross return over a fund's life due to selling at market highs and buying at lows. Computationally, it is similar to Kaplan and Schoar PME. However, *Timing Track Record* (TTR) measures the component of the fund's total returns that PME explicitly disregards:

$$\begin{aligned} TTR &= \overline{PME}/PME = \frac{\sum_{t=0}^{T} D_t \cdot exp\{r_{1:T} \cdot (1-t/T)\}}{\sum_{t=0}^{T} C_t \cdot exp\{r_{1:T} \cdot (1-t/T)\}} \Big/ \frac{\sum_{t=0}^{T} D_t \cdot exp\{r_{t+1:T}\}}{\sum_{t=0}^{T} C_t \cdot exp\{r_{t+1:T}\}} \\ &= \underbrace{\frac{\sum_{t=0}^{T} C_t \cdot exp\{r_{t+1:T}\}}{\sum_{t=0}^{T} C_t \cdot exp\{r_{1:T} \cdot (1-t/T)\}}}_{\text{Entry Timing}} \cdot \underbrace{\frac{\sum_{t=0}^{T} D_t \cdot exp\{r_{1:T} \cdot (1-t/T)\}}{\sum_{t=0}^{T} D_t \cdot exp\{r_{t+1:T}\}}}_{\text{Exit Timing}} , \end{aligned} \tag{1}$$

where $t = 0$ is the fund's inception, $r_{t+1:T}$ is a continuously compounded return on public benchmark between date t and the fund's resolution, T, setting $r_{t+1:T} := 0$ for $t \geq T-1$. D_t is the fund's distribution at end of period t, and C_t is capital calls.

Per equation (1), TTR is a ratio of two profitability indexes (PI) featuring the same cash flows but different discount rates. The discount rates in the denominator ratio, PME, reflect the *investment period* opportunity cost of capital. The discount rates in the numerator, $\overline{\text{PME}}$, reflect the average return on the benchmark during the fund's life and, therefore, can be thought of as the *commitment period* opportunity cost. A TTR value above one indicates that the PI is greater if measured against the fund commitment period opportunity cost and, hence, suggests positive value added by the GP.

The second line of equation (1) provides more insight by rewriting TTR as a product of two ratios. The first ratio compares (i) the period-T value of capital calls if invested in a public benchmark on the dates of those calls to (ii) the value of those call amounts if invested at a rate that public benchmark returned on average during the fund life. When (i) is greater than (ii), the GP called the fund's capital when future returns on the public benchmark (i.e., the proxy for an "identical company") were high relative to its return on average during the fund's life. A stylized example below develops this intuition further.

Consider two funds, A and B, that start at the same time with \$30 in committed capital and have up to two years to invest. Both funds liquidate in the fourth year. Assume that neither fund has company selection or nurturing skill and earns exactly the market rate of return on investments, so that $PME = 1.0$ for both funds. However, fund A chooses to draw capital in equal installments over three years, whereas fund B, having correctly anticipated a market downturn in year 2, draws less capital initially:

Entry Timing Example

Year	r_{mkt}	**Fund A** Cash Flows	**Fund B** Cash Flows	**Fund A** EoY NAVs	**Fund B** EoY NAVs
0	-	-10	-5	10	5
1	5.0%	-10	-5	20.50 $=10\cdot 1.05+10$	10.25
2	-13.6%	-10	-20	27.71	28.86
3	5.0%	0	0	29.09	30.30
4	5.0%	**30.55**	**31.81**	0	0
	PME	1.00	1.00		
	$\overline{PME}$	1.02 $=30.55/30$	1.06 $=31.81/30$		
	$\boldsymbol{TTR} = \overline{PME}/PME$	**1.02** $=1.02/1.00$	**1.06** $=1.06/1.00$		

While both funds have PME of one, fund B creates potentially more value to its LPs than fund A: 1.81 versus 0.55. This is reflected in a higher $\overline{PME}$ and thus a higher TTR for fund B. In this way, TTR measures market timing by the managers of fund B.

The money multiple (i.e., $\sum D_t / \sum C_t$) is an absolute performance metric widely utilized by practitioners and would reflect the difference in returns to LPs from funds A and B. The money multiples of A and B are 1.02 and 1.06, respectively. In this example, they equal to TTRs because the cumulative market return is zero and the PME of each fund is unity. This is, however, almost never true in practice, as the market trends over fund lives and the funds' holding period excess returns vary.

Note also that in this example, the exit timing ratio (the last term in equation 1) is equal to one, since there is only one distribution made at the very end of fund life. In practice, this is rather unusual, as funds tend to make many interim distributions. The exit ratio would be greater than one if public benchmark returns that follow the distributions were lower (i.e., reducing the denominator) than on average during the life of the fund. Internet Appendix provides more general examples in which TTR captures the timing of exits as well.

An alternative formulation for TTR is the residual from money multiple, PME, and the fund's duration-adjusted trend in the public benchmark:

$$ln(TTR) = ln(MM) - ln(PME) - \bar{r} \cdot FundDuration \quad . \tag{2}$$

Appendix A derives equation (2) and shows its equivalence to equation (1).

By construction, TTR is reasonably robust to heterogeneity in funds' risk levels. As shown in Korteweg and Nagel (2016), the bias in PME arises because the realized risk premium on the benchmark tends to be different from that under CAPM with log-utility preferences. This bias is at least partially mitigated in TTR because the realized risk premium for $\overline{\text{PME}}$ (the numerator of equation 1) is close to that for PME (the denominator).[7] The difference amounts to weighting the realized risk premia equally during the fund's life as opposed to proportionally to the fund's NAVs.

Finally, while a level of one is a natural reference, the realized TTR can also be compared with a TTR derived from a hypothetical cash flow schedule between the dates that the fund

[7] Note that, as ratios, neither entry and exit TTRs nor PME and $\overline{\text{PME}}$ depend on whether future- or present values (more typical for PME notation) are used to form them. Also, by using the industry portfolios as benchmarks, I reduce the deviation of fund cash flows' betas (with respect to these benchmarks) from unity, which significantly improves the precision (Korteweg and Nagel, 2018).

was active. It is also evident that, insofar capital calls and distributions span changes in the portfolio weights, TTR can be viewed as a particularly scaled measure of covariance between the holding weight change and the subsequent return, as in Grinblatt and Titman (1993).

B. Empirical Analysis of Timing Track Records

Panel A of Figure 1 plots frequency distributions of TTRs for the sample funds against Industry returns separately for buyout and venture subsamples. First, there is a significant variation across funds, suggesting that TTR is indeed a potentially important dimension of performance. About 10% of funds managed to lose in excess of 20%, whereas the 90^{th}-percentile fund (venture and buyout samples combined) gained over 50% by timing the within fund-life industry valuation cycles. Second, the means are statistically greater than one although smaller in magnitude than for PMEs, which measure the holding period returns. Adjustments for typical holding periods suggest a mean "timing alpha" of about 1% per year versus 2–4% per year from the PME-based inference about the "holding alpha."

[Place Figure 1 here]

Panel B of Figure 1 better gauges the importance of TTR in the cross-section of fund returns by reporting the variance decomposition of the money multiple (following equation 2) by PME quartiles. It shows that the dominance by PME is limited to the top- and bottom-quartile funds. In contrast, the contribution from timing is as large as that from holding, and the two components are virtually uncorrelated and therefore quite likely to offset each other for funds in the middle two quartiles by PME. For 44% of sample funds, the TTR's difference from one exceeds that of PME.

Note that TTR equals one for any cash flow schedule whenever the benchmark's return is equal across periods. Accordingly, since TTR is bounded by the benchmark's variance over the fund's life (unlike PME), it is unsurprising to observe more extreme values for PME in either tail of the distribution. The benchmark variance bounds also help explain a larger dispersion of TTRs in the venture subsample that is skewed to riskier industries (e.g., IT, Healthcare) and suggests that the sign on log TTR may provide for a more consistent signal about GP skill, since the magnitudes may have limited comparability across industries and time. More interesting is the non-zero and opposite-sign covariances between TTR and PME in the extreme quartiles, as depicted in Panel B of Figure 1. This pattern suggests that for the best performing funds, timing and holding returns tend to be positively related. However, timing tends to somewhat mitigate the inferior returns from holding in the bottom PME quartile.

B.1. Relations with Fund Characteristics

Table 2 reports regression results of TTRs computed against the fund's focal industry on GP characteristics that proxy for institutional quality (e.g., Kaplan and Schoar, 2005; Robinson and Sensoy, 2016). Fund size is positively related to end-of-life TTR, while the size squared loads negatively. However, coefficients on size become insignificant when temporal variation is controlled for via vintage-year fixed effects, as per specification (2). According to specifications (1)–(3) and (6), TTR positively relates to the fund's ordinal sequence in a given GP$\times$industry. This indicates that funds run by GPs with more experience in the industry tend to better navigate industry peaks and troughs.

[Place Table 2 here]

The positive coefficients on PME in specifications (3), (5), and (6) corroborate the variance decomposition analysis discussed above. Funds with higher PME also tend to be better at timing the industry valuation cycles, even when the inception year and other covariates are controlled for. This pattern may arise due to a number of reasons that are not mutually exclusive. First, very few bottom-quartile funds attain high enough absolute return for GPs to receive carried interest. Consequently, these GPs have little incentive to avoid a reduction in the funds' asset values. Second, the selection and nurturing skill (that PME encompasses) can genuinely relate to GPs' knowledge of the industry, which enables successful timing of its cycles as well. It is also possible that PMEs pick up the effects of inherent market timing decisions that do not trigger fund-level cash flows. These could be mergers and acquisitions by the fund's portfolio companies that did not require new equity injections from the fund. Specifications (4) through (6) show a positive relation between a GP's previous and current funds' TTR. This indicates that timing ability is persistent at the GP level.

In Appendix A, I report robustness and falsification tests for the results in Table 2 and the univariate analysis reported earlier. Specifically, Panel A of Table A.1 reports similar regressions but with additional control variables that proxy for possible measurement errors in TTRs. The results are largely unchanged from those in Table 2. Panel B of Table A.1 reports analysis based on simulated fund cash flows under various assumptions about individual fund risk (as indicated by the subpanel headers) while keeping the fund start dates and the industry returns fixed to the actually realized values. The key takeaways from this analysis are as follows.

The average fund delivers 70–80% of the feasible gains from timing (measured by the interdecile range of simulated TTRs). The unconditional probability that a fund's TTR will exceed that of a random cash flow schedule is 52-53%. Even though neither of these magnitudes strikes as very large economically, each one is statistically different from 50%. As for the multivariate relations reported in Table 2, none of them hold with the simulated TTRs on average across replications. Perhaps the only exception is the coefficient on PME, which came back at 0.02–0.03 with a t-statistic of 1.5 in simulations. While both are a factor of two-to-three smaller than with the actual fund TTRs and PMEs, I conduct additional analysis in Internet Appendix. It shows (i) positive association between TTRs and PMEs in settings that are more robust to risk heterogeneity and fund life overlaps; (ii) weaker associations of TTR with PME computed against the broad market and with the fund's ordinal sequence unconditionally on industry.

Just like PME, TTR can be computed on a to-date basis by assuming a particular date to be the last and the NAV as of that date to be a liquidating distribution. Panel A of Figure 2 compares such interim TTRs (measured at the fifth anniversary) with the final TTRs for the funds that operated for at least nine years. Importantly, the mean market return for

$\overline{PME}$ computation is also date specific, so that no information beyond that date is utilized. It appears that funds with good TTRs as of midlife tend to further improve it by endlife.

[Place Figure 2 here]

To preclude a spurious correlation between the interim and final values of TTR, panels B and C of Figure 2 plot the growth in TTR after the fifth year on the y-axis. Panel B limits the sample to funds with net-of-fees IRR exceeding the Hurdle rate as of the fifth anniversary, while Panel C covers the complement set. The charts reveal a positive relation between the interim and final TTRs when GPs' option to receive the fraction of fund assets is in-the-money (Panel B) and a negative-to-flat relation when incentives for GPs are less well aligned (Panel C). However, the relation is mostly flat among funds with TTR above one suggesting that the variation in magnitude is less predictive than the sign of its log.

B.2. Entries versus Exits

I now examine the entry and exit contribution to the fund's overall TTR, as implied by equation (1). I begin with the variance decomposition of log TTR in Panel C of Figure 1. To preclude a mechanical relation between exit and entry TTRs, I measure $r_{1:T}$ over the first six years for computing the entry TTR, and start with the fourth year in computing the exit TTR. The panel shows that the exit TTR has higher variance than the entry TTR and that the covariance between the two is positive. The panel also shows that the covariance is larger for funds with higher overall TTR in the current vintage and higher previous fund TTRs, but is smaller when the average vintage peer exhibits good entry timing.

In untabulated analyses, I find that the average entry TTR is just below one, at 0.997 [0.982] for venture [buyout] funds, as opposed to being statistically greater than one for both subsamples with regards to exits (1.071 on average). Table 3 reports multivariate analyses of these TTR components.[8] Specifically in Panel A [B], I regress the log of entry [exit] TTR on the overall to-date TTR as of the fund's 5th anniversary and other variables. I examine the

[8] The number of observations varies across specifications, as I do not condition on observing the GP identifiers in each, unlike for Table 2. The results are very similar if the sample constrained to feature only known GP identifiers. For inference, unknown GP funds are assumed to have different GPs.

relations with the indicator for whether the declared industry comprises more than half of the fund investments ("Declared Ind.>50%P" see section II), the peers' average entry [exit] log TTR, and the indicator for whether the GP had an overall TTR greater than one in the previous fund ("Previous fund TTR≥1").

[Place Table 3 here]

The regressions reveal several interesting patterns. First, both entry and exit TTRs strongly and positively relate to the overall TTR, even if measured at a fund's midlife, with the coefficient being nearly twice as high for the entry case. Second, the portfolio concentration in the primary industry positively associates with both components, although the relation is statistically weak and not robust to vintage year fixed effects (specifications 4 through 6). For exit TTR, vintage fixed effects turn the coefficient from zero to significantly positive. For entry TTR, vintage fixed effects attenuate the previously significant positive coefficient on *Declared Ind.>50%P*. Interestingly, vintage fixed effects also have a different effect on the magnitude of the very strong association between the fund's entry and exit track records with those of its peers. For entry, the coefficient attenuates from 0.946 to 0.71, much less so than it does for exits—from 0.953 to 0.237. Finally, the correlation with the past fund TTR indicator is only weakly positive for the exit TTR and actually negative for the entry TTR. This result stands in contrast to the the strongly positive relation for the overall TTRs reported in Table 2, which also holds with the dummy variable definition.

These patterns are consistent with a fund entry TTR being stronger associated with vintage year and peer characteristics than its exit TTR, perhaps reflecting tighter contractual constraints on GPs with regards to investing of funds' capital in comparison to divesting of funds' assets. Investment period start and duration are subject to less discretion by GPs than are the individual investments' holding periods. Nevertheless, it appears that both exit and entry TTRs are complementary indicators of GPs' timing skill.

It is noteworthy that the *Declared Ind.>50%P* dummy reflects GPs' discretion about how much to concentrate investments in the fund's focal industry. Therefore, another interesting angle is the dummy's relation with the difference between TTRs computed against the focal industry and that against the broad market returns. This analysis is reported in Table A.2 and suggests that funds with more concentrated portfolios deliver 1.5–3% higher entry TTRs if measured against the industry benchmark. However, this relation is not statistically significant amongst venture funds. It is also attenuated for exit TTRs, as follows from panel B of the table. The panel suggests that venture funds are unconditionally better at timing their industry peaks (rather than market-wide) if vintage fixed effects are accounted for. Given that the carry role is more salient in venture fund compensation (see, e.g., Chung et al., 2012), these results point to the potential importance of carry-related incentives for exit timing, as do the post-interim trends in TTR depicted in Figure 2. The following section explores the incentives margin in great detail.

IV. Detecting Superior Information

I begin by reviewing explanations for TTR exceeding one and persisting that do not imply value creation by GPs. I then develop and conduct tests that detect superior information-based market timing regardless of whether these alternative explanations also hold.

A. Identification Challenge

First, fund cash flows may simply reflect the broad market and industry conditions for entry and exits. Schultz (2003) shows that mean-reversion coupled with a decision rule of issuing after market's run-ups is observationally similar to informed trading. Pástor and Veronesi (2005) model "rational IPO waves", whereby issuance varies endogenously as a function of market conditions without any overreactions by investors or differences in signal precision. Following Ball et al. (2011), I refer to this alternative as "Pseudo-timing".

While Pseudo-timing can be implemented without the costly intermediation of a GP, it can also generate utility losses to LPs. In a portfolio choice framework featuring both types of risky asset—liquid and illiquid—Pseudo-timing by GPs commands a higher expected return on the PE portfolio (Ang et al., 2014; Bollen and Sensoy, 2016). This happens because consumption can only be financed with liquid wealth and such contra-cyclical PE cash flow patterns increase [reduce] the weight of illiquid wealth in high [low] marginal utility states. It therefore can be argued that delegating cash flow timing rights to GPs offers little benefit if Pseudo-timing is all they do.[9]

The second group of alternative explanations pertains to possible causal effects of PE fund operations on the behavior of public firms and investors. Several recent studies document that firms respond to governance threats and improvements in peer firms by changing their investing and operating policies (Aldatmaz and Brown, 2020; Bernstein et al., 2016; Gantchev et al., 2019). For example, Aldatmaz and Brown (2020) find that PE investments cause financial and operating changes in publicly listed firms in the same country-industry. Harford et al. (2019) find that leveraged buyouts predict merger waves and higher valuations in the industry. These finding may suggest that the industry cash flows change *because* PE funds alter their involvement in the industry. I refer to this alternative as "Footprint-on-Firms".

Positive and persistent TTRs can also arise when the market prices temporarily decrease to absorb the increased supply of certain types of assets coming from potentially more informed investors (i.e., the PE GPs). I refer to this as the "Price Distortion" alternative. Note that if those fund exits had less negative spillover effect on comparable firm cash flows or prices, the overall portfolio returns would have been higher at least for some LPs (e.g., those who held stakes in these comparable firms, or sold into temporarily depressed prices). Therefore, neither Footprint-on-Firms nor Price Distortion imply economic gains to LPs, while possibly having adverse effects on capital market efficiency.

We also know that the current fund's profit is not the only objective that GPs maximize (Chung et al., 2012; Metrick and Yasuda, 2010) and fund distributions can be a signaling

[9] Since LPs know their liquidity needs better, co-investing strictly dominates committing to commingled funds. See Munk, N., "Rich Harvard, Poor Harvard," *Vanity Fair*, August 2009 and Ang, A., "Liquidating Harvard," Columbia Business School case study. For certain LPs even pseudo-timing may create value however, provided that it does not jeopardize the holding period returns (see section 3.1 of Internet Appendix). These LPs are, for some reason, unable to implement such counter-cyclical investment strategies at a lower (than hiring a PE GP) overall cost.

device. In particular, PE funds often "rush" to make distributions from a current fund to mitigate reputational concerns with LPs and secure a follow-on fund (i.e., to "grandstand", as per Gompers, 1996). While this Grandstanding alternative should actually counteract Pseudo-timing in aggregate, it induces heterogeneity in cash flow patterns across funds, as some GPs experience less pressure to make premature distributions. Therefore, the variation across fund TTRs, as well the by-GP and within-fund persistence in TTRs reported in section III, could be explained by a combination of Pseudo-timing and Grandstanding.

Finally, the evidence needs to be robust to heterogeneity in systematic risk at the fund- and industry levels, as well as to possible NAV manipulations by GPs (Brown et al., 2019).

A.1. Ideal Setup

To test for the presence of the superior information-based market timing, I utilize differences in the *propensity to deploy* this skill (or information) due to shifts in contractual incentives to GPs. The differences are induced by the fund to-date performance, which reflects a great deal of luck (Korteweg and Sorensen, 2017), and the finite-life feature of the PE fund contract. The idea can be conveyed via the following diagram that depicts a dilemma faced by GPs of a fund that has already deployed its capital. These predictions arise from a standard setup for optimal stopping under uncertainty, a brief review of which is given in the Internet Appendix.

Do you want to rush your fund's exits?

Fund return to-date \ **Market Outlook**	Negative	Positive
Above Hurdle rate	**Yes**	Not as much
Below Hurdle rate	Not as much	Not as much

The columns indicate GPs' outlook (unobservable to the public) on the market for assets similar to the fund's holdings, while the rows indicate the fund's to-date performance. Net IRR above [below] the Hurdle rate implies that the fund GPs would secure [destroy the option for] performance fees if the fund were resolved at current NAVs. Importantly, the predictions in the diagram do not assume that GPs have no other incentives to time exits (e.g., charm LPs to raise a larger next fund) but only that carry-related incentives affect the fund distribution patterns, at least marginally. The results in Robinson and Sensoy (2013) support this assumption. Should it (or the carry approximation) fail for my sample, I would be unable to reject the null hypothesis that GPs have no superior information.

Now consider a population of PE funds that are *identical to each other* in every respect except for the inception date and the amount of luck they experienced with idiosyncratic returns on the investments they had made. If each fund had only one investment (and could exit it instantaneously and only in whole), then the following OLS regression would provide a robust test for the presence of market timing skill among the funds' GPs:

$$\begin{aligned} \text{MarketReturn}_{i,t+1} = {} & \boldsymbol{\gamma}\, \mathbb{I}(\text{Exit})_i + \boldsymbol{\alpha}\, \mathbb{I}(\text{Exit}|\text{IRRaboveHurdle})_i \\ & + \mathbb{E}[\text{MarketReturn}_{i,t+1}|\text{PublicData}_t] + e_{i,t+1} \quad , \end{aligned} \tag{3}$$

where $\mathbb{I}(\cdot)$ and $|$ denote, respectively, indicator variables and conditioning operator, while $\mathbb{E}[\text{MarketReturn}_{i,t+1}|\text{PublicData}_t]$ is the expected market return conditional on public information as reflected in market prices at the time of fund i exit occurrence. Henceforth, I will denote it with $\mathbb{E}_t^P[\text{Market}_{i,t+1}]$ for brevity.

The setup is analogous to the standard test for the presence of asymmetric information by comparing *ex post* risk realization (the observable outcome) and *ex ante* contract choice (the observable action) in the literature on adverse selection in insurance (e.g, Chiappori and Salanie, 2000). If GPs have superior (relative to the public) information, they would choose to exit before the market downturn when the carry is at stake, resulting in a negative α-coefficient in model (3), since less incentivized GPs would exit more randomly. If GPs merely respond to market conditions (e.g., Ball et al., 2011), $\mathbb{E}_t^P[\text{Market}_{i,t+1}]$ should absorb the variation in these conditions insofar the public interprets them correctly.

What if GPs were not identical? If we observed an *ex ante* proxy for their market timing skill, we could incorporate it in the above regression as follows:

$$\begin{aligned} \text{MarketReturn}_{i,t+1} = {} & \boldsymbol{\gamma}\, \mathbb{I}(\text{Exit})_i + \boldsymbol{\alpha}\, \mathbb{I}(\text{Exit}|\,\text{IRRaboveHurdle}, \text{Skill})_{i,t-1} \\ & + \boldsymbol{\alpha_1} \mathbb{I}(\text{Exit}|\text{IRRaboveHurdle})_i + \alpha_0\, \mathbb{I}(\text{Exit}|\text{Skill})_{i,t-1} + \mathbb{E}_t^P[\text{Market}_{i,t+1}] + \varepsilon_{i,t+1} \quad . \end{aligned} \tag{4}$$

Controlling for the proxy of GP skill increases the estimates' efficiency, as variance of $\varepsilon_{i,t+1}$

should be lower than that of $e_{i,t+1}$ from model (3) if the proxy is indeed relevant. In addition, this specification provides for a nested test of whether all PE exits are informative conditional on aligned incentives (i.e., $\boldsymbol{\alpha_1} < 0$ so as $\boldsymbol{\alpha}$) and absorbs the variation in exiting times due to GP heterogeneity via coefficient α_0. The latter can emerge, as a result of Grandstanding as discussed in the previous section, whereby less reputable GPs might be forced to markedly divest the current fund before raising a new one.

In tests for adverse selection in the context of insurance contracts choice, omitted heterogeneity is a potent concern because it can correlate with *both* ex ante choices and ex post outcomes. I argue that applying the same identification idea to PE mitigates such concerns markedly. First, it is hard to see how predetermined characteristics of GPs would predict public market returns. Second, conditional on $\mathbb{E}_t^P[\text{Market}_{i,t+1}]$, the predictions for a higher rush to exit hold even for risk-neutral agents.

Nonetheless, the possibility that the ex ante choice is causing the outcome (rather than reflecting pure self-selection) remains a concern in my analysis and needs to be "assumed away" to some extent.[10] Aside from the lack of a rift in incentives for timing of entries, this is another strong reason to focus on exit decisions for identification, because the literature reviewed earlier has established causal spillover effects from PE entries. However, as discussed below, I take advantage of PE institutional settings to scrutinize the assumption that heterogeneity in Footprint-on-Firms and Price Distortion does not drive the results on exits.

A.2. Feasible Proxies

Implementing the incentives-based identification scheme outlined above involves two more[11] measurement issues because (i) PE funds almost never divest their portfolios in "one shot", and (ii) $\mathbb{E}_t^P[\text{Market}_{i,t+1}]$ is not directly observable.

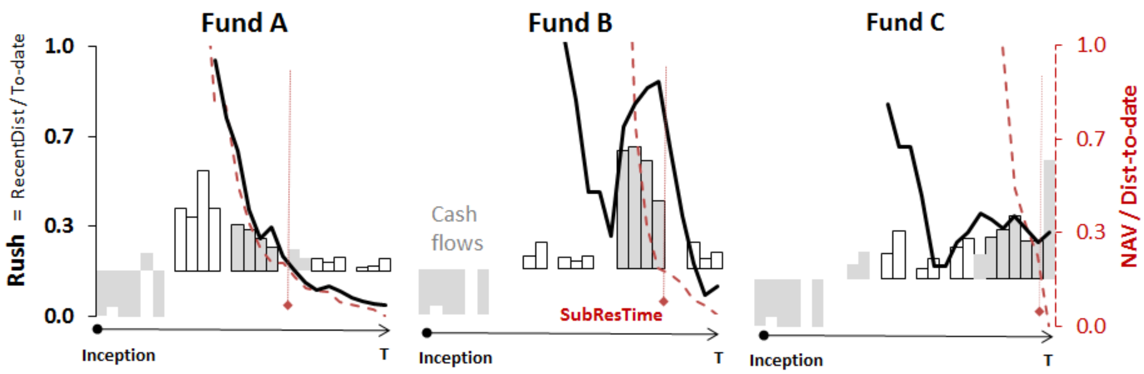
In practice, a PE fund distribution process spans many years via dozens of installments, and often never fully completes with respect to a small fraction of assets (see Internet Ap-

[10] This is analogous to the assumption that the scope for moral hazard associated with agent choice of a higher coverage insurance contract is minimal (see, e.g., Finkelstein and McGarry, 2006).

[11] In addition to using net IRR level as proxy for accrued carry—see section II for discussion.

pendix for details). I therefore approximate $\mathbb{I}(\text{Exit})_i$-indicator with a continuous variable that reflects a fraction of the fund distributions that occurred shortly before the fund assets became *small* in comparison to the fund total distributions to date (henceforth SubResTime—short for "Substantially Resolved"). The fraction is closer to one [zero] when most of the fund divestments took place on the eve of [long before] SubResTime. Hence, it measures the extent that GPs were "rushing" to exit ahead of that quarter. The chart below provides the intuition for how the combination of Rush and SubResTime maps to $\mathbb{I}(\text{Exit})$.

Key Variables' Intuition



The bars in the chart indicate cash flows for three hypothetical funds. Capital calls are negative, followed by positive distribution towards the end of contractual life (T). The dashed red lines indicate the ratio of fund NAVs to the total distributions to date with values reported on the right-hand y-axis. When this ratio is high (only values <1 are plotted), the remaining exposure to the market is large relative to the already "harvested" amount. Subsequent distributions reduce this exposure for the fund and, hence, for GP carry. The quarters in which these ratios cross 15% are marked with a vertical arrow line and indicate SubResTime; that is, when remaining exposures become inconsequential for the fund lifetime results. In this example (and in the actual tests), I use a six-quarter window to compute Rush, plotted in solid black line.[12] Accordingly, the distributions that contribute to the numerator of Rush as of SubResTime are highlighted in gray, while the distributions indicated with

[12] I find similar magnitudes with four- and eight-quarter windows. This approach reduces differences between exit venue choices (i.e., trade sale versus IPO). See Internet Appendix for more discussion. For NAV thresholds, I examine a range between 5% and 25% and report tests for 15% and 20%. Since the funds are nearly fully resolved, possible NAV manipulations are unlikely to meaningfully affect the measurement.

white bars only contribute to the denominator of Rush (i.e., total distributions to date).

From the example chart, it is clear that fund B rushed the most and, if its GPs had in-the-money carry, it would correspond to $\mathbb{I}(\text{Exit}|\text{IRRaboveHurdle})_i = 1$ most closely. By contrast, fund A would be coded to have rushed less than fund C, indicating a likely more favorable market outlook held by its GPs. Meanwhile, the fact that PE funds also make substantial distributions long before and after SubResTime yields natural settings for a placebo test concerning possible heterogeneity in Footprint-on-Firms: if future returns tend to dip because the gray bars somehow cause it, so should the white bars.

I use the sector index returns corresponding to the funds' industry specialization (see section II) for $\text{MarketReturn}_{i,t+1}$. As discussed in the introduction, industry-level timing eclipses the relevance of market-wide timing from the LPs' perspective. Because PE funds cannot recall the capital once it has been distributed to LPs during the post investment period, it makes sense to focus on relatively long-lived market downturns. For this reason, I set the predictive horizon to 12-month following SubResTime.

To control for $\mathbb{E}_t^P[\text{Market}_{i,t+1}]$ as prescribed by models (3–4), I use a combination of market return predictive covariates established in the literature (redefined at the industry level where possible, see Appendix C) and a simulation-based estimator. As discussed in the following section, this approach allows for weaker identifying assumptions across my battery of tests and reduces confounding from a potentially misspecified regression equation.

B. Test Results

Going forward, I will not separate buyout and venture samples—the identification scheme applies to both and section III suggests qualitatively similar results.

B.1. Informed Rush versus Uninformed

Table 4 reports feasible estimates of models (3–4) via the following regression:

$$(5) \quad IndustryReturn_{ij}^{1:12} = \alpha \cdot Informed_{ij} Rush_{ij} + \gamma_0 \cdot Informed_{ij} + \gamma_1 \cdot Rush_{ij} + \text{Controls}_{ij} + \epsilon_{ij} \quad ,$$

where $IndustryReturn_{ij}^{1:12}$ is the mean monthly industry return over the 12 months following fund i's SubResTime; Controls_{ij} include vintage j fixed effects and (in specifications 3 and 4 only) Predictive covariates as of fund's i SubResTime; and ϵ_{ij} is the unobservable error term, spatially correlated across i and j. Across all panels, the odd and even specifications of SubResTime is based on, respectively, 15% and 20% NAV thresholds.

$Informed_{ij}$ is a dummy that denotes the fund group of interest. In panel A, these are funds that satisfy both toDateTTR>1 and toDateIRR>Hurdle at SubResTime, as coded by the interaction of the respective dummies. Funds that don't satisfy either of the criteria are considered *Uninformed* and serve as the control group. Hence, the identifying assumption in this setup is that Informed exits have *same* Footprint-on-Firms, as do Uninformed exits.

[Place Table 4 here]

Panel A shows that the main parameter of interest—the coefficient on the interaction between Informed and Rush, α—is significantly negative across all specification. The magnitude of α indicates how much lower a monthly returns is expected if Informed Rush increases from zero to one. The inter-quartile range for Rush of approximately 0.3 translates into 0.3% to 0.7% lower return per month for 12 months.

The magnitude of α estimates is about twice as large in specifications (1) and (2) as compared to those in (3) and (4), indicating that substantial variation in Informed Rush could be explained by publicly observable signals about expected returns (and/or exit conditions predictive of returns). This fact suggests that GPs tend to not distribute capital back to LPs when observables point to elevated risk premia (consistent with the results in Robinson and Sensoy, 2013). Nonetheless, as follows from specifications (3) and (4), the exit decisions by skilled and incentivized GPs contain a significant component that appears to be missing in the public information set.

Panel B breaks down the Informed-dummy into its constituents, toDateTTR>1 and toDateIRR>Hurdle, and examines the effect of each interaction with Rush separately (i.e, α_0 and α_1 in model 4). For example, the coefficient on toDateTTR>1×Rush measures the predictive effect of Rush by funds that appear skilled but do not have "skin in the game"—for their GPs there is no in-the-money option that may vanish before the normal resolution time is past due. We see that none of these individual conditions has Rush associated with lower subsequent returns. However, the negative coefficients on toDateTTR>1×IRR>Hurdle×Rush gets stronger than in Panel A. This result also indicates that TTR is a good proxy of GPs' market timing skill, as it significantly *predicts* funds' propensity to sell at industry highs.

Panel C examines whether the return predictability strengthens when the actual portfolio of the fund is more concentrated in the focal industry, as suggested by the exit TTR analysis in Table 3. I interact the Informed dummy as defined for panel A with a dummy indicating whether the focal industry comprises more than 50% of the actual investments made by the fund. The panel shows that Rush by incentivized and skilled GPs with more concentrated portfolios is not more informative of the future return in the focal industry than similar Rush by holders of more dispersed portfolios. The coefficients on Rush-interactions with *Declared Ind.>50%P.* are negative but far from being statistically significant individually or jointly.[13]

I carefully examine the sensitivity of inference to different types of the dependency in ϵ_{ij}. I follow Conley (1999) to model the spatial correlation between the return intervals arising from the proximity of SubResTime; I also cluster by vintage year as Kaplan and Schoar (2005) and in two dimensions simultaneously. As shown in Table A.3, (i) the standard errors reported in Table 4 tend to be the largest, and (ii) estimated αs remain negative at the 5% (or better) confidence level for each of the seven inference methods considered.

Next, I scrutinize the claim that fund heterogeneity does not drive the results in Table 4. First, I examine if clustering of fund distributions at least a year away from SubResTime also results in predictability of industry returns. The alternative explanation—that the inherent heterogeneity across funds makes their distribution patterns potentially incomparable—predicts α to be different from zero away from SubResTime as well. However, these placebo tests reported in Table A.4 reveal no statistically or economically significant coefficients.

[13] In an untabulated analysis, I find that Declared Ind.>50%P.×Rush has a t-statistics of -1.5 if used in place of Informed-dummy in eq. (5).

Second, I implement the fuzzy RDD with the fund distance of toDateIRR from the Hurdle as a forcing variable. Naturally, the difference determines the assignment of Informed-indicator, while GPs have limited ability to manipulate performance via NAV reports when the funds are substantially resolved. Table A.6 reveals that the inclusion of the third-order polynomial of the forcing variable does not move the point estimate on α from -0.013 in specification (3) of Table 4 and barely increases the standard error estimate. Table A.6 also shows that α estimates remain well within the baseline standard deviation when the sample heterogeneity is reduced. For example, when IRRs are within 2.5% from the Hurdle, α is estimated at -0.011, although the standard error increases to 0.016 as the sample shrinks to just 108 funds. It is noteworthy that the carry approximation error embedded in my data should be particularly costly for the power in such discontinuity-based tests.

[Place Figure 3 here]

Third, I conduct event studies to mitigate Price Distortion concerns. Figure 3 reports the cumulative Industry returns around SubResTime based on the 15% NAV threshold for funds with Rush above the vintage year median. The solid line represents the mean returns around Informed exits, defined as satisfying both toDateTTR>1 and toDateIRR>Hurdle.[14]

Panel A of the figure reports the results for the entire sample period, while Panel B shows that a clear difference remains even after excluding two years with particularly dramatic declines (2001 and 2008). The figure indicates that the industry returns' dip following Informed Rush does not revert back over the 10-quarter horizon. A reversion would be expected if the underperformance were driven by Price Distortion, whereby selling pressure was not followed by a deterioration in the industry fundamentals.

[Place Figure 4 here]

Finally, I run a calendar time portfolio analysis with the fund industry sectors. Figure 4 and Table A.5 show that a quarterly rebalanced portfolio based on Informed Rush yields a

[14] The sample median Rush is 0.2. A total of 205 funds (i.e., just under a quarter of the sample) satisfy all three conditions: TTR>1, IRR>*Hurdle*, and Rush>0.2. Internet Appendix shows that a regression analysis with a binary Rush definition yields results very close to Table 4 and reports additional event studies.

statistically significant 80 basis points per quarter over the Fama-French three-factor model and 30–40% higher annualized Sharpe ratios than those of the equally weighted portfolio of industries. It is therefore highly unlikely that differences in future risk realizations across industries are responsible for inference about α from regression (5). These results also prove that industry timing is more salient than market-wide timing, regardless of whether the portfolio of industries is value-weighted or equally weighted.

B.2. Informed Rush versus Random

To obtain stronger evidence against the Pseudo Timing alternative, I also estimate regression (5) with random (hypothetical) SubResTime and Rush as a control group. In particular, I seek to mitigate concerns that the residual variation in Rush examined in section IV.B.2 merely reflects non-linear and interaction effects of Predictive covariates.

I jointly model Rush and SubResTime and simulate multiple hypothetical exits for each actual fund.[15] The resulting permutations enable *fund fixed effects* that reflect a rich set of fund characteristics and the variation in exit conditions during the times they have operated (see Table B.1). Since these absorb significant variation in risk premia over time, the inference should be less sensitive to the inclusion of Predictive covariates and, hence, to the omission of some potentially relevant predictors.

The advantage of the random control group with respect to the superior measurement of $\mathbb{E}_t^P[\text{Market}_{i,t+1}]$ comes at a cost of a stronger *identifying assumption* required with respect to the potential causal effects of PE exits on public equities. Specifically, for this setup to recover α as in models (3–4), PE fund exits must have *neither* Footprint-on-Firms nor Price Distortion. Therefore, it is important to view the analysis in Table 5 in the context of the results established in the previous section.

To begin, Panel A of Table 5 shows what we could not learn when the control group

[15] The procedure is asymptotically equivalent to the *Simulated Method of Moments*, accounts for uncertainty of *auxiliary model* parameter estimates, and involves three steps: (i) estimating a model of fund fixed effects for SubResTime and Rush, (ii) independently simulating 1,000 blocks of 100 random exits per fund and estimating the *main model* (i.e., equation 5) within each block, and (iii) pooling the *main model* estimates over these independent simulations. See Internet Appendix for details.

comprised actual funds—whether aggregate PE distributions predict future industry returns unconditionally on GP incentives. Consistent with results in Ball et al. (2011), the coefficient on ActualFund×Rush, while negative, is economically small and statistically insignificant. However, the estimates in panels B and C, in which I limit the actual fund groups to match the Informed dummy definitions used in Table 4, strongly support the presence of selection on superior information in PE fund exits.

[Place Table 5 here]

As in Table 4, specifications (1) and (2) of Table 5 correspond to SubResTime under the 15% and 20% thresholds for the fixed-effects-only model, whereas specifications (3) and (4) also include Predictive covariates. Unlike in Table 4, the point estimates with Predictive covariates included are very close to those with just the fixed effects—between 0.014 and 0.017 for α. This result means that the projections of fund fixed effects for SubResTime and Rush indeed absorb much of their joint variation with Pseudo-timing factors, alleviating the regression and factor misspecification concerns.

I scrutinize the robustness and statistical properties of this simulation-based estimator. Specifically, I verify (i) that α-estimates are largely insensitive and statistically robust to the exclusion of various permutations of vintage and exit years (see Figure B1), and (ii) that, while fitted values of Informed Rush never predict returns, the actual size of the tests based on asymptotic standard errors is close to the nominal size (Figure B2, panels A and B). By contrast, in panel C of Figure B2, I show that the return predictability vanishes for industries that did not correlate with the funds' primary industry in the recent past.

Importantly, Panel B and C of Table 5 are the simulation-based counterparts of Panel A and B of Table 4 with directly comparable magnitudes. From this comparison, it follows that (i) Footprint-on-Firms effects are likely negligible for PE fund exits (since estimates in columns 3–4 match closely across tables), and (ii) superior information explains 52–69%, with the remainder attributable to Pseudo-timing. However, because of the false-negative bias in measuring exit incentives, this analysis likely overstates the share of Pseudo-timing somewhat.

B.3. Predictability Sources

In this section, I seek to understand which sources of the industry return formation process are likely responsible for the predictability results established in the previous sections.

Per Campbell and Shiller (1988), the unexpected asset returns can be decomposed into (i) the revision of expectations about current and future cash flows it pays ($\equiv N_{CF,t+1}$), and (ii) the revision in expectations about future discount rates the investors require ($\equiv N_{DR,t+1}$):

$$
\begin{aligned}
(6) \qquad r_{t+1} - \mathbb{E}_t r_{t+1} &= (\mathbb{E}_{t+1} - \mathbb{E}_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - (\mathbb{E}_{t+1} - \mathbb{E}_t) \sum_{j=1}^{\infty} \rho^j r_{t+1+j} \\
&= N_{CF,t+1} - N_{DR,t+1} \quad ,
\end{aligned}
$$

where $\rho = 1/e^{\overline{d-p}}$ and d_t (p_t) is the asset log dividend (price) in period t, while r_t is the log rate of return for the period.

Given GPs' potential involvement in the operational management of their portfolio companies and their special position in the capital market as firsthand observers of portfolio demands of large public and private investors, both $N_{CF,t+1}$ and $N_{DR,t+1}$ can be at play. To account for the correlation between these sources of returns while maintaining the identification framework outlined in section IV.A, I use two-stage least squares to estimate the following equation:

$$
(7) \qquad \mathbb{E}[Rush_{ij}] = \alpha^R [Informed_{ij} \quad IndustryRerturn_{ij}^{1:12} \times Informed_{ij} \quad IndustryReturn_{ij}^{1:12}] + \text{Controls}_{ij} \quad .
$$

Thus, relative to the preceding analyses, I swap returns with Rush as the outcome variable, so that equation (7) can be thought of as equation (5) but written in the standard causal inference framework with the identifying assumption that future returns *cause* past Rush. Meanwhile, instrumenting the return terms (rather using the reduced form) insures that inference accounts for the measurement error in the proxy of $N_{CF,t+1}$ and/or $N_{DR,t+1}$.

I use the industry unexpected earnings to proxy for $N_{CF,t+1}$ and changes in the ratios of index values to the earning forecasts to proxy for $N_{DR,t+1}$. Both variables are computed from analyst estimates aggregated to the respective S&P500 subindex (see section II). Accordingly, the instruments' validity hinges on (i) this proxy of cash flow and discount rate news being indeed related to the industry return realizations tightly enough, and (ii) Rush being unrelated to cash flow and discount rate news through other channels.

[Place Table 6 here]

Table 6 reports the results. First-stage regression results are summarized by the Kleibergen-Paap Wald test statistics, which levels suggest that the excluded instruments are indeed relevant. All specifications include Predictive covariates (Appendix C). Specifications (1) and (3) use the actual fund exits as control group, corresponding to the approach in Table 4, while specifications (2) and (4) use hypothetical fund exits, as in Table 5.

In specifications (1) and (2), the excluded instruments are IndEPSsurprise and its interaction with the Informed dummy, while IndForwardMultΔ and its interaction with Informed are added to the first- and second-stage regressions along with other covariates. Significantly negative coefficients of Informed$\times$IndustryReturn indicate that skilled GPs foresee the industry cash flow news that cause the industry returns to fall. These estimates suggest that the industry earnings surprise that triggers a 10% drop in the industry return causes a 25–38 percentage point higher Informed Rush over the preceding six quarters.

Specifications (3) and (4) use the terms with IndForwardMultΔ as excluded instruments while including IndEPSsurprise in the set of other covariates. Hence, these tests show whether GPs foresee innovations in the discount rates that investors require beyond the variation in the industry earning news. Although the point estimates on Informed$\times$IndustryReturn and IndustryReturn are negative according to specification (3), they are far from being significant statistically. Furthermore, these coefficients are not even negative (and still insignificant) according to specification (4), which uses hypothetical exits as the control group.

It therefore appears that GPs' forecasting edge is limited to the cash flow process in the industry of specialization, while their capital market activities do not yield important insights about swings in the marginal investor's risk preferences. This is consistent with the predictability of returns vanishing outside the native industry, as discussed in section IV.B.2.

I also examine whether the simultaneity of Rush and Informed variables is a relevant concern. I find similar results if both IndustryReturn and Informed are instrumented with, respectively, IndEPSsurprise and the propensity score determined by the performance of the current fund's peers and the GP's previous fund TTR. The exclusion restrictions for this test are: (i) industry future earning surprises do not affect the fund exits today except through GP's industry return outlook, and (ii) strategy-by-vintage median "luck" does not affect the fund exits today except through the odds that the fund carry is in-the-money. This analysis is reported in Internet Appendix.

V. Conclusion

In this paper, I show that GPs appear to be more informed about industry valuations than marginal investors in public markets are. This informational advantage creates value for LPs beyond what the literature has analyzed. GPs' learning through the private investment/divestment process appears to be the source of this knowledge, lending itself to an increased ability to time industry peaks and troughs. This skill persists and pertains to the industry cash flow fundamentals, as measured by public firms' earnings news.

My tests isolate GPs' likely superior information from reactions to time-varying market conditions and certain causal effects of PE activity spillovers on public firm policies. However, such informed trading by GPs is unlikely to go completely unnoticed by other investors. As a result, PE activities may increase the informational efficiency of the capital market, providing a channel for how private information becomes impounded into public market prices, as studied in Asriyan et al. (2017).

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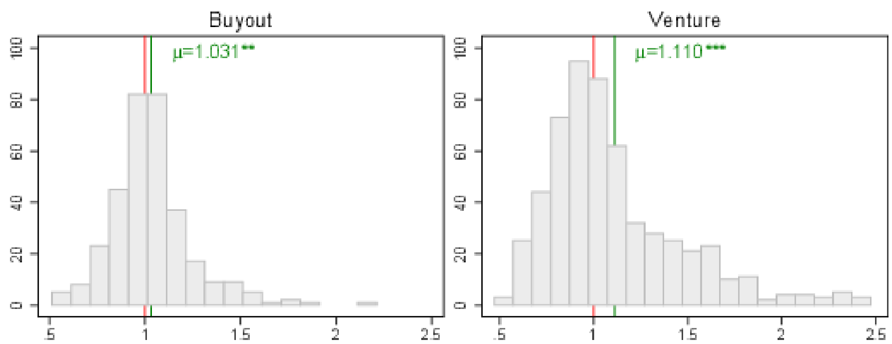
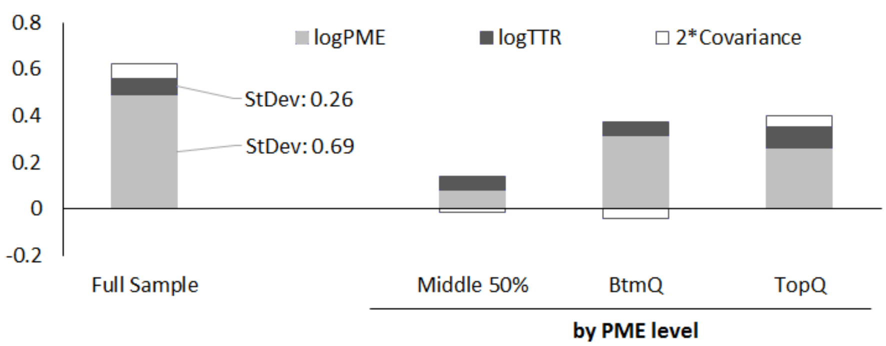
Figure 1
Timing Track Records: univariate analysis

This figure summarizes the distributional properties of the sample TTRs, which measure a fund's gross-return due to selling near the market peaks and buying near the troughs. Panel A left (right) chart shows the frequency distributions of TTRs for buyout (venture) funds using the complete history of the fund cash flows. Lines and text indicate the sample means and a two-sided test for their equality to one (i.e., the null hypothesis of no abnormal returns due to timing, **/*** denote significance at 5/1%). Panel B reports the variance decomposition of end-of-life money multiples adjusted for the trend in the Industry into the selection (as measured by log PME) and timing as measured by log TTRs. 'Full Sample' indicates all funds (buyout and venture), other three columns report results by subsample based on the relative rank of the fund's PME within fund type (venture or buyout) and vintage year. Panel C, breaks down the variation in TTR into two sources – entry and exit (per eq. 1) similarly for the full sample and subsamples. Table 1 describes the sample, Appendix C defines the variables.

Panel A: TTRs by fund type



Panel B: Variance decomposition of funds total returns



Panel C: Variance decomposition of funds TTRs

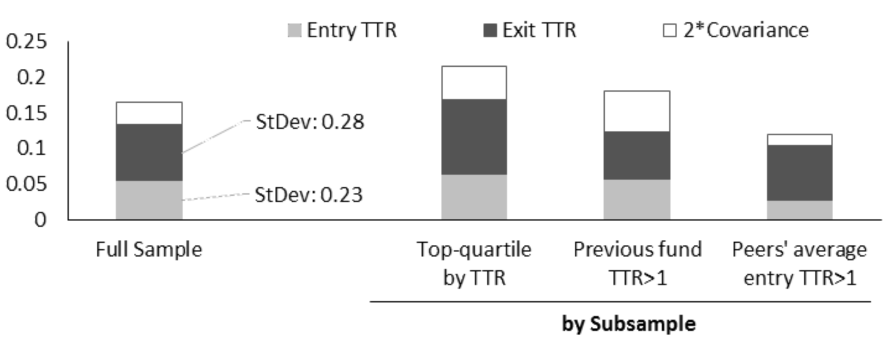
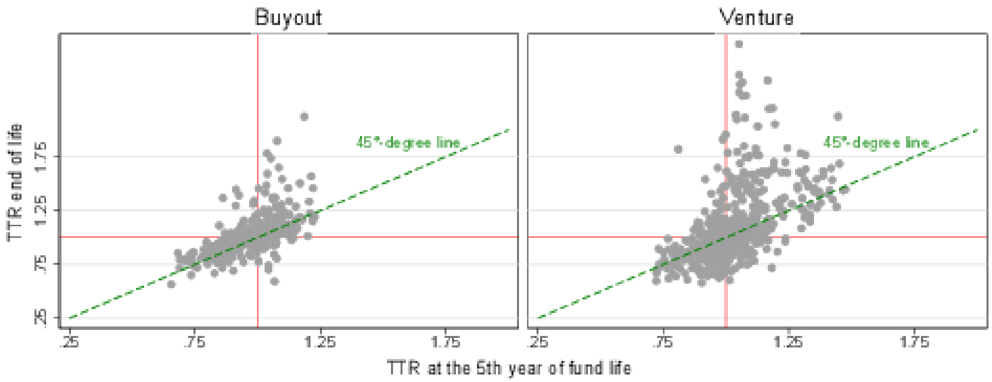


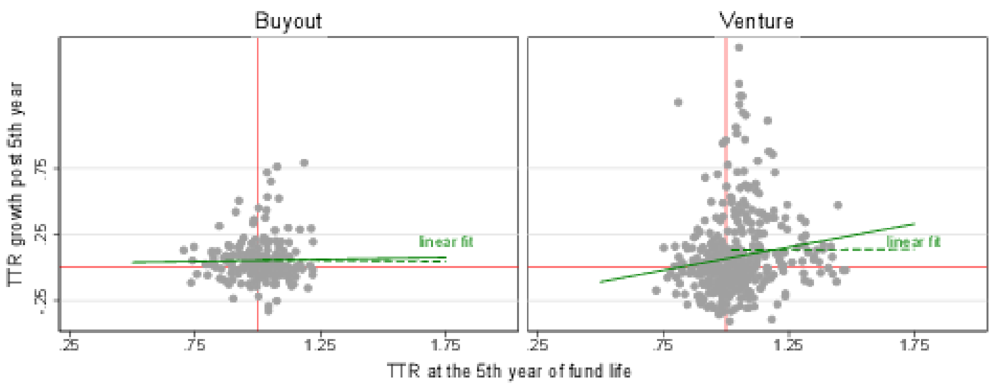
Figure 2
Sample fund TTRs: Fifth anniversary versus Final

This figure compares the sample funds *toDateTTR* as of fifth year since inception with their end-life *TTRs* (Panel A) and reports the post-fifth year growth conditional on the fund's fifth anniversary IRR being above [below] the Hurdle rate (8% for buyouts and 0% for venture funds) in Panel B [C]. *TTR* measures fund's gross-return due to selling near the market peaks and buying near the troughs. Table 1 describes the sample, Appendix C defines the variables. Results are reported separately by buyout and venture subsamples in, respectively, left-hand and right-hand plots.

Panel A: Fifth anniversary versus end-life



Panel B: Post-interim growth if *toDateIRR* <u>above</u> the Hurdle rate



Panel C: Post-interim growth if *toDateIRR* <u>below</u> the Hurdle rate

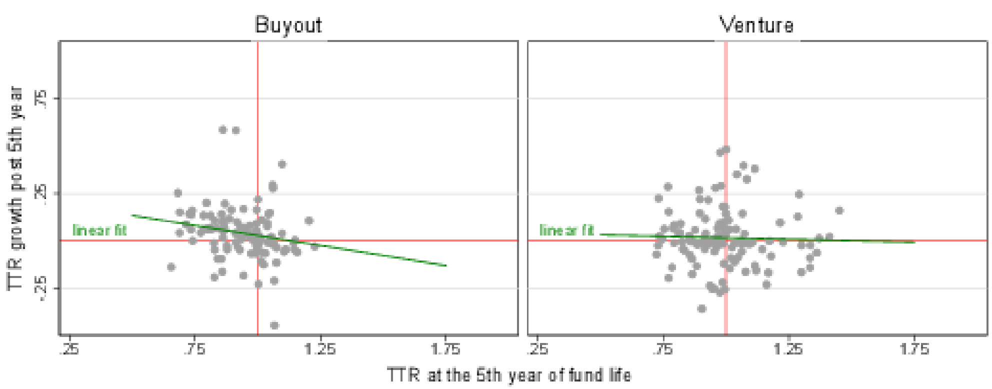
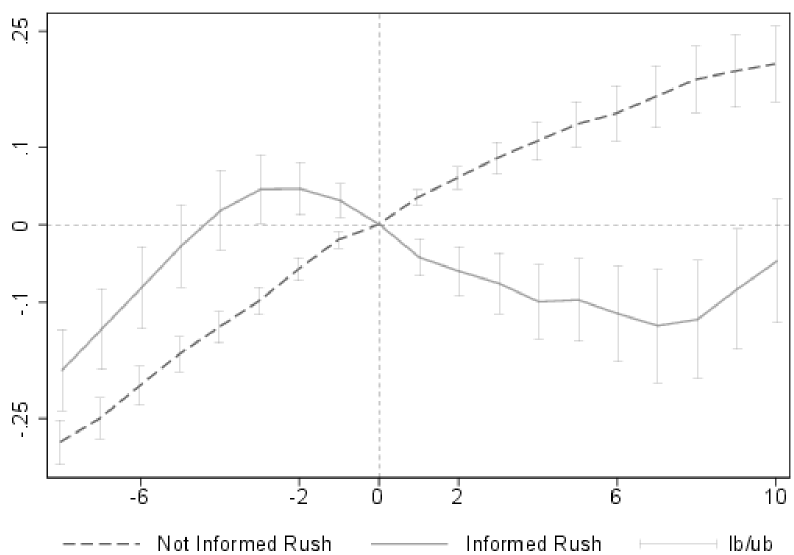


FIGURE 3
Informed Rush and Industry returns: Event Studies

This figure plots cumulative return on *Industry* portfolio around *SubResTime* for funds with *Rush* above vintage year medians. *Rush* measures the intensity of fund's distributions to LPs right before *SubResTime*, based on 15% NAV threshold. The medians are computed by fund type (venture or buyout) and vintage year. The solid line (*Informed Rush*) is the mean across *Informed* funds that have incentives and market-timing skill, as measured by both *toDateTTR>1* and *toDateIRR>HR* as of *SubResTime*. The dashed line comprise of all other funds. Panel A reports results for the full sample. Panel B excludes *SubResTime* that occurred in 2001 and 2008. The bars denote 95% confidence intervals. Table 1 describes the sample, Appendix C defines the variables.

Panel A: Full Sample of Exits: 1990-2013



Panel B: Excluding Extremes: 2001 and 2008

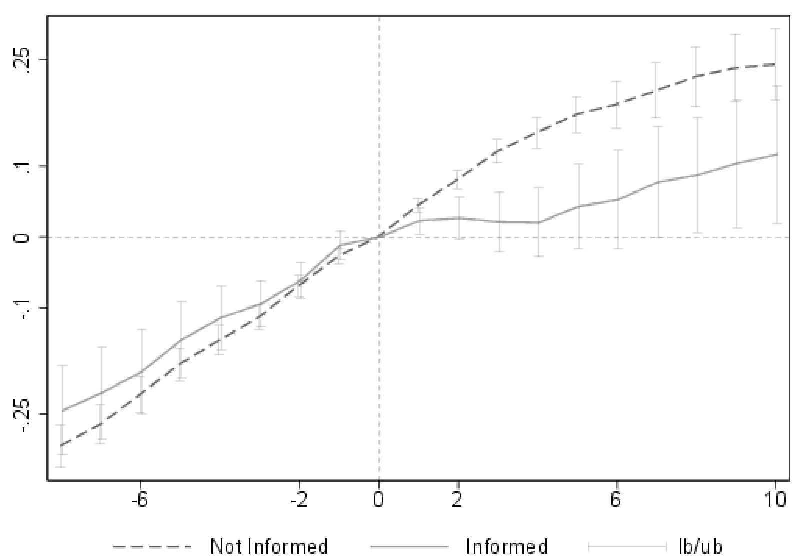


FIGURE 4
Calendar Time Portfolios: Cumulative Returns

This figure compares cumulative returns and Sharpe ratios for two portfolios. *Portfolio A* is equally-weighted 10 S&P500 GICS sector portfolio. Portfolio B sells GICS sectors for which two or more *Informed* funds exhibited above-median *Rush* right before their *SubResTime* over the past 3 or 7 quarters (i.e. [0,+2q] or [0,+6q] observation window respectively) and buys the remaining sectors (equally-weighted). *Informed* are funds with incentives and market-timing skill, as measured by both *toDateTTR>1* and *toDateIRR>HR* as of *SubResTime*, based on the 15% NAV threshold. *Rush* measures the intensity of fund's distributions to LPs right before *SubResTime*. The medians are computed by fund type (venture or buyout) and vintage year. Table 1 describes the sample, Appendix C defines the variables. Table A.5 reports abnormal return estimates of *Portfolio B* as well as '*B minus A*' against Fama-French three-factor model.

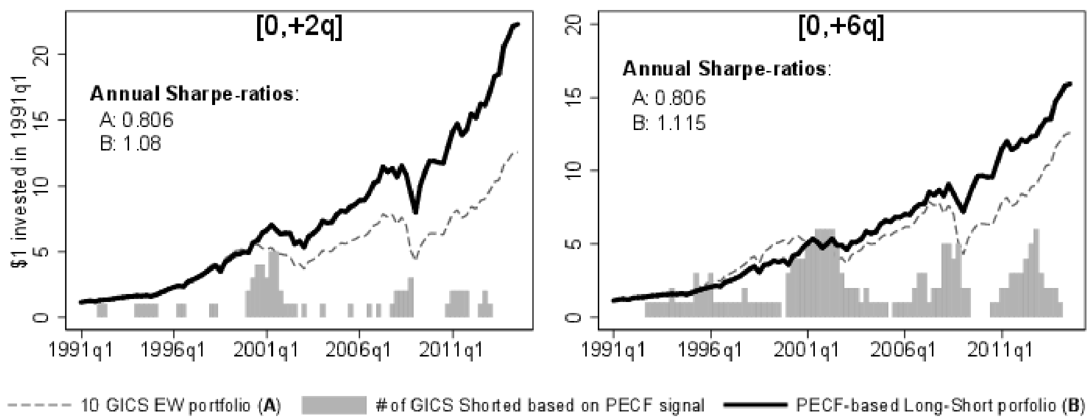


Table 1
Summary Statistics

This table reports summary statistics for the data used in this study. Panel A reports sequence order, vintage year, life since inception, size, and the last-most performance statistics for 349 (592) U.S.-focused buyout (venture) funds of which 126 (169) continue operations as of March 2013. *Overall* and *Industry Sequence* report the fund chronological order of the inception date within GP and GP-industry respectively or zeros when fund's GP affiliation is not available (~15% of sample funds). IRR stands for internal rate of return. PME vs Industry denotes Kaplan and Schoar (2005) Public Market Equivalent index computed using S&P500 subindex corresponding to the GICS sector of the fund specialization. Panel B reports statistics for monthly returns, price-to-earning and book-to-market ratios of these subindexes for the period from January 1989 through October 2013. Panel C reports statistics for the rest of the variables used in this study.

Panel A1: PE funds

	Variable	Mean	SD	p1	p5	p25	p50	p75	p95	p99
Buyout	Overall Sequence	3.0	2.7	0.0	0.0	1.0	2.0	4.0	9.0	12.0
	Industry Sequence	2.1	1.7	0.0	0.0	1.0	2.0	3.0	6.0	8.0
	Vintage Year	1996	5	1982	1986	1994	1997	2000	2003	2005
	Life in Quarters	48	11	20	30	41	48	55	65	81
	Fund Size ($mln)	745	955	25	60	160	400	910	2920	5000
	IRR	0.165	0.227	-0.195	-0.077	0.060	0.130	0.225	0.488	1.017
	Money Multiple	13.32	181.21	0.52	1.00	1.69	2.28	3.44	8.69	51.92
	PME vs Industry	1.34	0.87	0.26	0.48	0.87	1.24	1.63	2.48	3.08
Venture	Overall Sequence	3.1	2.8	0.0	0.0	1.0	2.0	4.0	9.0	13.0
	Industry Sequence	2.7	2.5	0.0	0.0	1.0	2.0	4.0	8.0	11.0
	Vintage Year	1993	6	1980	1982	1987	1994	1999	2001	2003
	Life in Quarters	49	11	23	33	42	49	56	68	78
	Fund Size ($mln)	156	178	11	19	47	98	190	510	850
	IRR	0.227	0.524	-0.248	-0.155	0.004	0.094	0.222	1.107	2.735
	Money Multiple	4.42	6.49	0.36	0.78	1.69	2.69	4.33	13.74	37.65
	PME vs Industry	1.38	1.69	0.13	0.32	0.62	0.99	1.45	3.68	10.22

Panel A2: Funds sample by industry and vintage year

	'79-83	'84-86	'87-89	'90-92	'93-94	'96-98	'99-01	'02-06	Total
Consumer Discretionary	6	7	6	7	19	30	32	9	116
Consumer Staples	0	1	1	0	2	3	7	1	15
Energy	0	0	1	1	0	3	3	1	9
Financials	3	2	5	1	8	12	14	2	47
Healthcare	5	11	21	15	25	39	32	8	156
Industrials	16	28	37	15	17	31	31	9	184
Internet Technology	27	35	39	20	48	83	95	9	356
Meterials	0	0	1	0	1	4	2	1	9
Telecommunications	2	2	4	4	6	13	17	1	49
Utilities	0	0	0	0	1	0	0	0	1
Total	59	86	115	63	127	218	233	49	942

Table 1—*Continued*

Panel B: Industry benchmarks returns an ratios

	Returns			Book-to-Market			Price-to-Earnings		
	Mean	SD	Skew	Mean	p25	p75	Mean	p25	p75
Consumer Discretionary	0.009	0.052	-0.737	0.379	0.319	0.438	27.0	15.7	22.9
Consumer Staples	0.009	0.040	-1.047	0.238	0.178	0.291	20.1	15.9	21.1
Energy	0.010	0.053	-0.397	0.438	0.358	0.521	17.6	12.4	19.4
Financials	0.007	0.065	-0.984	0.629	0.467	0.840	24.6	12.8	17.7
Healthcare	0.010	0.047	-0.461	0.247	0.165	0.320	20.0	15.9	21.3
Industrials	0.009	0.046	-1.107	0.323	0.283	0.369	23.3	16.7	27.2
Internet Technology	0.008	0.072	-0.796	0.327	0.224	0.451	27.5	15.2	35.6
Materials	0.008	0.057	-0.627	0.424	0.359	0.460	23.6	14.8	28.4
Telecommunications	0.007	0.055	-0.402	0.406	0.280	0.509	21.0	15.6	23.0
Utilities	0.008	0.044	-0.616	0.554	0.484	0.678	15.2	12.3	16.7

Panel C: Other variables

Variable	Mean	SD	p1	p5	p25	p50	p75	p95	p99
Market Return (*100)	0.95	4.53	-10.21	-7.42	-1.74	1.54	3.92	7.53	10.20
CAY Ratio (*100)	0.23	2.30	-3.35	-3.13	-2.08	0.51	2.25	3.46	3.96
CBOE VIX	20.4	7.8	10.9	11.7	14.9	18.9	23.9	34.5	46.4
BBB-AAA spread	0.98	0.40	0.55	0.60	0.73	0.90	1.14	1.44	3.00
AAA-UST spread	1.33	0.48	0.49	0.72	0.91	1.31	1.70	2.11	2.53
10-year yield (*100)	5.45	2.04	1.68	2.01	3.96	5.28	7.09	8.86	9.26
3-month yield (*100)	3.56	2.46	0.02	0.04	1.13	4.14	5.33	7.64	8.43
IndEPSsurprise	0.02	0.77	-1.43	-1.22	-0.59	0.03	0.62	1.29	1.56
IndForwardMultΔ	-0.01	0.83	-1.66	-1.37	-0.61	-0.05	0.58	1.47	1.71

Table 2
Timing Track Records: Associations and Persistence

This table reports regression estimates of the log of funds' end-life *TTRs* on a set of fund/GP characteristics. *TTR* measures the gross-return due to selling near the market peaks during the fund life-time and buying near the troughs. Table 1 describes the sample, Table Appendix C defines key variables. The explanatory variables are all in logs: 'Fund size' ['Fund size squared'] – size [size-squared] of the fund dollar amount of capital committed; 'Sequence' – chronological order of the fund inception date within same GP; 'PME' – the fund's *PME*; 'Previous fund TTR' – the GP's previous fund TTR. Specifications (2) through (6) include fund vintage fixed effects. Table A.1 reports additional specifications and robustness. Standard errors in parentheses are clustered by GP, */**/*** denote significance at 10/5/1% confidence level.

	(1)	(2)	(3)	(4)	(5)	(6)
Fund size	0.515***	0.082				
	(0.162)	(0.150)				
Fund size squared	−0.014***	−0.003				
	(0.004)	(0.004)				
Fund sequence	0.057***	0.049***	0.040**			0.055**
	(0.021)	(0.018)	(0.017)			(0.024)
Fund PME			0.040***		0.059***	0.054***
			(0.015)		(0.020)	(0.020)
Previous fund TTR				0.135**	0.115**	0.107**
				(0.052)	(0.051)	(0.049)
Vintage year fixed effects	No	Yes	Yes	Yes	Yes	Yes
Observations	756	756	756	404	404	404
R^2	0.025	0.387	0.386	0.431	0.449	0.457

Table 3
Timing Track Records: Entry versus Exit

This table reports regression estimates of the log of funds' *Entry TTRs* in Panel A and *Exit TTRs* in Panel B on a set of fund/GP characteristics. TTR measures the gross-return due to selling near the market peaks during the fund life-time and buying near the troughs, which can be broken down to the entry [exit] components dues to the pattern of capital calls [distributions] as shown in equation 1. Table 1 describes the sample, Table Appendix C defines key variables. The explanatory variables are: 'TTR at 5th anniversary' – the log of overall fund to-date-TTR measured as of the end of the 5th year since inception, 'Declared Ind.>50%P' – a dummy taking the value of 1 if a single industry represents more than 50% of the fund investments made during its life-time, 'Peers' entry [exit] TTR' – the log of the average entry [exit] TTR computed across the fund's strategy $\times$ vintage peers (excluding the fund itself), 'Previous fund TTR$\geq$ 1' – a dummy taking the value of 1 if the GP's previous fund TTR exceeded 1. Specifications (4) through (6) include fund vintage fixed effects. Standard errors in parentheses are clustered by GP, */**/*** denote significance at 10/5/1% confidence level.

Panel A: Entry TTR

	(1)	(2)	(3)	(4)	(5)	(6)
TTR at 5th anniversary	0.685***					
	(0.067)					
Declared Ind.>50%P		0.024*			0.012	0.019
		(0.014)			(0.010)	(0.012)
Peers' entry TTR			0.946***			0.710***
			(0.032)			(0.109)
Previous fund TTR$\geq$1				−0.038**		−0.026*
				(0.015)		(0.015)
Vintage year fixed effects	No	No	No	Yes	Yes	Yes
Observations	941	941	886	802	941	756
R^2	0.237	0.002	0.582	0.564	0.559	0.594

Panel B: Exit TTR

	(1)	(2)	(3)	(4)	(5)	(6)
TTR at 5th anniversary	0.398***					
	(0.067)					
Declared Ind.>50%P		−0.004			0.026*	0.029*
		(0.018)			(0.014)	(0.016)
Peers' exit TTR			0.953***			0.237**
			(0.063)			(0.111)
Previous fund TTR$\geq$1				0.014		0.014
				(0.019)		(0.019)
Vintage year fixed effects	No	No	No	Yes	Yes	Yes
Observations	941	941	884	802	941	754
R^2	0.057	0.000	0.261	0.497	0.474	0.505

Table 4
Informed Rush versus Uninformed

This table reports predictive regressions of *Industry returns* by *Informed Rush*, a proxy for the carried interest "cashed-in" by GPs with a positive track record of market timing in the past:

$$\mathbb{E}[IndustryReturn_{ij}^{1:12}] = \alpha \cdot Informed_{ij} \cdot Rush_{ij} + \gamma_0 \cdot Informed_{ij} + \gamma_1 \cdot Rush_{ij} + \beta c_i + \lambda_j \ ,$$

where $IndustryReturn_{ij}^{1:12}$ is the mean monthly *Industry* return over 12 months following the fund i *SubResTime*, $Rush_{ij}$ measures the intensity of fund's distributions to LPs right before *SubResTime*. Table 1 describes the sample, Table Appendix C—the variables. In Panel A, $Informed_{ij}$ is a single indicator variable denoting funds with both *toDateTTR>1* and *toDateIRR>HR* as of *SubResTime* based on 20 (15)% residual NAV threshold in even (odd) specifications. In Panel B, $Informed_{ij}$ is a set of three indicator variables: for *toDateTTR>1* and *toDateIRR>HR* separately, and the interaction thereof. Panel C examines the interaction of *Informed* fund definition from Panel A with the fund's portfolio actual industry concentration—*Declared Ind.>50%P* takes the value of 1 if a single industry represents more than 50% of the fund investments made during its lifetime (and 0 otherwise). In all panels, specifications (3) and (4) include *Predictive covariates* (c_i) in addition to the vintage year fixed effects (λ_j). Standard errors in parentheses are robust to heteroskedasticity and autocorrelation, */**/*** denote significance at 10/5/1%. Table A.3 reports inference results using other methods. Table A.4 reports placebo tests.

Panel A: Informed ≡ (toDateTTR>1)·(toDateIRR>HR)

	15%thld (1)	20%thld (2)	15%thld (3)	20%thld (4)
toDateTTR>1 × toDateIRR>Hurdle × Rush	−0.025***	−0.023***	−0.013***	−0.013**
	(0.007)	(0.008)	(0.005)	(0.005)
toDateTTR>1 × toDateIRR>Hurdle	0.002	0.003	0.003	0.003
	(0.003)	(0.003)	(0.002)	(0.002)
Rush	0.004	0.002	0.007*	0.006*
	(0.004)	(0.004)	(0.004)	(0.004)
Controls:				
Industry CAR			−0.219	−0.224
			(0.306)	(0.276)
Industry P/E			−0.005**	−0.005**
			(0.002)	(0.002)
Industry B/M			−0.037***	−0.023**
			(0.013)	(0.011)
CAY-ratio			0.549***	0.521***
			(0.132)	(0.123)
CBOE VIX			0.040	0.036
			(0.028)	(0.028)
BAA-AAA spread			0.009	0.009
			(0.007)	(0.007)
AAA-UST spread			−0.030***	−0.029***
			(0.006)	(0.005)
UST 10-year yield			−0.009***	−0.010***
			(0.002)	(0.002)
UST 3-month yield			−0.003***	−0.003**
			(0.001)	(0.001)
Vintage year fixed effects	Yes	Yes	Yes	Yes
Observations	894	942	893	941
R^2	0.218	0.234	0.446	0.464

Table 4—*Continued*

Panel B: Informed ≡ (toDateTTR>1)+(toDateIRR>HR)+(toDateTTR>1)·(toDateIRR>HR)

	15%thld (1)	20%thld (2)	15%thld (3)	20%thld (4)
toDateTTR>1 × toDateIRR>Hurdle × Rush	−0.031**	−0.024**	−0.022**	−0.021***
	(0.013)	(0.011)	(0.010)	(0.008)
toDateTTR>1 × Rush	0.006	0.001	0.008	0.004
	(0.009)	(0.006)	(0.008)	(0.006)
toDateIRR>Hurdle × Rush	0.001	0.001	0.004	0.009
	(0.009)	(0.009)	(0.007)	(0.007)
toDateTTR>1 × toDateIRR>Hurdle	−0.002	−0.004	0.006*	0.005
	(0.004)	(0.004)	(0.003)	(0.003)
toDateTTR>1	−0.000	0.002	−0.002	−0.000
	(0.003)	(0.003)	(0.003)	(0.002)
toDateIRR>Hurdle	0.002	0.004	−0.003	−0.003
	(0.003)	(0.003)	(0.003)	(0.003)
Rush	0.002	0.000	0.003	0.001
	(0.006)	(0.006)	(0.006)	(0.005)
Controls:	Same as in the respective column of Panel A			
Observations	894	942	893	941
R^2	0.064	0.064	0.446	0.466

Panel C: Interaction with Portf. composition, Informed ≡ (toDateTTR>1)·(toDateIRR>HR)

	15%thld (1)	20%thld (2)	15%thld (3)	20%thld (4)
Declared Ind.>50%P. × Informed × Rush	−0.004	−0.004	−0.002	−0.001
	(0.012)	(0.014)	(0.009)	(0.010)
Informed × Rush	−0.022***	−0.020**	−0.012*	−0.012*
	(0.008)	(0.009)	(0.006)	(0.007)
Declared Ind.>50%P. × Rush	0.004	−0.003	0.003	−0.003
	(0.006)	(0.006)	(0.005)	(0.006)
Declared Ind.>50%P. × Informed	0.004	0.005	0.004	0.003
	(0.004)	(0.005)	(0.003)	(0.004)
Informed	−0.000	−0.000	0.001	0.001
	(0.003)	(0.004)	(0.002)	(0.003)
Declared Ind.>50%P.	−0.003	−0.002	−0.003	−0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Rush	0.002	0.004	0.005	0.008
	(0.005)	(0.005)	(0.004)	(0.005)
Controls:	Same as in the respective column of Panel A			
Observations	893	941	892	940
R^2	0.219	0.237	0.447	0.466

TABLE 5
Actual Rush versus Random

This table reports simulation-based estimates of predictive regressions of *Industry returns* by *Informed Rush*, a proxy for the carried interest "cashed-in" by GPs with a positive track record of market timing in the past:

$$\mathbb{E}[IndustryReturn_{ij}^{1:12}] = \alpha \cdot Informed_{ij} \cdot Rush_{ij} + \gamma_0 \cdot Informed_{ij} + \gamma_1 \cdot Rush_{ij} + \beta c_i + \lambda_j \ ,$$

where $IndustryReturn_{ij}^{1:12}$ is the mean monthly *Industry* return over 12 months following the fund i *SubResTime*, $Rush_{ij}$ measures the intensity of fund i distributions to LPs right before *SubResTime*. Table 1 describes the sample, Table Appendix C—the variables. The estimation proceeds in three steps: (i)—estimate a model of fund fixed effects for *SubResTime* and *Rush* (*auxiliary model*, Table B.1), (ii)—independently simulate 1,000 blocks of 100 random exits per fund under the *auxiliary model*, and (iii)—pool the main model estimates over these independent simulations. In all panels, $Informed_{ij}$ indicator equals one for actual funds and zero for the simulated funds, even (odd) specifications report results results for *SubResTime* based on 20 (15)% residual NAV threshold, specifications (3) and (4) include *Predictive covariates* (c_i) in addition to fund fixed effects (λ_j) that reflect expected *SubResTime* and *Rush* from the *auxiliary model*. Panel A includes all actual funds in the sample along with the corresponding simulated funds. Panel B includes actual funds with both *toDateTTR>1* and *toDateIRR>HR* and the corresponding simulated funds. Panel C includes actual funds with either *toDateTTR>1* or *toDateIRR>HR*. Standard errors in parentheses are robust to heteroskedasticity and autocorrelation, */**/*** denote significance at 10/5/1%.

	15%thld (1)	20%thld (2)	15%thld (3)	20%thld (4)
Panel A: Informed ≡ All Actual Funds				
ActualFund × Rush	−0.006	−0.007	−0.005	−0.005
	(0.004)	(0.005)	(0.005)	(0.004)
# of Actual funds	893	941	893	941
Pseudo funds per 1 Actual	95.0	94.3	94.9	94.2
Panel B: Informed ≡ (toDateTTR>1)·(toDateIRR>HR)				
toDateTTR>1 × toDateIRR>Hurdle × Rush	−0.017***	−0.017**	−0.016***	−0.014**
	(0.006)	(0.007)	(0.006)	(0.007)
# of Actual funds	373	387	373	387
Pseudo funds per 1 Actual	95.8	95.3	95.7	95.3
Panel C: Informed ≡ (toDateTTR>1)+(toDateIRR>HR)+(toDateTTR>1)·(toDateIRR>HR)				
toDateTTR>1 × toDateIRR>Hurdle × Rush	−0.032***	−0.026**	−0.034***	−0.027***
	(0.012)	(0.012)	(0.010)	(0.010)
toDateTTR>1 × Rush	0.008	0.002	0.012	0.005
	(0.009)	(0.007)	(0.007)	(0.006)
toDateIRR>Hurdle × Rush	0.006	0.007	0.006	0.007
	(0.005)	(0.007)	(0.005)	(0.006)
# of Actual funds	756	791	756	791
Pseudo funds per 1 Actual	83.4	82.5	83.3	82.4
Applies to Each Panel:				
# of independent simulations	1000	1000	1000	1000
Rush, Informed(D)	Yes	Yes	Yes	Yes
Fund fixed effects	Yes	Yes	Yes	Yes
Predictive covariates	No	No	Yes	Yes

Table 6
What Are GPs Informed About?

Panel A of this table reports instrumental variable regression estimates of the following model:

$$\mathbb{E}[Rush_{ij}] = \lambda_j^R + \beta c_{ij}^R + \alpha^R \left[Informed_{ij} \quad IndReturn_{ij}^{1:12} \times Informed_{ij} \quad IndReturn_{ij}^{1:12} \right] ,$$

where $Rush_{ij}$ is a fraction of distributions over the last 6 quarters in fund's i total to-date; $Informed_{ij}$ is an indicator for the presence of incentives and market-timing skill (both *toDateTTR>1* and *toDateIRR>HR*); $IndReturn_{ij}$ is the mean monthly return on publicly traded *Industry* benchmark over 12 months following the fund i *SubResTime*, and a_j^R are the vintage year fixed effects. Table 1 describes the sample, Table Appendix C—the variables. In specifications (1) and (2), the excluded instruments are *IndEPSsurprise* and its interaction with *Informed*-dummy, while *IndForwardMult*Δ and its interaction with *Informed*-dummy are added to the 1st and 2nd stage regressions along with *Predictive covariates* and fund cohort fixed effects. Therefore, specifications (1) and (2) test whether GPs foresee the industry cash flow news and act accordingly. While specifications (3) and (4) treat the terms with *IndForwardMult*Δ as excluded instruments—while including *IndEPSsurprise* in the set of other covariates—and, therefore, test whether GPs foresee innovations in the discount rates at the industry level. *IndEPSsurprise* and *IndForwardMult*Δ are computed from 12-month EPS forecasts for the respective S&P500 GICS subindex. Specifications (1) and (3) use other sample funds as the control group and fund inception year fixed effects while specifications (2) and (4) use hypothetical fund exits as the control group (reported are the pooled estimates across 1,000 simulations, the methodology is described in section IV.B.2 and Internet Appendix). Standard errors in parentheses are robust to heteroskedasticity and autocorrelation, */**/*** denote significance at 10/5/1%.

Excluded Instrument:	IndustryEPSsurprise		IndustryForwardMultΔ	
	(1)	(2)	(3)	(4)
Informed(D) × IndustryReturn	−3.825**	−2.465**	−1.194	0.846
	(1.733)	(1.042)	(2.968)	(2.569)
IndustryReturn	0.315	0.097	−1.517	0.300
	(1.249)	(0.228)	(1.842)	(0.343)
Informed(D)	0.012	0.017	−0.032	−0.025
	(0.023)	(0.038)	(0.026)	(0.015)
Included instrument	IndustryForwardMultΔ		IndustryEPSsurprise	
Included instrument × Informed dummy	Yes	Yes	Yes	Yes
Predictive covariates	Yes	Yes	Yes	Yes
Control funds	Actual	Simulated	Actual	Simulated
Fixed effects	Vintage	Fund	Vintage	Fund
1st stage K-P Wald statistic	17.9	332.4	6.8	15.3
Observations	848	32,832	848	32,832
R^2 (# of simulations)	0.158	(1,000)	0.15	(1,000)

Appendix A. Additional Data and Results

This section reports additional PE fund data and analysis.

TTR and money multiple decomposition. Denote $\Delta := ln(MM) - ln(\overline{PME})$ with MM being the fund's money multiple and $\overline{PME}$ defined as per equation (1) for a fund fully resolved as of $t = T$:

$$\overline{PME} = \frac{\sum_{t=0}^{T} D_t e^{-t\bar{r}}}{\sum_{t=0}^{T} C_t e^{-t\bar{r}}} \quad \text{, where} \quad \bar{r} = r_{1:T}/T \quad . \tag{A1}$$

Because $ln(MM) = ln(\sum_{t=0}^{T} D_t) - ln(\sum_{t=0}^{T} C_t)$, we can write:

$$\begin{aligned}\Delta &= ln\big(\textstyle\sum_{t=0}^{T} D_t\big) - ln\big(\sum_{t=0}^{T} C_t\big) - \Big[ln\big(\sum_{t=0}^{T} D_t e^{-t\bar{r}}\big) - ln\big(\sum_{t=0}^{T} C_t e^{-t\bar{r}}\big)\Big] \\ &= ln\Big(\textstyle\sum_{t=0}^{T} D_t \Big/ \sum_{t=0}^{T} D_t e^{-t\bar{r}}\Big) - ln\Big(\sum_{t=0}^{T} C_t \Big/ \sum_{t=0}^{T} C_t e^{-t\bar{r}}\Big) \quad . \end{aligned} \tag{A2}$$

Without loss of generality, assume that only one capital call has been made—in the beginning, i.e. $C_0 > 0,\ C_t = 0\ \forall t > 0$, so that $\sum_{t=0}^{T} C_t / \sum_{t=0}^{T} C_t e^{-t\bar{r}} = 1$.

$\Delta = \bar{r} \cdot FundDuration$ so long as:

$$\frac{\sum_{t=0}^{T} D_t}{\sum_{t=0}^{T} D_t e^{-t\bar{r}}} - 1 \simeq \bar{r} \cdot \frac{\sum_{t=0}^{T} t \cdot D_t e^{-t\bar{r}}}{\sum_{t=0}^{T} D_t e^{-t\bar{r}}}$$

$$\Longleftrightarrow$$

$$\sum_{t=0}^{T} D_t - \sum_{t=0}^{T} D_t e^{-t\bar{r}} \simeq \sum_{t=0}^{T} t\bar{r} \cdot D_t e^{-t\bar{r}} \quad . \tag{A3}$$

It therefore has to be that:

$$\begin{aligned} &\sum_{t=0}^{T} D_t(1 - e^{-t\bar{r}}) - \sum_{t=0}^{T} t\bar{r} \cdot D_t e^{-t\bar{r}} \simeq 0 \\ \rightarrow &\sum_{t=0}^{T} D_t[1 - (e^{-t\bar{r}} + t\bar{r} \cdot e^{-t\bar{r}})] \simeq 0 \quad . \end{aligned} \tag{A4}$$

Condition (A4) is true whenever $1 + t\bar{r} \simeq e^{t\bar{r}}$ and, since $\overline{PME} = PME \cdot TTR$ by definition, equation (1) is equivalent to equation (2). $\square$

Table A.1
TTR Cross-section: Robustness and Placebo

This table reports regression estimates of the log of funds' end-life *TTRs* on a set of fund/GP characteristics. *TTR* measures the gross-return due to selling near the market peaks during the fund life-time and buying near the troughs. Table 1 describes the sample, Appendix C defines key variables. The explanatory variables are: $ln(FundSize)_i$ ($ln(FundSize)_i^2$) - log (log-squared) of the fund dollar amount of capital committed; $ln(Sequence)_i$ - chronological order of the fund inception date within GP; $ln(PME)_i$ - log of the fund's PME; $ln(TTR)_{i-1}$ - log of the previous fund TTR within GP; *Industry* return over the fund life time (*Trend*) and its interaction with the other explanatory variables. Panel A reports regression estimates using actual values of *TTR*. Specifications (2) through (6) include fund vintage-year fixed effects. Standard errors in parentheses are clustered by GP, */**/*** denote significance at 10/5/1% confidence level. Panel B reports selected coefficients from simulations based on hypothetical exit schedules but actual funds' operation dates and industry return paths. The capital calls and distribution magnitudes and frequencies are calibrated to match the sample means conditional only on time since a fund inception. The underlying fund holding period return-generating process (α, σ_i and β—as indicated by the subpanel header) is specified relatively to the realized *Industry* returns at the quarterly frequency. For each combination of the parameters (i.e. *Case*) of the parameters we produce 1,000 replications, keeping the seed fixed across cases. Pr{A>S} is the fraction of funds for which actual TTR exceeds the simulated TTR. IDRfrac is the ratio of (i) the difference between the actual TTR and the 10th percentile of simulated TTRs, and (ii) the interdecile range across the simulated TTRs on fund-by-fund basis. The reported values are means across replications with standard deviations provided in parentheses.

Panel A: TTRs based on the actual exit schedules

	(1)	(2)	(3)	(4)	(5)	(6)
$ln(IndSequence)_i$	0.060**	0.061***	0.051**			0.053**
	(0.023)	(0.021)	(0.021)			(0.024)
$ln(PME)_i$			0.058***		0.083***	0.080***
			(0.017)		(0.024)	(0.025)
$ln(TTR)_{i-1}$				0.149***	0.103*	0.093*
				(0.050)	(0.052)	(0.051)
Vintage year fixed effects	No	Yes	Yes	Yes	Yes	Yes
(Industry) Trend	Yes	Yes	Yes	Yes	Yes	Yes
Sequence × Trend	Yes	Yes	Yes	No	No	Yes
PME × Trend	No	No	Yes	No	Yes	Yes
Past TTR × Trend	No	No	No	Yes	Yes	Yes
Observations	756	756	756	404	404	404
R^2	0.049	0.384	0.397	0.440	0.463	0.470

Panel B: TTRs based on random exit: Mean(SD) coefficient across 1,000 simulations

Case 1: $\alpha = 0,\ \sigma_i = 0,\ \beta = 1.0$

Pr{A>S} = 0.528(0.010), IDRfrac = 0.81(0.08)

	(2)	(3)	(4)	(5)
Ind. Seq.	0.009			0.009
	(0.011)			(0.011)
Curr. PME	0.016		0.016	0.016
	(0.052)		(0.052)	(0.053)
Past TTR		−0.017	−0.018	−0.018
		(0.048)	(0.048)	(0.048)

Case 2: $\alpha = 0,\ \sigma_i = 0.20,\ \beta = 1.0$

Pr{A>S} = 0.531(0.011), IDRfrac = 0.77(0.09)

	(2)	(3)	(4)	(5)
Ind. Seq.	0.009			0.009
	(0.012)			(0.012)
Curr. PME	0.017		0.017	0.017
	(0.037)		(0.037)	(0.037)
Past TTR		−0.016	−0.017	−0.017
		(0.050)	(0.050)	(0.050)

Case 3: $\alpha = 0.006,\ \sigma_i = 0.20,\ \beta = 1.0$

Pr{A>S} = 0.533(0.010), IDRfrac = 0.78(0.09)

	(2)	(3)	(4)	(5)
Ind. Seq.	0.009			0.009
	(0.012)			(0.012)
Curr. PME	0.019		0.019	0.019
	(0.036)		(0.036)	(0.037)
Past TTR		−0.018	−0.018	−0.019
		(0.050)	(0.050)	(0.050)

Case 4: $\alpha = 0.006,\ \sigma_i = 0.20,\ \beta = 1.5$

Pr{A>S} = 0.518(0.010), IDRfrac = 0.70(0.09)

	(2)	(3)	(4)	(5)
Ind. Seq.	0.016			0.016
	(0.018)			(0.018)
Curr. PME	0.030		0.030	0.030
	(0.020)		(0.020)	(0.020)
Past TTR		−0.018	−0.017	−0.019
		(0.058)	(0.057)	(0.057)

Table A.2
Industry minus Broad market TTRs

This table reports OLS regression estimates for the industry timing track records in excess of that of the broad market. The dependent variable in each model is a difference between the fund TTR computed against the industry benchmark and its TTR computed against the broad market. Panel A reports results for *Entry TTRs*, Panel B—*Exit TTRs*. *TTR* measures the gross-return due to selling near the market peaks during the fund life-time and buying near the troughs, which can be broken down to the entry [exit] components dues to the pattern of capital calls [distributions] as shown in equation 1. Table 1 describes the sample. The explanatory variables are: 'Declared Ind.>50%P' – a dummy taking the value of 1 if a single industry represents more than 50% of the fund investments made during its life-time, 'Venture' – a dummy that takes the values of 1 if the fund type is venture, the interaction thereof, and the fund industry and vintage year fixed effects. Standard errors in parentheses are clustered by GP, */**/*** denote significance at 10/5/1% confidence level.

Panel A: Entry TTRs

	(1)	(2)	(3)	(4)	(5)	(6)
Declared Ind.≥50%oP	0.016*	0.015	0.038**	0.015	0.017*	0.034**
	(0.009)	(0.010)	(0.015)	(0.009)	(0.010)	(0.017)
Venture		0.005	0.024*		−0.010	0.005
		(0.011)	(0.014)		(0.011)	(0.015)
Venture × Declared Ind.≥50%oP			−0.038**			−0.028
			(0.019)			(0.020)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Vintage FE	No	No	No	Yes	Yes	Yes
Observations	941	941	941	941	941	941
R^2	0.029	0.029	0.033	0.192	0.193	0.195

Panel B: Exit TTRs

	(1)	(2)	(3)	(4)	(5)	(6)
Declared Ind.≥50%oP	0.004	0.003	0.004	0.017**	0.013	0.016
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.012)
Venture		0.009	0.010		0.027***	0.030**
		(0.009)	(0.012)		(0.009)	(0.013)
Venture × Declared Ind.≥50%oP			−0.003			−0.005
			(0.016)			(0.016)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Vintage FE	No	No	No	Yes	Yes	Yes
Observations	939	939	939	939	939	939
R^2	0.036	0.037	0.037	0.203	0.209	0.209

Table A.3

Informed Rush: Robustness to Inference Methods

This table reports standard errors (SEs) computed under different assumptions for the coefficient on *TTR>1* × *IRR>Hurdle* × *Rush* from Table 4, Panel A and B respectively (and the respective specifications (1) through (4)). *Spatial HAC* denotes standard errors obtained by using the overlap in the return measurement window following the respective *SubResTime*, following the method of Conley (1999). Since the returns are 12-month average, the maximal overlap is 4 quarters corresponding to a weight of 1 in the outer product of residuals and, hence an correlation of 1 between those two exits. This auto-correlation is set to decay linearly to zero for return intervals that are more than two quarters away from overlapping, e.g. one ends in December 1999 and the other starts in June 2000. *Two-way* clustered standard errors are obtained as a linear combination of one-way clustered covariance matrices as shown in Thompson (2011).

Panel A: Informed ≡ (toDateTTR>1)·(toDateIRR>HR)

	Fund FE		Fund FE+PseudoTiming	
	15%thld (1)	20%thld (2)	15%thld (3)	20%thld (4)
Cluster by Exit quarter (Table 4A)	0.00667	0.00780	0.00464	0.00538
Spatial HAC	0.00670	0.00719	0.00555	0.00447
Cluster by Vintage year	0.00680	0.00663	0.00602	0.00549
Cluster by Industry sector	0.00680	0.00429	0.00293	0.00214
Two-way clustered:				
by Exit and Industry	0.00722	0.00560	0.00276	0.00321
by Vintage and Industry	0.00740	0.00467	0.00487	0.00253
by Exit and Vintage	0.00750	0.00823	0.00578	0.00587

Panel B: Informed≡(toDateTTR>1)+(toDateIRR>HR)+(toDateTTR>1)·(toDateIRR>HR)

	Fund FE		Fund FE+PseudoTiming	
	15%thld (1)	20%thld (2)	15%thld (3)	20%thld (4)
Cluster by Exit quarter (Table 4B)	0.01180	0.01013	0.00959	0.00783
Spatial HAC	0.01021	0.00843	0.00744	0.00656
Cluster by Vintage year	0.01905	0.01654	0.01312	0.01143
Cluster by Industry sector	0.01387	0.01068	0.00628	0.00865
Two-way clustered:				
by Exit and Industry	0.01749	0.00867	0.00995	0.00546
by Vintage and Industry	0.01643	0.00734	0.00943	0.00414
by Exit and Vintage	0.01067	0.00911	0.00718	0.00551

Table A.4
Informed Rush versus Uninformed: Placebo

This table reports predictive regressions of *Industry returns* by placebo-substitutes for *Informed Rush* to provide further support for the identification scheme deployed in Table 4, Panel A. The empirical model, the dependent variable, and all other controls as the same as in the respective specification of Table 4. Specifications (3)-(4) have predictive covariates added but otherwise are identical to (1)-(2). *Informed* funds group is the same as in Table 4 Panel A but *Rush* and return measurement period are defined differently—based on a 4-quarter period with maximal cumulative distributions *outside* the (-6,+4)-quarter window around the *SubResTime*. *before15%*[*after15%*] measures *IndReturn* after the largest cluster of distributions by each fund but starting at least six quarters before [for quarter after] the quarter when residual NAVs dropped under 15% of cumulative distributions, therefore, having arguably far less consequences for the GP's carry interest in the fund. Also, for the purpose of tests reported in this table, I measure rush magnitude in US dollars but to insure magnitudes and distributional properties close to those of actual *Rush*, I define *MaxRush* as the probit function of *log*($*mln*/10). SEs in parentheses are robust to heteroskedasticity and autocorrelation, */**/*** denote significance at 10/5/1%.

	before15% (1)	after15% (2)	before15% (3)	after15% (4)
toDateTTR>1 × toDateIRR>Hurdle × MaxRush	−0.001	−0.001	−0.002	−0.000
	(0.005)	(0.005)	(0.005)	(0.005)
toDateTTR>1 × toDateIRR>Hurdle	0.002	−0.001	0.002	−0.003
	(0.003)	(0.003)	(0.003)	(0.004)
MaxRush	0.001	−0.001	0.001	0.004
	(0.002)	(0.004)	(0.002)	(0.003)
Vintage year fixed effects	Yes	Yes	Yes	Yes
Predictive covariates	No	No	Yes	Yes
Observations	562	500	556	500
R^2	0.001	0.003	0.052	0.287

Table A.5
Calendar Time Portfolios: Quarterly Abnormal Returns

This table reports abnormal return estimates of portfolio B in excess of risk-free rate (*rf*) or portfolio A relatively to value-weighted CRSP or three-factor Fama-French model. Both portfolios are rebalanced quarterly. Portfolio A is equally-weighted 10 GICS sector returns. Portfolio B sells GICS sectors for which two or more *Informed* funds exhibited above-median *Rush* at their *SubResTime* over the past three or seven quarters (i.e. [0,+2q] or [0,+6q] respectively) and buys the remaining sectors (equally-weighted). *Rush* measures the clustering of fund distributions before the *SubResTime*, when fund residual NAVs become small in front of fund total-to-date distributions. *Informed* funds group is the same as in Panel A of Table 4 as of *SubResTime*. Median *Rush* is computed over all funds of the same type (venture or buyout) incepted in the same year. Standard errors in parentheses are robust to autocorrelation, */**/*** denote significance at 10/5/1% confidence level.

	Formation window [0,+2q]			Formation window [0,+6q]		
	B–rfr	B–rfr	B–A	B–rfr	B–rfr	B–A
α	0.014***	0.011***	0.008***	0.014***	0.011**	0.008**
	(0.005)	(0.003)	(0.003)	(0.005)	(0.004)	(0.004)
Mkt *minus* rfr	0.664***	0.734***	−0.187***	0.472***	0.541***	−0.379***
	(0.092)	(0.066)	(0.054)	(0.083)	(0.082)	(0.073)
SML		−0.182***	0.055		−0.176***	0.062
		(0.045)	(0.036)		(0.067)	(0.052)
HML		0.268***	0.125*		0.284***	0.141*
		(0.101)	(0.067)		(0.105)	(0.074)
Quarters #	95	95	95	95	95	95

Table A.6
Informed Rush versus Uninformed: Fuzzy RDD

This table reports predictive regressions of excess *Industry* returns by *Informed Rush*, a proxy for the carried interest "cashed-in" by GPs with a positive track record of market timing in the past:

$$IndReturn_i^{1:12} - \mathbb{E}[IndustryReturn_{ij}^{1:12}|c_i] = \alpha\big[Informed_{ij}Rush_{ij}\ \ Informed_{ij}\ \ Rush_{ij}\big] + \beta X_{ij} + \lambda_j + \epsilon_{ij} \qquad ,$$

where $IndustryReturn_{ij}$ is the mean monthly *Industry* return over 12 months following the fund i *SubResTime*, the dependent variable is obtained as a residual of full-sample regressions of $IndustryReturn_{ij}$ on c_i, return *Predictive covariates*. Appendix C provides variable definitions. $Rush_{ij}$ measures the intensity of fund's distributions to LPs right before *SubResTime*. $Informed_{ij}$ is the indicator variable denoting funds with both *toDateTTR>1* and *toDateIRR>Hurdle* as of *SubResTime* based on 15% residual NAV threshold. Specification (1) includes all funds from the sample (see Table 1 for sample description) whereas specifications (2), (3), and (4) only include funds for which *ToDateIRR* is, respectively within 7.5%, 5%, and 2.5% distance from Hurdle rate. All specifications also control for the third-order polynomial of *ToDateIRR*-distance from Hurdle rate (i.e. the "forcing variable", X_{ij}) as well as vintage year fixed effects (λ_j). Standard errors in parentheses are clustered at *SubResTime*, */**/*** denote significance at 10/5/1%.

	Full	Distance from Hurdle rate (%)		
	sample	-7.5 to +7.5	-5.0 to +5.0	-2.5 to +2.5
	(1)	(2)	(3)	(4)
toDateTTR>1 × toDateIRR>Hurdle × Rush	−0.013**	−0.015	−0.009	−0.011
	(0.006)	(0.011)	(0.010)	(0.016)
toDateTTR>1 × toDateIRR>Hurdle	0.002	0.003	0.003	0.004
	(0.002)	(0.004)	(0.005)	(0.008)
Rush	0.005	0.009	0.004	0.007
	(0.005)	(0.009)	(0.009)	(0.014)
(toDateIRR *minus* Hurdle) 3^{rd}-order polynom	Yes	Yes	Yes	Yes
Vintage year fixed effects	Yes	Yes	Yes	Yes
Observations	893	281	186	108
R^2	0.046	0.084	0.079	0.128

Appendix B. Simulation-related Supplement

This section provides the intuition about the simulation-based estimates reported in section IV.B.2. Additional details and risk-shifting tests are reported in Internet Appendix.

TABLE B.1

The Model of Fund Fixed Effects for *SubResTime* and *Rush*

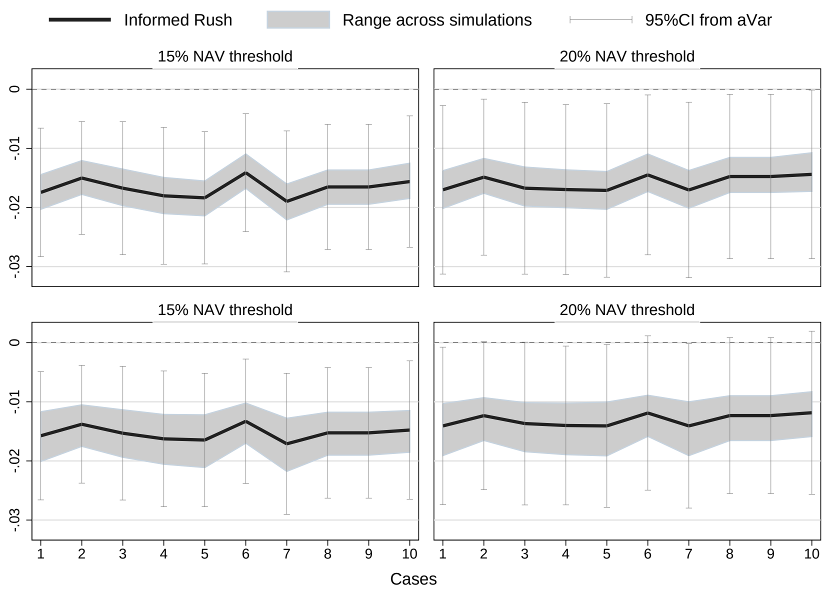
This table reports a model of funds' SubResTimeand *Rush* amounts estimated as *S*eemingly *U*nrelated *R*egressions for all funds in my sample. The dependent variables are (1) the natural logarithm of number of quarters since the fund's inception when a threshold of the NAV to total distributions has been crossed from above (has to be a quarter with non-zero distributions to LPs); (2) a probit function of a fraction of distributions (to LPs) over the last 6 quarters in the funds' total-to-date. The explanatory variables are same in both linear equations: $ln(Size)_i$—log of the fund \$ capital committed; *toDatePME*—Kaplan-Schoar PME against *Industry*; *Top-tercle toDateIRR*—indicator if the fund IRR is in the top-tercile over the fund-type×vintage-year peers; *Follow-on fund raised* – indicator if at least one more fund by the same GPs have started investments two years after the current fund inception date; *Follow-on fund w/n 6 qtrs*—indicator if another fund by the same GPs starts investments within six quarters from the current fund *SubResTime*; *Follow-on fund capital called*—fraction of capital called by the last-most follow-on fund by GPs as a fraction of committed (0 if no follow-on exists); *Industry-year fixed effects*—*Industry*–by–vintage fixed effects. I include two observations per fund where 15% and 20% thresholds were not crossed simultaneously and the resulting *SubResTime* is different. This is the auxiliary model to obtain the fitted values of fund fixed effects (with respect to *SubResTime* and *Rush*) and parametrize random exit simulations (via the covariance matrix of *SUR* residuals). */**/*** denote significance at 10/5/1%.

	$ln(SubResTime)$		$\Phi^{-1}(Rush)$	
	Coefficient	SE	Coefficient	SE
ln(Size)	0.017***	(0.006)	−0.092***	(0.023)
toDatePME	−0.036***	(0.004)	0.128***	(0.016)
Top-tercle toDateIRR (D)	−0.165***	(0.014)	−0.151***	(0.052)
Follow-on fund raised (D)	−0.056**	(0.024)	0.122	(0.086)
Follow-on fund w/n 6 qtrs (D)	−0.110***	(0.021)	0.143*	(0.075)
Follow-on fund capital called (%)	0.063***	(0.016)	−0.054	(0.057)
Industry-year fixed effects	Yes		Yes	
R^2	0.442		0.132	
Observations	1242			

Figure B1
Robustness

This figure reports robustness tests for the simulation-based estimates of predictive regressions of *Industry returns* by *Rush* reported in Table 5. Top-left (right) and bottom-left (right) correspond to specifications 1 (2) and 3 (4) respectively. In both panels of the figure, *Case 1* corresponds to the coefficient estimates on toDateTTRover1×toDateIRRoverHurdle×MaxRush reported in Panel B of Table 5. The solid black line is the mean coefficient value across 1,000 *independent simulations*, while the area denotes the range of the values. The 95% confidence interval is based on a mean of asymptotic variance estimates across the simulations. For *Cases 2 through 10*, Panel A reports estimates for the same model but the following fund vintage year being excluded from the estimation: 1993, 1992, 1990, 2001, 1992-93, 1990&2001, 1990&1993&2001, 1990&1992&2001, 1990&1992-93&2001. While in Panel B, *Cases 2 through 10* include all vintages but augment the model with a dummy denoting the actual fund *SubResTime* falling in the following years: 2007, 2009, 2000, 2008, 2007&'09, 2000&2008, 2000&2007, 2000&2007&2009, 2000&2007&2008, 2000&2007-09.

Panel A: Exclude Selected Vintage Years



Panel B: Dummy-out Selected Exit Years

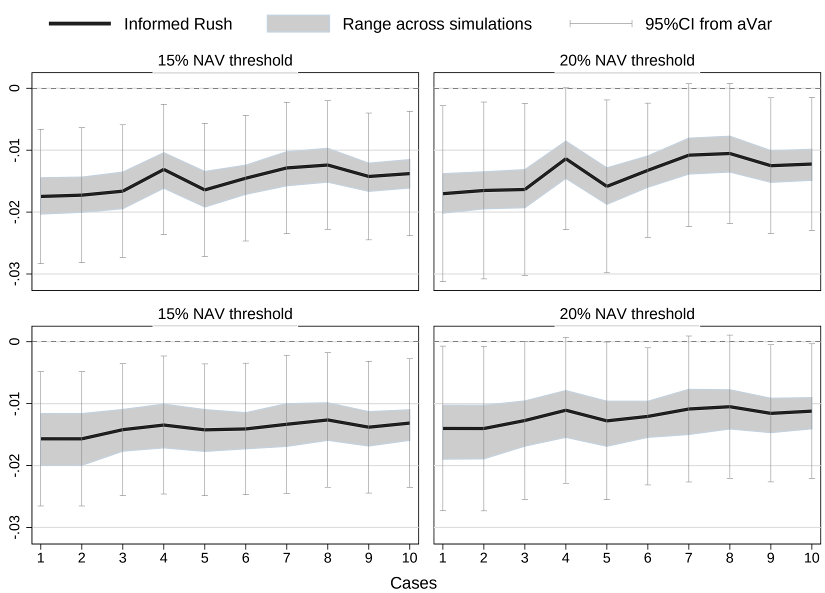
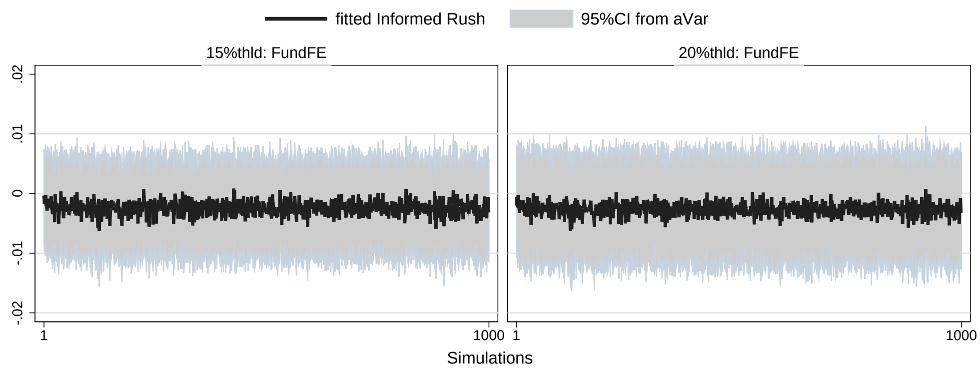


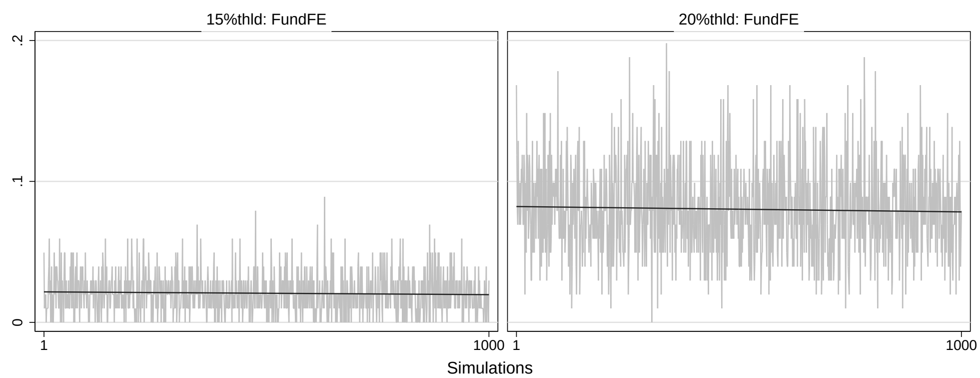
Figure B2
Placebo Tests

This figure reports placebo tests for the simulation-based estimates of predictive regressions of *Industry returns* by *Rush* reported in Table 5. Left (right)-hand charts correspond to specification 3(4). Panel A plots α estimates and 95% confidence intervals over these *independent simulations* if the actual funds SubResTimeand distributions were replaced by the expected ones from the *fund fixed effect* model reported in Table B.1. Panel B plots the fraction of placebo exits that have t-statistic lower than that of the actual funds in each *independent simulation* as well as the mean value across simulations. *Case 1* of the figure's Panel C corresponds to the coefficient estimates on toDateTTRover1×toDateIRRoverHurdle×MaxRush from Panel B of Table 5. *Cases 2 though 10* replace the fund's *Industry* with the another S&P500 GICS subindex so that 10 corresponds to results against the GICS that is the least correlated with the fund's *Industry* (based on monthly returns over the five-year rolling window). The solid black line is the mean coefficient value across 1,000 *independent simulations*, while the area denotes the range of the coefficient across the simulations. The 95% confidence interval is based on a mean of asymptotic variance estimates across the simulations.

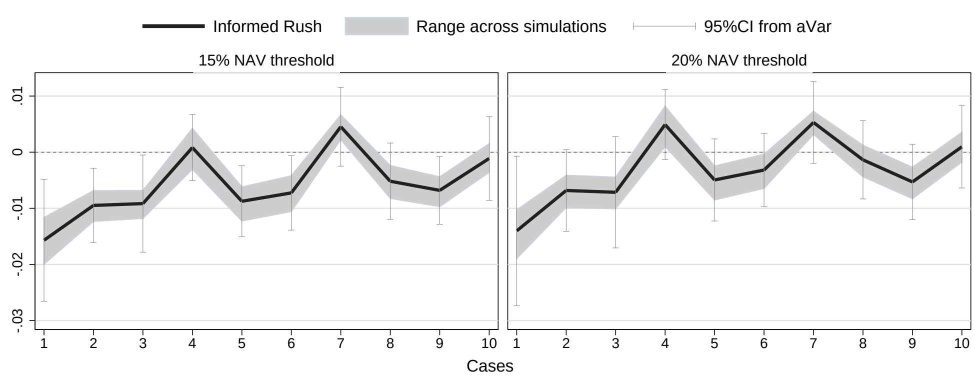
Panel A: Fund Fixed-Effect Predictions



Panel B: Fraction of Random Draws with t-statistic < Actual Fund



Panel C: Proximity-ranked Industries



Appendix C. Key Variable Definitions

Variable Name	Description
Industry	S&P500 Global Industry Classification Sector subindex that the PE fund primarily specializes in according to Burgiss. *Sources: Burgiss, Compustat.*
PME	Public Market Equivalent of Kaplan and Schoar (2005) with respect to the fund's public equity benchmark, defined as $PME = \sum_{t=1}^{T} Distrib_t \cdot e^{r_{t,T}} / \sum_1^T CCalls_t \cdot e^{r_{t,T}}$ where $r_{t,T}$ is the return on *Industry* from the cash flow date until the fund resolution. *Tables 2, A.1; Figures 1. Sources: Burgiss, Compustat.*
TTR	Timing Track Record is the gross-return due to selling near the market peaks during the fund life-time and buying near the troughs, defined as $TTR = \overline{PME} / PME$ where $\overline{PME} = \sum_{t=1}^{T} Distrib_t \cdot e^{r_{1,T} \cdot (1-t/T)} / \sum_1^T CCalls_t \cdot e^{r_{1,T} \cdot (1-t/T)}$ and $r_{1,T}$ is the return on *Industry* from the fund inception (unlike from the *cash flow date* in the *PME* defined above) until the fund resolution. See section III.A for details. *Tables 2, A.1; Figures 1, 2. Sources: Burgiss, Compustat.*
Entry [*Exit*] *TTR*	Timing Track Record with respect to Capital Calls [Distributions] measures the gross-return due to buying near the troughs only [selling near the market peaks only] following the decomposition per equation 1. Unlike with *TTR*, the measurement of the life period is not from inception to end but from 1st [4th] to 6th [last] year for *Entry* [*Exit*] *TTR*. *Tables 3; Figures 1. Sources: Burgiss, Compustat.*
toDateTTR	Same as *TTR* but excludes cash flow and return data beyond that Date. Specifically, both $\overline{PME}$ and PME are computed using the latest NAV available as of the Date as the terminal cash flow and $r_{t,T}(r_{1,T})$ are measured with T set to the Date (e.g., 5 years since the fund inception, as of the time fund NAVs fall below 15% of cumulative distributions, etc). Similarly defined are *toDatePME* and *toDateIRR*. *Figures 1, 2. Sources: Burgiss, Compustat.*
SubResTime	Time elapsed since the fund inception untill the quarter when the fund NAVs fall below either 15% or 20% of its cumulative distributions—indicates the calendar quarter when residual exposure of the fund assets to the market fluctuations becomes relatively low (and so is the exposure of GPs' personal wealth for the in-the-carry funds). *Tables 4, 5, 6, A.3, A.5, B.1; Figures 4, 3. Sources: Burgiss.*
toDateTTR>1	Indicator variable taking a value of 1 if the fund's *to-date-TTR* in the quarter right before *SubResTime* exceeds one. *Tables 4, 5, 6, A.3, A.5; Figures 4, 3, B1, B2. Sources: Burgiss.*
toDateIRR>Hurdle	Indicator variable taking a value of 1 if the fund's reported IRR in the quarter right before *SubResTime* exceeds 8(0)% for buyout(venture) funds. *Tables 4, 5, 6, A.3, A.5; Figures 4, 3, B1, B2. Sources: Burgiss.*
Rush	Fraction of distributions over 6 quarters before the *SubResTime* in the fund's total distributions up to *SubResTime*. *Tables 4, 5, 6, A.3, A.5, B.1; Figures 4, 3, B1, B2. Sources: Burgiss.*
Informed [Rush]	The interaction of *toDateTTR>1* and *toDateIRR>Hurdle* indicators [and *Rush*].
Predictive covariates	A set of macroeconomic and financial variables that has been used in the literature (e.g., Welch and Goyal, 2008) to explain variation in risk premia, all measured as of the respective fund's *SubResTime*: *Industry*'s price-earning and book-to-market ratios, CAY-ratio of Lettau and Ludvigson (2001), CBOE VIX index, U.S. Treasury yields (10-year and 3-month), corporate credit spreads (BAA-AAA, and AAA-UST), and the industry 5-year CAR. *Tables 4, 5, 6, A.3, B.1; Figures B1,B2. Sources: Bloomberg, CRSP, Compustat, FRB, Sydney Ludvigson.*

The Internet APPENDIX to

Do Private Equity Managers Have Superior Information on Public Markets?

Oleg R. Gredil

July, 2020

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IA-1. Institutional background

1.1. Private information cycle

In a buyout, a company is acquired using a relatively small portion of equity and a large portion of outside debt financing. In a typical transaction, the fund buys the majority control of a mature firm (not necessarily publicly traded). In contrast, venture funds typically invest in young or emerging companies often through convertible debt or preferred shares, and usually do not seek to obtain a majority control. In both cases, however, the fund managers (general partners [GPs]), tend to closely monitor and exert influence on the acquired company activities, normally through active membership on the board of directors (Gompers and Lerner, 1999; Kaplan and Strömberg, 2009; Metrick and Yasuda, 2010).

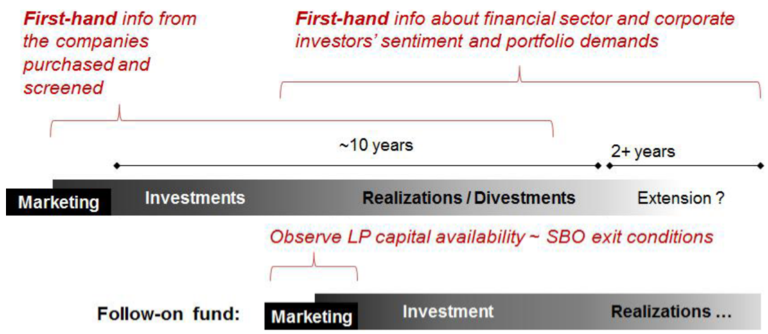
The company is one of many investments that the fund's GPs undertake which, in turn, is a small portion of candidates that get screened during the approximately five-year investment period. Unlike for portfolio investors in public companies, the information set of the fund's GPs is not be limited by standard disclosure requirements even if the fund have yet to become a stake holder. On a confidential basis, GPs are free to request any data about the company business that the management may possess. GPs tend to specialize in certain industries and types of businesses. Thus, the signals about the business fundamentals complement each other across deals.

Both, buyout and venture, would target a total life of about 10 to 13 years from the investment period start date. The holding durations tend to be 4 to 7 years with some exits occurring earlier [later] than 2 [10] years after the original investment. For investments that do not go bankrupt, the exit routes are either IPO or an acquisition. The latter can be further broken-down by the type of acquirer: (i) another PE fund or a group of investors or (ii) an operating firm, possible private too, that is strategically interested in the production capacity of the target's assets. The IPO route typically fetches the highest return on investment, yet other exit routes (except bankruptcy) are on average profitable as well (e.g., see Braun et al., 2017; Degeorge et al., 2016). As with the timing of divestment, the route is also chosen solely by GPs. The important contractual feature is that (after withholding their performance fees) GPs are obligated to pass the divestment proceeds to LPs (rather than reinvest).

Before the investment period concludes, buyout and venture GPs would normally attempt to raise a new fund. The interval between fund starts would be 2 to 5 years with the average being 3.5 years for both buyout and venture funds (e.g., Barber and Yasuda, 2017). There are, of course, numerous reasons for GPs (and LPs) to want the lives of the funds to overlap. One of the consequences of this practice is a continuous flow of information about similar company fundamentals, on the one hand, and investor portfolio demands, on the other.

These largely non-public information flows that GPs regularly participate in both, buyout and venture, can be summarized via the following chart.

Private Equity Information Cycle



1.2. Theoretical predictions

To accommodate the salient features of the institutional settings described above, I will model the GPs' divestment decisions as the optimal stopping time problem under uncertainty, as studied in Miao and Wang (2011). This framework distinguishes expected utility maximization with regards to well-measured risk from the situations in which agents are unsure about the likelihoods of the future state of the world. Furthermore, the set of these likelihoods is subject to updating itself, which is a natural way to incorporate changes in the GPs' medium- to long-term outlook changes about the value of their funds' assets they already run (as well as are yet to raise). In the real-option literature, this is also referred to as *ambiguity* about future (a.k.a, *Knightian uncertainty* in reference to Knight, 1921). Specifically, I will assume that GPs are expected utility maximizers at the horizon of about one year, and are ambiguity-averse at longer horizons.

Naturally, a GP seeks to maximize the utility of its wealth, which derives from the current and future (potentially indefinite) stream of fees. As such, the following Bellman equation characterizes her wealth process:

$$W_t(f) = u(f_t) + \alpha \mathbb{E}^q[W_{t+1}(f)] \qquad , \tag{IA-1}$$

where $u(\cdot)$ is a time-separable utility function; $\alpha \in (0, 1)$ is the subjective discount factor for time lapse; $\mathbb{E}^q$ is the conditional expectation operator with the probability measure $q \in \mathcal{P}_t$, a set of the one-step-ahead conditional probabilities given the information at date t (Epstein and Schneider, 2003); and $f = (f_t)_{t\geq 1}$ is the fee stream that is observable but stochastic.

For a given period t, say a year, define f_t as a sum of fees from funds j run the GP:

$$f_t = \textstyle\sum_j f_t^{(j)} \cdot I\{j = 1; t\} \qquad , \tag{IA-2}$$

where $f_t^{(j)}$ are dollar-measured fees from the fund $j = 1, 2, 3, \ldots$ run by the GP, and $I\{j = 1; t\}$ is an indicator for whether fund j has been raised before period t.

Without loss of generality, assume that a fund can hold only one asset, only exits it in whole, and the management fees cease after the exit. Accordingly, the fee contribution from fund j can be written as follows:

$$f_t^{(j)} = \begin{cases} 0 & \text{–if has already resolved before period } t \\ m_t^{(j)} & \text{–management fees if continues beyond } t \\ m_t^{(j)} + \mathcal{C} \cdot \max\{0, V_t^{(j)} - C_t^{(j)}\} & \text{–the payout if exits during } t \end{cases} \tag{IA-3}$$

, where $\mathcal{C}$ is the contractual carry rate; $V_t^{(j)}$ is the value of the fund assets if sold during period t; and $C_t^{(j)}$ is period t's cost basis for the carry computation. Note that normally $C_t^{(j)}$ increases in the cumulative management fees paid up to the period t, and a positive hurdle rate also pushes it further up.

The above definition for the fee process underscores that GPs' exit decisions are irreversible with respect to the carry claims on fund j's assets. It is therefore subject to the optimal stopping time toolbox that supports quite general assumptions about the underlying probability space and the state process (i.e., f in our case), as explained in Dixit et al. (1994) and Miao and Wang (2011), reproduction of which I omit from this appendix. The GP's optimal stopping time problem can thus be written as:

$$\max \begin{Bmatrix} \int W_t(f')\mathcal{P}_t(df'; f) \quad , \\ u\Big(\int f_t' Q(df'; f)\Big) + \alpha \int W_{t+1}(f')\mathcal{P}_t(dx'; f) \end{Bmatrix} \quad \begin{array}{l} \text{(A): value if stays through } t \\ \text{(B): value if exits in } t \end{array} \tag{IA-4}$$

, in which the following notation is obeyed:

$$\int g(x')\mathcal{P}(dx'; x) = \min_{q(\cdot;x)\in\mathcal{P}(x)} \int g(x')q(dx'; x) \qquad \text{for any function } g(x) \quad . \tag{IA-5}$$

In words, the GP stands to receive the continuation value, subject to the level of ambiguity implied by $\mathcal{P}_t$ if she decides to stay. Otherwise, she removes the fraction of her wealth deriving from the current fund's fee stream from being exposed to the most adverse likelihood scenario (as given by the probability density $\mathcal{P}_t(f)$ that results in the infimum expectation of W_t), even though it will remain exposed to some residual risk (as given by the density $Q(f)$), since $V_t^{(j)}$ can fluctuate during the period.

As shown in Miao and Wang (2011), a stopping problem like (IA-4) has a unique solution f^*, such that whenever f_t crosses this threshold from below, the agent prefers payout B over A, even though the choice does not absolve the risk completely. In our settings, this corresponds to GPs' choice to exit the current fund and, by doing so, cash-in its carry. The analysis in Miao and Wang (2011) suggests however, that an analytical solution to the choice problem (IA-4) is most likely not feasible. Therefore below I seek to merely characterize the probable changes to GPs' choice under certain relevant scenarios.

Assume $f_\tau < f^*$ for $\tau < t$, so that GP did not exit the current fund in the previous periods. First, suppose that the update in $\mathcal{P}_t$ from $\mathcal{P}_{t-1}$ was such that infimum expected wealth increased from the previous period.[ia1] In this scenario, the prediction about the GP choice is ambiguous. On the one hand, the value increase in (A) can exceed that of (B). This can happen because $\alpha < 1$, and the moneyness of the current fund carry decreases over time (i.e., due to past management fees and/or hurdle). On the other hand, the density $Q(f)$, which governs the payout from the current fund (conditional on exit), could have shifted rightwards enough that the sum of values from (B) choice exceeds that of (A). In other words, the change in $Q(f)$ could have been *more* favorable than that in $\mathcal{P}_t(f)$.

Suppose instead that the update in $\mathcal{P}_t$ from $\mathcal{P}_{t-1}$ was such that infimum expected wealth decreased from the previous period. This corresponds to the GP developing a more negative medium- to long-term outlook. In this scenario, the decrease in value of (A) will be larger that that in (B), so long as the current fund is in the carry—i.e., $\int f_t' Q(df'; f) > \sum_j m_t^{(j)} I\{j=1;t\}$. This is so because the change in $Q(f)$ *cannot be more* adverse than that of $\mathcal{P}_t(f)$, which returns the infimum by construction. Meanwhile, if the (immediately expected) carry is zero, the GP stands nothing to gain from exiting during period t since collecting the management fee from the current funds involves no risk even under $\mathcal{P}_t(f)$.[ia2]

The diagram in section IV.A.1 of the main text summarizes these scenario analysis.

1.3. Which PE exits are informative?

IPO versus non-IPO

Consider a hypothetical seven-year old buyout fund that has yet to liquidate most of its investments. Suppose the GP anticipates that the industry-wide cash flows will be notably below market expectations in the near term but healthy in the long run. Assume there is another fund approaching the end of its investment period that has yet to deploy its capital. GPs of the second fund may agree to buy the holdings of the first at prices close to publicly traded comparables. They may in fact do so while fully sharing the belief about an upcoming downturn and yet still be taking the first-best action from their LPs' perspective.[ia3] Hence, the exits by the first fund would be informative of industry return expectations even absent an IPO. Likewise, corporate buyers may have investment horizons different from that of the seller. Thus, exits through trade-sale can be as informative about GPs' expectations as sales through an IPO.

[ia1] That is, $\int W(f')\mathcal{P}_t(df'; f) > \int W(f')\mathcal{P}_{t-1}(df'; f)$

[ia2] This conclusion assumes that the exit decision per se does not effect the fundraising success probability however, as embedded in $\mathcal{P}_t(f)$.

[ia3] Just the wealth transfer from outside creditors who overestimate the collateral value may exceed the second fund overpayment. The portfolio company improvement may yet to be fully realized by the first fund.

Finite life considerations

Continue with the example fund that is beyond the phase when new or considerable follow-on investments are permitted. Assume that it has performed well enough for GPs to have a substantial performance fee to harvest in that fund. If the fund investment value deteriorates at the end of the fund contractual term (e.g., 10-12 years), the carried interest may vanish as well. By rushing to sell the fund holdings, not only do GPs secure performance fees, but they also lock-in a relatively high performance rank among peer funds, which can help attract investors in future funds.

In contrast, there are few benefits to GPs from premature divestments before the industry downturn if the performance to-date has been poor. Asset liquidation would amount to suboptimal early-exercise of an option (to earn carry and improve performance rank) and reduce asset management fees.[ia4] Therefore, it is possible that skilled GPs facing such a survival risk would likely seek to retain fund assets ahead of the turbulent times for the same reason that option-holders want the underlying asset volatility to increase. However, since such an asset-hoarding may tarnish GPs' reputation with investors and adversely affect future fundraising, one would expect it to be limited to GPs that face immediate survival risk only (i.e., were unable to raise a follow-on fund).

It is important to note that, because hedge fund (as well as mutual fund) managers typically operate open-end funds, it is costlier for them to keep low exposure to the market in the anticipation of the downturn over the next several quarters than for PE GPs. Lack of competitive returns reported for several quarters (while the market run continues) can result in capital outflow due to redemptions from dissatisfied fund investors precisely when the manager would want to maximize capital deployment ahead of the market rebound.

The finite life feature of PE funds is critical for the formation of incentives to reveal the timing signal through exits. A manager endowed with an infinite-life investment vehicle might rather view the expected downturn as an opportunity to acquire desired long-term exposures at attractive prices.[ia5]

When do PE exits convey less information?

Suppose that our hypothetical fund has performed very well but already divested its best deals (i.e., those yielding the highest performance fees). The remaining holdings in the fund's portfolio would then likely comprise the deals that failed to payout well. Provided that the fraction of this residual in the total distributions to-date is small, its option value

[ia4] Some funds have the basis for asset management fees switching from committed to invested capital after the investment period elapses.

[ia5] "You'd be making a terrible mistake if your stay out of a game you think is going to be very good over time because you think you can pick a better time to enter..." (Warrent Buffet, CNBC 2/27/17)

(which increases in the assets' idiosyncratic risk as well) may still dominate any expected loss of value to the fund's carry amount due to the likely deterioration in the industry-wide factors.

Thus, as the value of the residual fund assets reduces in front of the amount of carry already cashed-in, the incentive for GPs to reveal a negative market-timing signal diminishes. Meanwhile, a low pace of distributions over the remainder of the fund's life is also consistent with a scenario when GPs have been expecting improvements in the comparable valuations during that period (i.e., may contain a positive market-timing signal). As industry-wide returns improve (yet remain small in front of the assets' idiosyncratic returns), the exit choice will be increasingly driven by positive realizations of the idiosyncratic risks, which, by definition, are uncorrelated across assets. Hence, the remaining exits would be less clustered in time, all else being equal. Equivalently, there will be fewer distributions per unit of time.

Similarly, the divestments undertaken earlier in the fund's life, while the residual exposure of GP's carried interest has remained high (or very little carry accrued yet), should contain relatively less of the market-timing consideration.

Potential power drains

GPs might be too diversified or could hedge their undesired exposures elsewhere. However, finance professionals are often legally prohibited to undertake any personal investing activities potentially jeopardizing best actions in the interests of clients or their employers. There is little systematic evidence on how strong and common such clauses are but GP risk-aversion combined with basis risk could also limit these hedging activities. It is also likely that I measure skill and incentives with error (e.g., see subsection below). If anything, these should prevent me from finding significant predictability in my primary tests.

1.4. Net IRR as proxy for In-The-Money carry

In my data, I do not observe the amount of carry interest that GPs have 'at risk' to losing due to the dip in the market valuations. Instead, I use net of fees cash flows to infer whether the carry amount has been greater than zero at the time when fund is close to fully resolved. This approach results in a measurement error for the case when fund terms allow GPs to receive carry distribution before distribution to LPs exceeded the capital called by the fund.[ia6] The measurement error will be in the direction of underestimation of carry paid, especially when carry is determined on a deal-by-deal basis.

However, because the key coefficient of interest is on the interaction of the in-the-money carry proxy and the fraction of recent distributions to the total-to-date (i.e. *Rush*), the

[ia6] In the latter case, IRR less or equal [greater] to the Hurdle rate guarantees zero [positive] carry cash-in by GPs, since Hurdle rate is used to grow the net capital invested.

measurement error gets mitigated markedly—even for the deal-by-deal basis, high values of Rush insure that the proportional amount of carry has been harvested right before the hypothesized dip in the public benchmark is measured. Nonetheless, it is likely what causes the lack of power in the fuzzy RDD tests (reported in Table A.6 of the main text) in which I compare funds with net IRR just above the Hurdle rate to those with net IRR just below.

IA-2. Simulation-based estimator

2.1. Setup

In this section I provide additional details about the simulations-based method used to obtain results reported in section IV.B of the main text, as well as section IA-3.3.3 of this appendix.

The method involves three steps. First, I estimate an *auxiliary model* of expected *SubResTime*—time to quarter when fund NAVs dropped below 15% or 20% of total-distributions to date—and *Rush*—the fraction of distributions over the past 6 quarters relatively to the funds total to-date—for all funds in the sample as functions of: (i) vintage-by-industry fixed effects; (ii) fund size, PME-to-date, IRR-rank-to-date; (iii) GPs follow-on fund start dates and investments activity where available.[ia7] It is insightful to think about this *auxiliary model* as simply a density-mass filter for possible *SubResTime–Rush* combinations. To insure that simulated values have economically meaningful support, I take log of the stopping-time and probit of Rush. I treat the equation for $ln(SubResTime)$ and the equation for $\Phi^{-1}(Rush)$ as two linear Seemingly Unrelated Regressions as per Zellner (1962) but the final results are essentially unchanged if I allow simultaneity in $SubResTime$ and $Rush$ and use IV-estimates of the expected values (unreported, available upon request).[ia8] I utilize the pseudo-panel structure of *Rush* and *SubResTime* observations per fund where the pattern of fund distribution permits so.[ia9]

Table B.I of Appendix B in the main text reports the results of this estimation. For both equations Vintage-by-Industry FE provide the biggest portion of explained variation. Nonetheless, all other variables significantly explain $ln(SubResTime)$ and have signs consis-

[ia7] The sample industry-vintage universe is rather sparse before 1990 (relatively few funds to begin with) and post 2003 (as relatively few funds reach the stopping-time threshold). Whenever the industry-vintage bucket includes fewer than nine funds, I (i) consolidate "Energy" and "Materials" into "Industrials", "Consumer Staples" into "Consumer Discretionary" and (if still fewer than nine funds) (ii) consolidate vintages into triennial groups to allow for better estimations precision.

[ia8] Note that under the null hypothesis, *SubResTime* and *Rush* do not predict public equity returns, and thus possible simultaneity and variable omissions are not affecting the validity of inference in *main model* (described below).

[ia9] Namely, when a fund reaches 15% and 20% threshold of residual NAV to total distributions-to-date in different quarters.

tent with the economic intuition. Specifically, fund log-size is positively related to how long it takes to resolve it, while superior performance, as measured by PME and IRR-tercile, associates with shorter durations. Unsurprisingly, the duration of existing funds also correlates with the fundraising success by GPs, as the loadings on *Follow-on Raised*- and *Follow-on within six quarters*-dummies suggest, while positive loading on the fraction of capital called by the next fund may speak about the GPs' economic optimism (or asset-hoarding). The same set of covariates has less success in explaining $\Phi^{-1}(Rush)$ with R^2 being only 0.132.[ia10] Fewer explanatory variables are significant statistically, although the signs of all coefficients are economically intuitive still. The fitted values from these equations represent the projections of fund fixed effects on the set of above described covariates. I will use these projections in place of cohort fixed effects in estimating the *main model* (described below). The better the fit, the smaller the covariance matrix of stopping-times and *Rush* residuals that I will use to parametrize the simulations. Therefore, I do not include fund type indicators among other covariates that add more noise than explanatory power. Besides the fitted values, I also obtain the covariance matrix of the residuals for both equations.

Second, I randomly draw a sample of 100 bivariate normal shocks from a covariance matrix that is itself randomly drawn from Wishart distribution parametrized by the the covariance matrix of residuals estimated in the first step. In doing so, I allow for uncertainty about the *auxiliary model* estimates and admit heteroskedasticity in the return-predicting equation discussed in the third step. Adding same set of shocks to fund-threshold estimates of expected $ln(SubResTime)$ and $\Phi^{-1}(Rush)$ and reverting the functional transformations, obtains the simulated values of stopping-time and *Rush* for each fund-threshold in the sample that reflect (a) Industry-GPs-fund characteristics, (b) sample covariance of unpredicted portion of stopping-time and *Rush*, and (c) random shocks drawn from a random mixture of normal distributions. Although consistency of the third step will not depend on whether the distribution of actual $SubResTime$ and *Rush* are close to the simulated ones, it is useful to examine this question as it may affect inference. Figure IA-1 reports comparisons of univariate distributions and bivariate relations of actual $SubResTime$ and *Rush* (Actual Funds) in comparison to those of simulated funds for random draw. It appears that simulated bivariate distributions tend to have more weight in tails which, if anything, is likely to upward-bias the parameter variance estimates.

Applying the actual fund inception dates, for each fund-threshold-placebo exit I obtain the months corresponding to the actual and simulated $SubResTime$ and match the 12-month forward mean *Industry* return as well as the respective month and industry-month

[ia10] This is consistent with the findings in Robinson and Sensoy (2016) that fund age and calendar time (quarterly) fixed effects explain less than 8% of the aggregate PE cash-flow variation.

covariates that control for *Pseudo-timing* alternative. These variables are CAY-ratio, VIX, U.S. Treasury yields, corporate credit spreads, the industry index price-earnings and book-to-market ratios. See section II and Table I and II in the main text for details and summary statistics. The data end in October 2013, with the last actual fund stopping-month being March 2013. If the stopping-month is later than June 2014, this placebo exit is truncated so that the forward mean return is computed over at least 6 months. Hence, some of the funds post 2004 vintage will tend to have slightly fewer than 100 placebo exits. The results are robust to dropping these funds (available upon request).

Third, I compare how subsequent *Industry Returns* associate with *Rush* of actual funds of interest (denoted by *Informed*-dummy) as opposed to that in simulated exits corresponding to these funds (*main model*):

$$E[IndustryReturn_{ij}^{1:12}] = \alpha Informed_{ij} Rush_{ij} + \alpha_0 Informed_{ij} + \alpha_1 Rush_{ij} + \lambda_j.$$

The panel subscript j denotes a given actual fund ($Informed_{ij} = 1$) and its simulated exits($Informed_{ij} = 0$) corresponding to this fund. I then study different groups of actual funds, subsetting the control group accordingly each time (rather than re-simulating it). To insure that α estimates are robust to the simulation starting point (seed value) and yet to keep the procedure computationally attractive, I repeat the second and third steps 1,000 times. Each time I randomly choose simulation seeds for shocks and the covariance matrix draws which also alleviates the autocorrelation problem in pseudo-random number generators. Hence, I obtain independent estimates of *main model* from 1,000 samples of identical data for actual funds augmented with different simulated pseudo exits (henceforth *independent simulation*).

2.2. Statistical properties

My three-step estimation is quivalent to the following just-identified *Simulated Method of Moments*:

$$\begin{aligned}
E\Big[Z1_j\Big(SubResTime_j - f(\text{GP-fund characteristics}; \theta_t)\Big)\Big] &= 0 \\
E\Big[Z2_j\Big(Rush_j - g(\text{GP-fund characteristics}; \theta_r)\Big)\Big] &= 0 \\
E\Big[Z3_{ji}\Big(IndRet(\theta_{t,r}, \Sigma) - \boldsymbol{\alpha} InformedRush(\theta_{t,r}, \Sigma) + \alpha_0 Informed + \alpha_1 Rush(\theta_{t,r}, \Sigma) + FFE(j)\Big)\Big] &= 0 \\
E\left[\begin{pmatrix} SubResTime(\theta_{t,r}, \Sigma)_{ji} \\ Rush(\theta_{t,r}, \Sigma)_{ji} \end{pmatrix} \perp \ FFE(j)\right] &= 0 \\
E\left[\begin{pmatrix} SubResTime(\theta_{t,r}, \Sigma)_{ji} \\ Rush(\theta_{t,r}, \Sigma)_{ji} \end{pmatrix}\begin{pmatrix} SubResTime(\theta_{t,r}, \Sigma)_{ji} \\ Rush(\theta_{t,r}, \Sigma)_{ji} \end{pmatrix}' \perp \ FFE(j) - W_2(\Sigma, 1)\right] &= 0
\end{aligned}$$

where the first two restrictions use only the sample data while the remainder involve simulated data and:

(i) $Z1_j$, $Z2_j$ and $Z3_{ji}$ denoting the sets of all covariates in the respective moment restriction;
(ii) FFE is a set of dummies denoting expected stopping month and *Rush* for each actual fund j as per functions $f(...)$ and $g(...)$ evaluated at the parameters' values θ_t and θ_r respectively;
(iii) $W_2(\Sigma, 1)$ – a draw from Wishart distribution with 1 degree of freedom, parametrized by $2x2$ positive definite Σ, the covariance matrix of the sample fund residuals: $\big(SubResTime_j - E_j[SubResTime]\big)$ and $\big(Rush_j - E_{j)}[Rush]\big)$;
(vi) $SubResTime(\theta_{t,r}, \Sigma)$, $Rush(\theta_{t,r}, \Sigma)$ – simulated values of SubResTimeand *Rush* under the parameters θ_t, θ_r and Σ;
(v) $IndRet(\theta_{t,r}, \Sigma)$ – mean *Industry Return* over 12 quarters following the month according to $SubResTime(\theta_{t,r}, \Sigma)$ and fund j inception month.

Although consistency of moment-based estimations does not depend on distributional assumptions (provided the moment restrictions are valid), drawing shocks to *SubResTime* and *Rush* from a randomly drawn covariance matrix is important for correct inference in such situations. One way to think of this procedure is that it allows for error-term heteroskedasticity and clustering in *main model*, which is almost surely true in the population of funds. Another motivation for these simulation parameter perturbations is that they allow for uncertainty in the covariance matrix estimates (Σ). Again, absence thereof would be an unrealistically strong assumption. Similar intuition underlie imputations via the Gibbs sampler and some Bayesian inference methods (Efron and Tibshirani, 1994).

The point estimates [confidence intervals] for α that I report in Tables V and VI and in Figures B1 and B2 in the main text are based on equally weighted means of α_s [$a\hat{var}(\alpha)_s$] over 1,000 *independent simulation*.[ia11] In essence, I run Fama and MacBeth (1973) procedure which is asymptotically equivalent and typically as efficient as panel least-squares methods (Skoulakis, 2008). While the aggregation of point estimates is standard, my choice for the variance reflects the fact that α-estimates across our *independent simulation* must be perfectly correlated asymptotically.[ia12,ia13]

Besides α and the asymptotic variance-based confidence interval, Figure B1 in the main text plots the range for α_s across *independent simulations*. This range indicates how sensitive the estimates are to the seed value choice when we draw at most 100 random exits for each fund. In both Panels, A and B, top-left(right) charts report results for the baseline model with stopping-time defined as crossing 15 (20)% threshold of NAV/(total distributions

[ia11] Each $avar(\alpha)_s$ estimate is robust to error clustering at exit quarter.
[ia12] A GLS version of Ferson and Harvey (1999) yields almost identical point estimates in the cases I reviewed (untabulated).
[ia13] This variance estimator can also be viewed as obtained through a parametric bootstrap, e.g. see Efron and Tibshirani (1994).

to-date), while bottom-left (right)—for the baseline model augmented with *Pseudo-timing* controls and 15 (20)% threshold. Panel A investigates how robust the estimates are to exclusion of selected vintage years. Panel B—dummies-out selected exit years.

To examine the consequences of the parameter-dependence of the null hypothesis in *main model*, Panel A of Figure B2 in the main text plots α estimates over *independent simulations* when actual fund stopping month and *Rush* are replaced with their expectations estimated in the first step. These expected values indicate the location of the density masses for the simulated funds. Clearly, they are always zero statistically and, if anything, tend to be slightly negative. As with expected stopping month and *Rush*, I can compute coefficient and variance estimates for each one of the 100 bivariate draws. Panel B plots the fraction of simulated funds that have t-statistic lower than that of the actual funds by each *independent simulation*. We can see that these random rejection rates are consistent with (two-sided) 5% confidence level for the 15% threshold case as per asymptotic variance estimates in Table V of the main text, but somewhat higher for the 20% threshold case where, in which with asymptotic variance estimate we reject the null at 10% level.

2.3. Alternative approaches

Another viable econometric strategy to compare market returns following actual fund exits and rush from those under a random exit assumption would borrow tools from the survival analysis. In fact, a discrete time hazard-rate model would imply a very similar dataset (spanning the plausible range of stopping-times for each fund) to the one I use to estimate the main model but the observation weights would be governed by a parametric distribution (e.g. logistic) instead of a mixture of normals that my simulations imply, although the interpretation of coefficients would be less intuitive.[ia14]

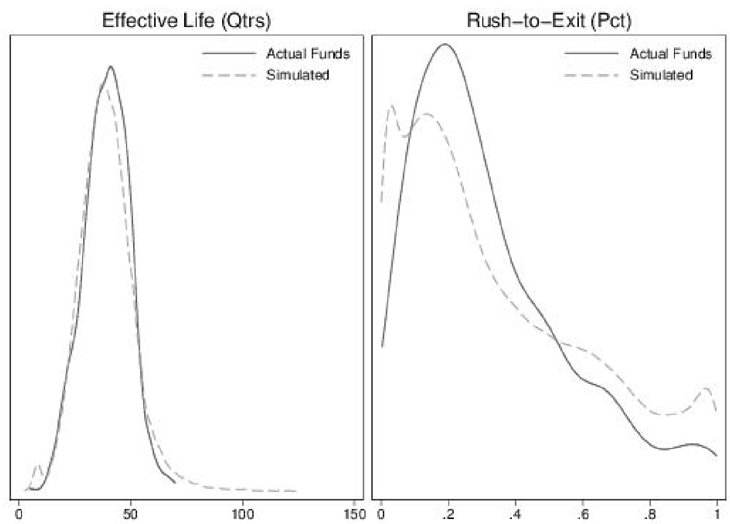
However, neither is such a discrete hazard-rate model more robust to functional form misspecification or variables omissions, nor is it less restrictive as it comes to the parameter variance estimation. Moreover, non-linear MLEs are prone to the incidental parameter problem with large set of fixed effects (Wooldridge, 2002). Finally, bypassing an auxiliary model of my approach would not be possible with a hazard-rate model still because the values of hypothetical *Rush* are not known. Essentially, for each quarter we observe a rolling window sum of distributions to the total sum of distributions to-date, conditional the actual "stopping quarter". What we need to observe is that amount conditional on "stopping" in that particular quarter.

[ia14] The dummy *Informed* and mean *Industry Return* would have to switch sides since the dependent variable needs to be binary.

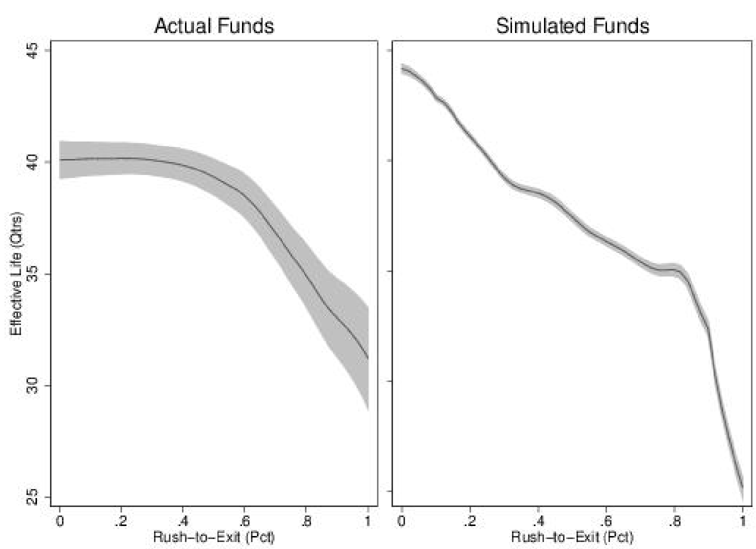
Figure IA-1
Actual fund exits versus simulated

This figure reports comparisons of *SubResTime* (labeled as 'Effective Life (Qtrs)' on the chart) and *Rush* ('Rush-to-Exit (Pct)') for actual funds in comparison to a random draw of simulated funds. See section IA-2.2.1 for details. Panel A reports kernel density estimates of *SubResTime* and *Rush* with solid (dashed) line being a separate estimate over the actual (simulated) values on the left- and right-hand charts respectively. Panel B plots local polynomial regressions estimates of *SubResTime* and *Rush* relations for actual and simulated values on the left- and right-hand charts respectively.

Panel A: Univariate Distributions



Panel B: Bivariate Relations



IA-3. Additional results and robustness

Figure IA-2 reports cash flow schedules against the time series of public benchmark for hypothetical funds and reports the corresponding values of Timing Track Records (TTRs) which are defined as: $\frac{\sum_{t=0}^{T} D_t \cdot exp\{r_{1:T} \cdot (1-t/T)\}}{\sum_0^T C_t \cdot exp\{r_{1:T} \cdot (1-t/T)\}} / \frac{\sum_{t=0}^{T} D_t \cdot exp\{r_{t+1:T}\}}{\sum_0^T C_t \cdot exp\{r_{t+1:T}\}}$, where $t = 0$ is fund inception, $r_{t+1:T}$ is continuously compounded return on public benchmark between date t and the fund's resolution, while $D_t[C_t]$ is the fund's distribution [capital call] at end of period t.

Figure IA-3 describes the fund sample distributions across vintage years and the annualized returns cross-sectional variation in the industry sector returns that correspond to the fund specialization.

Figure IA-4 depicts cross sectional variation in capital calls and distributions over time separately for buyout and venture funds. It follows from Panel A that, for example by the 30^{th} month since inception, a quarter of buyout funds would call 61% of its capital or less while another quarter would be fully invested by that time. Meanwhile, from the right-hand charts we learn that among almost fully resolved buyout funds, a quarter had about 40% of total distributions completed 30 months before last while another quarter had over 80% already distributed. Panel B shows that the dispersion is similarly wide for venture funds.

Figure IA-5 compares the sample fund distribution of TTRs computed against the broad market returns measured by CRSP VW index (Panel A) with those computed against the returns of S&P500 subindex corresponding to the GICS Industry sector focus (fund *Industry*) as assigned by Burgiss, the PE fund data provider. It follows that the means and variances are notably higher against the Industry returns for both venture and buyout funds.

Figure IA-6 reports additional event studies for Informed Rush (by exit year group, to complement those in Figure 3 in the main text) and for Informed "No Rush" (i.e. Rush$<$ vintage median). It appears that when Informed and incentivized GPs procrastinate with trimming remaining exposures as manifested by low values of Rush the industry share price performance tends to improve. However, the returns do not become abnormally good as if there were some short-lived distortions in the valuations caused by the 'copycat' behavior of some investors taking long positions in the industry. Rather, the returns become very close to these around the control group exits, which, in turn, appear unchanged from before the SubResTime.

3.1. Robustness tests

Table IA-1 reports results of a multivariate analysis of the sample fund TTR properties. Panel A repeats the corresponding table from the main text, whereas Panel B runs same tests but using TTRs and sequencing against the fund *Industry*. It follows that the persistence and correlation with PME is weaker for the case with broad market index.

Table IA-2 reports predictive regressions of return by Informed Rush just as those in Table IV of the main text but using a dummy variable to denote *Rush* which is a fraction of distributions (to LPs) over the last 6 quarters in the funds' total-to-date. Specifically, $Rush20 = 1$ if $Rush >= 0.2$. *Industry returns* are of S&P500 subindex corresponding to the GICS industry sector of the fund specialty. From this analysis, it follows that results are very similar to those reported in the main text using continuous *Rush* and are not driven by a non-representative minority of funds—(toDateTTR>1 × toDateIRR>Hurdle × Rush20) =1 for 205 funds which is 22% of the sample.

Table IA-3 additionally scrutinizes the potential for simultaneity between Rush and *Informed* indicator to drive the predictability of returns in the main tests. In this analysis, I instrument both, IndustryReturn the Informed indicator. I continue using IndEPSsurprise as the source of variation for IndustryReturn and use a propensity score to instrument Informed indicator. The propensity score is determined by the performance of the current fund's peers and the timing track record of the previous fund managed by the that GP. Therefore, the remaining variation in Informed indicator (and that of Informed×IndustryReturn) is less susceptible to the Grandstanding and Footprint-on-Firms concerns. More specifically, the exclusion restrictions for the validity of this test are: (i) industry future earning surprises do not affect the fund exits today except through GP's industry return outlook, and (ii) strategy-by-vintage median "luck" does not affect the fund exits today except through the odds that the fund carry is in-the-money. This analysis is reported in Table IA-3. It reveals the negative and significant interaction on Informed×IndustryReturn and, thus, supports the hypothesis that future industry returns cause Informed Rush.

3.2. Does Rush hurt holding period returns?

If holding period returns were sacrificed, we would expect that the gains from company selection and nurturing (as measured by holding period returns) to be negatively correlated with those from buying (selling) near the industry troughs (peaks). Although the results in Table IA-1 suggest that this correlation seems to be positive, they are prone to spurious correlation due to fund risk misspecification (see section II.A of the main text) and the overlap in lives across several funds (Korteweg and Sorensen, 2017). Moreover, it is interesting to examine holding period returns of funds in which GPs might have refrained from divesting ahead of the market downturns. If their decisions "to not rush" were driven by the objective to maximize the total return for LPs, we should expect that the average holding period abnormal returns of their funds to be higher (so that those decisions could have been optimal still).

Utilizing funds' holding period abnormal performance as dependant variable in a model used to predict industry returns in the main text (Table IV) and Table IA-2 of this appendix yields the required tests. Table IA-4 reports the results. As before, *Informed* group is represented by its constituents, to-date $TTR > 1$ and $IRR > Hurdle$ and the interaction thereof, whereas *Rush* is a ratio of the fund distributions over 6 quarters to the fund's total to-date. To zoom at GPs' portfolio company selection and nurturing effects, I add industry fixed effects to vintage year fixed effects while there is no purpose to condition on the risk-premia covariates as of the stopping time in this case (dropping industry fixed effects leaves the estimates largely unchanged).

The differences across specifications in Table IA-4 derive from the dependent variable only. In specifications (1) and (2), it is Kaplan-Schoar PME at the latest available date (henceforth, *Last PME*) against the fund industry and the broad market, respectively. While the funds that had neither performance in excess of the hurdle rate nor a good timing track record ($TTR > 1$), indeed appear to attain lower lifetime PMEs when their exits cluster significantly towards the last few quarters of active operations (i.e., $Rush \approx 1$), all the interaction terms with Rush are positive. The cumulative effect on PME for *Informed Rush* (reported in the bottom of the table) is actually positive, although not significant statistically. Thus, I conclude that there is no evidence of holding period returns' sacrifice by GPs exhibiting *Informed Rush*.

The significantly negative coefficient on $TTR > 1$ indicates that the "non-Rushing" *Informed* GPs who were not making any performance fees, have had significantly lower holding period returns for their investors than the control funds. This would be expected if those GPs were primarily concerned with keeping their option to earn performance fees alive (at the cost of LPs' value maximization objective).[ia15]

In specifications (3) and (4), I focus on holding period returns specifically during the periods of exits (i.e., while *Rush* is measured). Therefore, I define the dependent variables as a log of a ratio of last PME (industry and broad market, respectively) to the PME as of the fund's fifth anniversary. The main-effect coefficient is no longer even negative while the interactions with just $TTR > 1$ and just $IRR > Hurdle$ are much closer to zero, suggesting that *Rush* relates to returns attained earlier during the funds' lives (motivating the inclusion of *PME-to-date* in the conditioning set for the simulation-based estimations, see section IA-2). The key result—the positive cumulative effect of *Informed Rush*—remains qualitatively unchanged from specifications (1) and (2), showing no evidence of holding period performance cannibalization from market timing of exits by *Informed*. However, the positive association

[ia15] In the untabulated analysis, I also verify that funds run by *informed* GPs that appear to rush have significantly shorter life than the control group, whereas when *Rush* is near zero, the life is longer, albeit insignificantly.

between *Rush* with holding period returns appears stronger economically and statistically during the later periods of fund lives when most divestments occur.

3.3. Evidence on risk shifting

In this section, I test whether GP skills can also hurt LP interests through more successful "asset-hoarding" ahead of high volatility periods.[ia16] While LPs can also benefit from the option value of a distressed equity claim, it appears unlikely that such risk shifting by GPs implements a first-best portfolio choice from their LP perspective. Instead of keeping the assets in the fund, most LPs could obtain equivalent systematic and comparable idiosyncratic volatility exposures while not footing the bill for the GP's call-option. To proceed with the tests, I simply change the dependent variable in the baseline model used in the main text (i.e. Table V) from *future mean* of *Industry returns* to *past volatility,* and redefine the *Informed* funds group.

I estimate volatility as annualized standard deviation of monthly returns -6 to 0 and -12 to -8 quarters relative to the respective fund's *stopping-time*. The first window corresponds to the period over which *Rush* is measured. Hence, it shall speak about how the fund distributions' clustering associates with abnormal industry volatility. The second window is even more interesting since high values of *Rush* imply that there were very few distributions made *before* the Rush measurement window while the fund fixed effect projections ensure that the volatility is abnormal relative to the fund inception date×industry and other fund- and firm-level covariates (as per the *auxiliary model* in Table B.1 in the main text). The results for the first window can be considered a placebo experiment that informs about the differences in abnormal volatility within *Informed Rush* period, which (if present) may confound our interpretation of the results for the {-12 to -8}-window .

The informed group now comprises funds that (a) have a positive track record of market timing ($TTR{>}1$), and/or (b) where GPs face a survival risk beyond the term of the current fund. I assume the survival risk to be determined by a combination of the following two conditions: (i) whether net-of-fees IRR was in the bottom or top tercile among type×vintage peers (*Btm*/*Top*), and (ii) whether a successor fund has been raised (*NoNext*/*YesNext*).[ia17] To not engage more than three-level interaction terms, I define three non-overlapping groups: *Btm*|*NoNext*, *Btm*|*YesNext*, and *Top*|*NoNext*. In addition, to preclude a look-ahead bias and unrealistic assumptions, I measure *TTR* and *IRR* as of the *fifth* anniversary of the respective

[ia16] Similar to management seeking to increase the riskiness of company assets when incentivized by distressed equity as per Jensen and Meckling (1976), and Galai and Masulis (1976), among others.

[ia17] Clearly, an existence of a follow-on fund commitment from investors keeps the GPs "in-business" for the next decade while the current fund performance is a significant determinant of the fundraising odds as per Barber and Yasuda (2017).

fund and constrain the sample to funds with actual stopping-times at least *eight* years from inception. This ensures that the funds are not too young to make any distributions during the {-12 to -8}-window, while the to-date performance signals are meaningful and yet not overlapping with the volatility observation windows.

Arguably, *Btm|NoNext*-funds face the highest incentive to hoard the fund assets since their GPs likely have no performance fees to collect from the current and future funds. The trade-off is less clear for *Btm|YesNext*-funds' GPs. On the one hand, the asset-hoarding benefits the value of their out-of-the-money option to earn performance fees in the current fund. On the other hand, such a behavior may tarnish their relationships with investors and negatively affect the odds of successful fundraising in the future. Chung et al. (2012) show that the present value of expected fees (performance-based and fixed) from the future funds (yet to be raised) may exceed those from the current fund. Meanwhile, the examination of the effects for *Top|NoNext*-funds completes the analysis by highlighting the role of current performance with respect to the risk-shifting incentives. There should be zero effects insofar performance fees in the current fund reduce GPs risk-appetite and/or high performance significantly increases the odds of fundraising success (Barber and Yasuda, 2017).

Table IA-5 reports the results for the stopping time defined based on 15% NAV/"total distributions to-date" threshold. All specifications include the projections of fund fixed effect (see Appendix B in the main text) and the main terms of *Rush* and *Informed*. Specifications (3) and (4) also include the levels of VIX index as the fund stopping-quarter and the -12 to -8 quarters or -6 to 0 quarters, respectively, to better absorb heterogeneity across informed funds and zoom at the industry-specific innovations to the volatility. Specifications (1) and (3) show that the volatility during the *Rush* periods is neither abnormal (relative to the hypothetical exits) nor meaningfully different within *Informed* funds across the incentive and skill dimensions. Therefore, the results for {-12 to -8} window shall provide us with a clean test of risk shifting hypothesis.

Meanwhile, specifications (2) and (4) of Table IA-5 strongly support the hoarding hypothesis. While the industry volatility associations with the divestment schedules continue to be insignificant for funds that appear to have just timing skill but no incentive to risk-shift (and vice versa), there is a singificant difference when both conditions are satisfied. A positive and significant coefficient of *TTR>1* $\times$ *Btm|NoNext* $\times$ *Rush* in specification (2) suggests that an inter-quartile (=0.3) increase in *Rush* by such funds associates with approximately 2.5 percentage points higher per annum volatility of the industry returns during the quarters preceding the *Rush*. Since the fraction of distributions prior to the sixth quarter before the stopping equals 1-*Rush*, it follows that these funds had distributed abnormally small fraction of fund assets before the industry volatility became abnormally high. Controlling for the systematic volatility levels within the window and at the fund resolution date (as per specification (4)) does not change the result.

The projections of fund fixed effects reflect funds' inception dates. Therefore, the fund-specific control-groups of hypothetical exits account for differences in the volatility paths since fund inception (e.g., as of the fifth anniversary). Besides, negative but insignificant from zero coefficients of *TTR>1* $\times$ *Top|NoNext* $\times$ *Rush* speak against the effects on *TTR>1* $\times$ *Btm|NoNext* $\times$ *Rush* being driven by other factors (e.g., when many funds had no successor by mid-life). Thus, we can conclude that *Informed* GPs who have incentives to "hoard" fund assets are significantly more likely to "drag" their fund assets through periods of high turbulence in the industry.

Finally, the effectively zero coefficients on *TTR>1* $\times$ *Yes|NoNext*-terms indicate that, skilled timers or not, poorly performing GPs that nonetheless have a successor fund already do not exhibit such risk shifting behaviors. This suggests that expected flows from future funds do restrain managers from "destroying value", consistent with the analysis in Chung et al. (2012).

Figure IA-2
Timing track records: examples

This figure plots pair-wise comparisons of TTRs for eight hypothetical fund capital calls ($CCalls_t$) and distribution ($Distrib_t$) schedules (#1–#8) and a common (mean-zero) market return (r_t) schedule. The cash-flow schedules are from the LPs' perspective so that the negative values represent capital calls that sum to \$50 for all but fund #2. All are derived from the following value process—$FundValue_t = FundValue_{t-1}(1 + r_{m,t}) + CCalls_t - Distrib_t$. As discussed in the main text, in this case the fund money-multiple equals TTR. TTR measures the gross-return due to selling near the market peaks during the fund life-time and buying near the troughs and defined as $\frac{\sum_{t=0}^{T} D_t \cdot exp\{r_{1:T}\cdot(1-t/T)\}}{\sum_0^T C_t \cdot exp\{r_{1:T}\cdot(1-t/T)\}} / \frac{\sum_{t=0}^{T} D_t \cdot exp\{r_{t+1:T}\}}{\sum_0^T C_t \cdot exp\{r_{t+1:T}\}}$, where $t = 0$ is fund inception, $r_{t+1:T}$ is continuously compounded return on public benchmark between date t and the fund's resolution, while $D_t[C_t]$ is the fund's distribution [capital call] at end of period t. Top-left panel demonstrates that very different schedules can be equally market-timing neutral. Top-right panel reviews the case of buying at trough. Bottom-left panel demonstrates the effect of selling at peak whereas bottom-right panel shows timing of entry and exit.

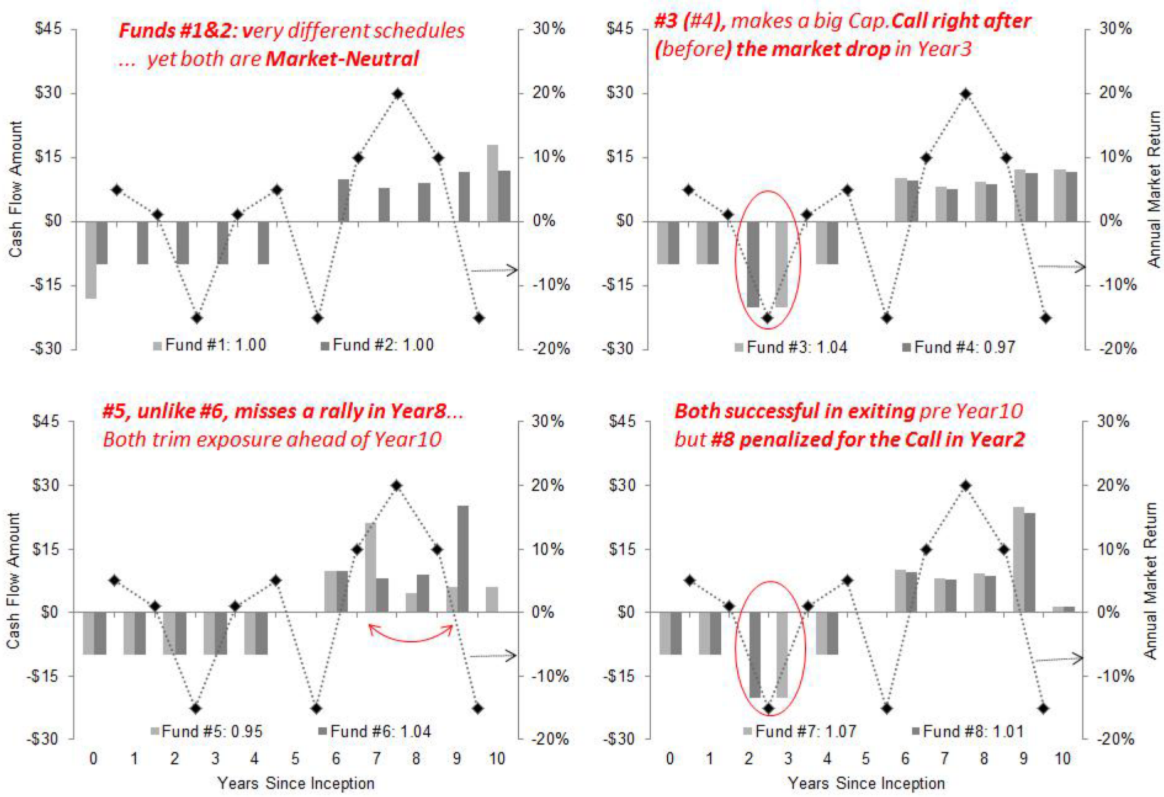
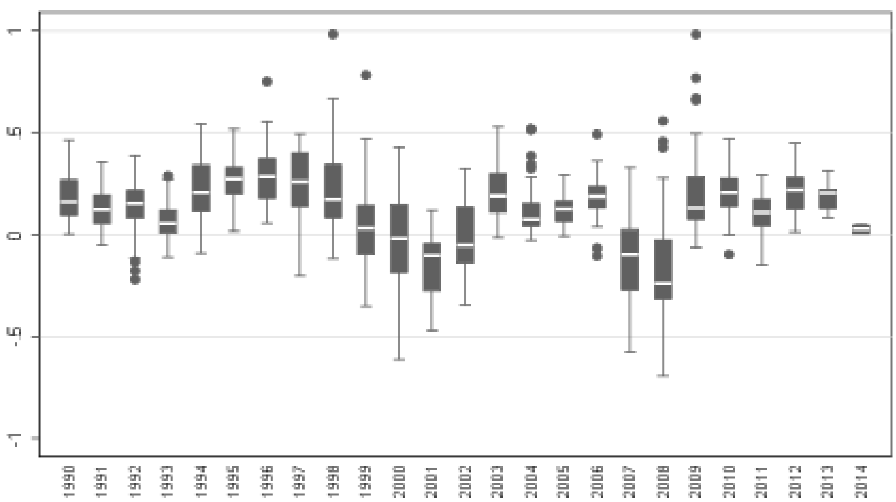


Figure IA-3
Sample description

This figure reports intertemporal distributions of *Industry returns* in Panel A and the sample private equity funds in Panel B. Each observation in the box-plot of Panel A represents a 12-month return of S&P500 GICS industry sector subindex. The increment between intervals is one month so that there are 12 observations for each of the 10 industry sectors. Panel B plots total number of funds in the sample by vintage-year as well as the number of funds with a positive track record of market timing in the past, as measured by TTR – the gross-return due to selling near the Industry peaks during the fund life-time and buying near the troughs (see figure IA-2 for denifition). The sample is comprised of 349 (592) U.S.-focused buyout (venture) funds.

Panel A: Industry returns



Panel B: Funds by vintage and TTR group

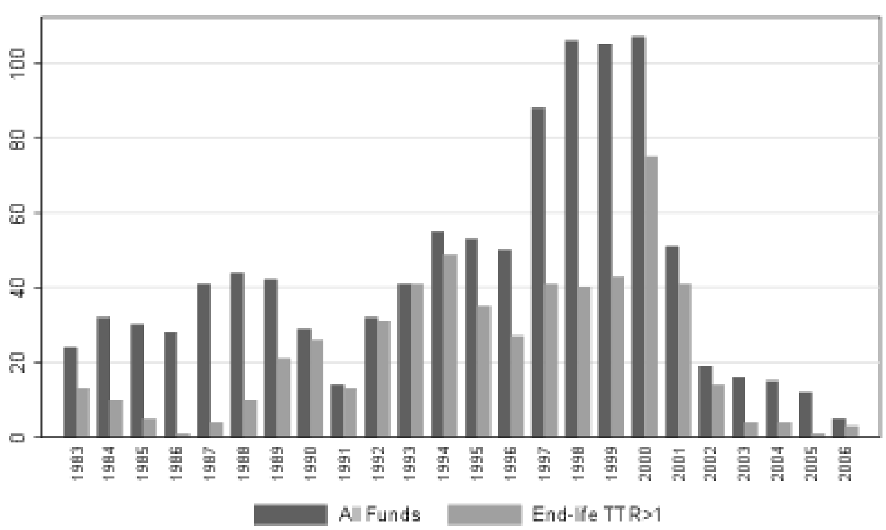
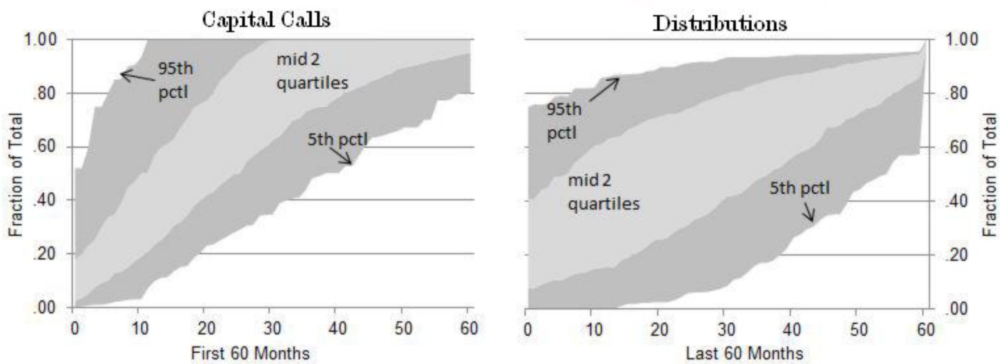


FIGURE IA-4

Private equity fund cash flows: cross-section

This figure reports the 5^{th}, 25^{th}, 75^{th}, and 95^{th} percentiles for the fraction of to-date capital calls (distributions) in the total amount eventually to be called (distributed) by each fund during the first (last) 60 months of its operation. Panel A plots results for the buyout subsample. Panel B reports this analysis for the venture subsample.

Panel A: Buyout



Panel B: Venture

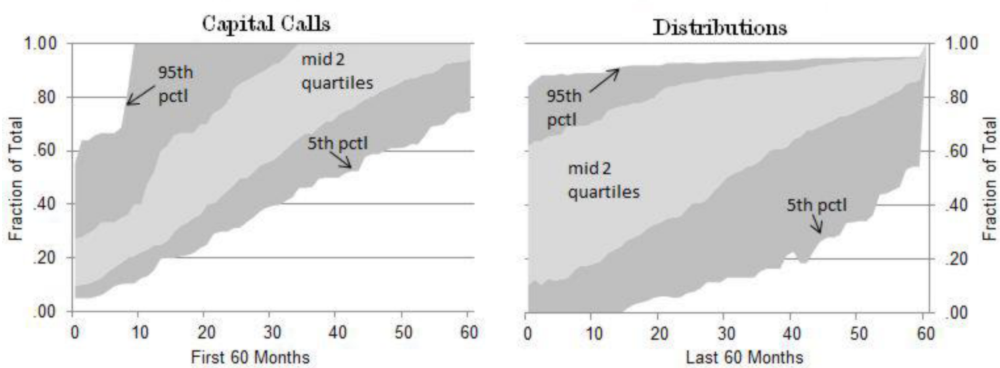
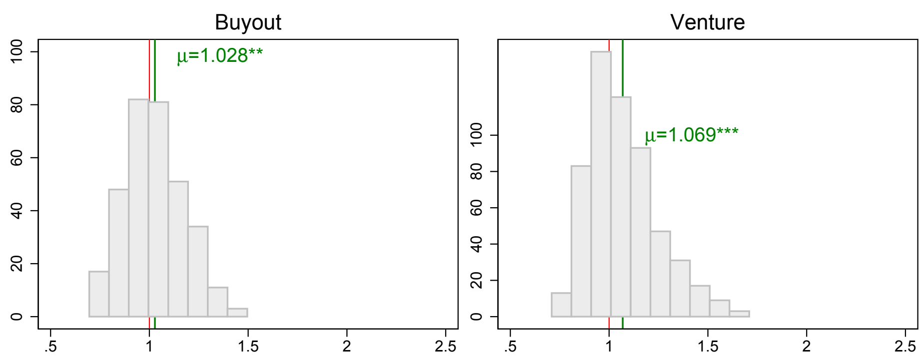


FIGURE IA-5
Timing track records: industry versus overall market

This figure plots Timing Track Record (TTR) values for the sample private equity funds. TTR measures the gross-return due to selling near the market peaks during the fund life-time and buying near the troughs and defined as $\frac{\sum_{t=0}^{T} D_t \cdot exp\{r_{1:T} \cdot (1-t/T)\}}{\sum_{0}^{T} C_t \cdot exp\{r_{1:T} \cdot (1-t/T)\}} / \frac{\sum_{t=0}^{T} D_t \cdot exp\{r_{t+1:T}\}}{\sum_{0}^{T} C_t \cdot exp\{r_{t+1:T}\}}$, where $t = 0$ is fund inception, $r_{t+1:T}$ is continuously compounded return on public benchmark between date t and the fund's resolution, while $D_t[C_t]$ is the fund's distribution [capital call] at end of period t. Panel A left (right) chart shows the frequency distributions of $TTRs$ computed against the broad market index for the buyout (venture) funds using the complete history of the fund cash flows. The width of each bin is 0.1 which corresponds to 10% differnce in fund life-time return. Panel B shows $TTRs$ for the respective subsample against (S&P500 subindex of) GICS industry sector that the respective fund specializes in (*Industry TTRs*).
The sample is comprised of 349 (592) U.S.-focused buyout (venture) funds of which 159 and 358 invested at least 50% of the funds capital of the specialization industry. Among these funds, the means for industry-based TTR are 1.076 and 1.146 for buyout and venture funds, which exceeds the broad market-based TTRs by 0.027 and 0.054 respectively. As with the full sample, the difference is statistically significant only for venture funds. See section III.B.3 of the main text for multivariate tests, separately for entries and exits.

Panel A: Broad market TTRs



Panel B: Industry TTRs

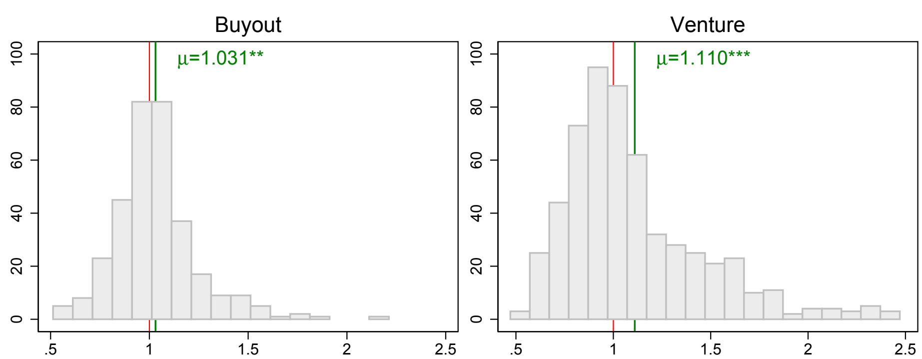
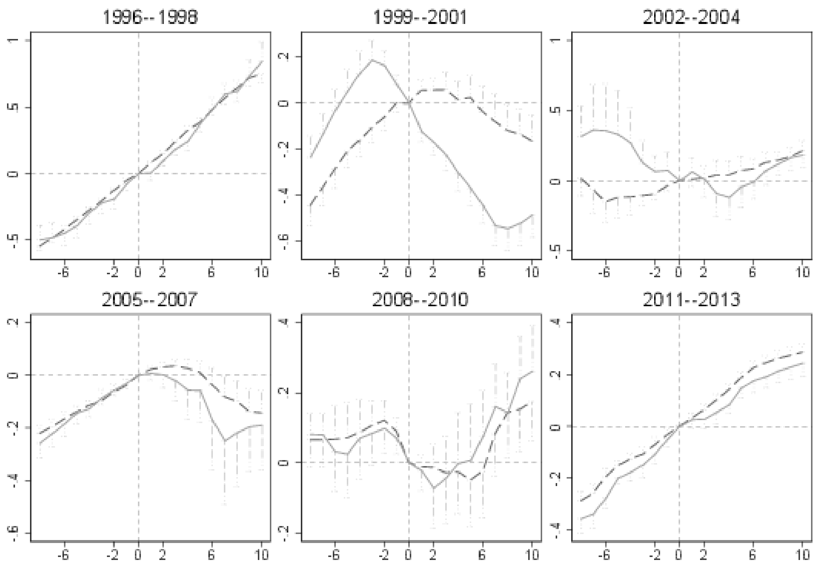


FIGURE IA-6
Informed Rush: more event studies

This figure plots cumulative return on *Industry* portfolio around *SubResTime* for funds with *Rush* above vintage year medians. *Rush* measures the intensity of fund's distributions to LPs right before *SubResTime*, based on 15% residual NAV threshold. The medians are computed by fund type (venture or buyout) and vintage year. The sample is comprised of 349 (592) U.S.-focused buyout (venture) funds. The solid line (*Informed Rush*) is the mean across *Informed* funds that have incentives and market-timing skill, as measured by both *toDateTTR>1* and *toDateIRR>HR* as of *SubResTime*. The dashed line comprise of all other funds. Panel A reports results by triennial intervals (of *SubResTime* occurance) for funds with above-median *Rush* while Panel B pools across all *SubResTimes* and below-median *Rush*. The bars denote 95% confidence interval.

Panel A: High Rush by exit year



Panel B: Full sample: what if no Rush?

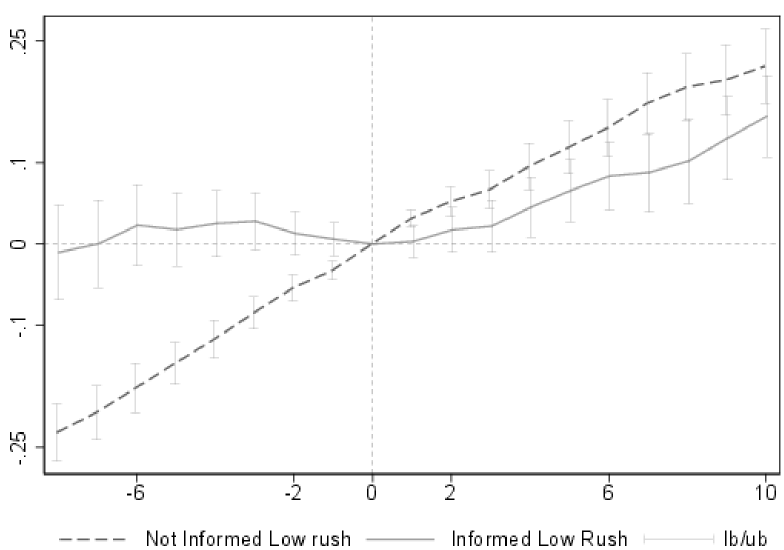


TABLE IA-1
Timing track records: associations and persistence

This table reports linear regression model estimates of the log of funds' end-life $TTRs$. TTR measures the gross-return due to selling near the market peaks during the fund life-time and buying near the troughs and defined as $\frac{\sum_{t=0}^{T} D_t \cdot exp\{r_{1:T} \cdot (1-t/T)\}}{\sum_0^T C_t \cdot exp\{r_{1:T} \cdot (1-t/T)\}} / \frac{\sum_{t=0}^{T} D_t \cdot exp\{r_{t+1:T}\}}{\sum_0^T C_t \cdot exp\{r_{t+1:T}\}}$, where $t = 0$ is fund inception, $r_{t+1:T}$ is continuously compounded return on public benchmark between date t and the fund's resolution, while $D_t[C_t]$ is the fund's distribution [capital call] at end of period t. The explanatory variables are: $ln(Size)_i$ ($ln(Size)_i^2$) - log (log-squared) of the fund $ capital committed; $ln(Sequence)_i$ - chronological order of the fund inception date by given GPs (the private equity management firm); $ln(PME)_i$ - log of the fund's Kaplan and Schoar (2005) Public Market Equivalent Index; $ln(TTR)_{i-1}$ - log of the GP's previous fund TTR. TTR, $ln(Sequence)_i$ and PME are measured versus to the GICS industry sector of the fund specialty in Panel A, and versus the broad market/ all funds by that GPs in Panel B. Specifications (2) through (6) include fund vintage-year fixed effects. Standard errors in parentheses are clustered at GP-level, */**/*** denote significance at 10/5/1% confidence level. The sample is comprised of 349 (592) U.S.-focused buyout (venture) funds.

Panel A: TTR versus Industry

	(1)	(2)	(3)	(4)	(5)	(6)
Fund size	0.515***	0.082				
	(0.162)	(0.150)				
Fund size squared	−0.014***	−0.003				
	(0.004)	(0.004)				
Fund sequence	0.057***	0.049***	0.040**			0.055**
	(0.021)	(0.018)	(0.017)			(0.024)
Fund PME			0.040***		0.059***	0.054***
			(0.015)		(0.020)	(0.020)
Previous fund TTR				0.135**	0.115**	0.107**
				(0.052)	(0.051)	(0.049)
Vintage year fixed effects	No	Yes	Yes	Yes	Yes	Yes
Observations	756	756	756	404	404	404
R^2	0.025	0.387	0.386	0.431	0.449	0.457

Panel B: TTR versus Broad Market

	(1)	(2)	(3)	(4)	(5)	(6)
$ln(Size)_i$	0.164*	0.002				
	(0.085)	(0.072)				
$ln(Size)_i^2$	−0.005**	−0.001				
	(0.002)	(0.002)				
$ln(Sequence)_i$	0.048***	0.034***	0.015*			0.011
	(0.009)	(0.008)	(0.009)			(0.014)
$ln(PME)_i$			0.037***		0.044***	0.043***
			(0.007)		(0.010)	(0.010)
$ln(TTR)_{i-1}$				0.108**	0.093*	0.093*
				(0.055)	(0.049)	(0.050)
Vintage fixed effects	No	Yes	Yes	Yes	Yes	Yes
Observations	756	756	756	404	404	404
R^2	0.035	0.468	0.482	0.470	0.516	0.517

Table IA-2
Informed Rush: robustness to variable definition

This table reports predictive regressions of the fund industry returns by *Informed Rush*, a proxy for the carried interest "cashed-in" by GPs with a positive track record of market timing in the past. As discussed in the main text, a negative α-estimate from the following model identifies market timing skill by GPs:

$$E[IndustryReturn_{ij}^{1:12}] = \alpha \cdot Informed_{ij}Rush20_{ij} + \alpha_0 Informed_{ij} + \alpha_1 Rush20_{ij} + \lambda_j \quad ,$$

where $IndustryReturn_{ij}^{1:12}$ is a mean monthly return on S&P500 subindex for the GICS industry sector that fund i specializes in over 12 months following the fund i *SubResTime*, λ_j – fund vintage year fixed effects; *Rush* is a fraction of fund distributions over the last 6 quarters in the funds' total-to-date: $Rush20 = 1$ if $Rush >= 0.2$ and zero otherwise. In specifications (1) and (3) [(2) and (4)], $Informed_{ij}$ is the interaction between two dummies $toDateTTR > 1$ and $toDateIRR > Hurdle$, while specifications (2) and (4) also include the two dummies separately as well. TTR measures the fund gross return to date due to selling at market peaks and buying at troughs and is defined as $\frac{\sum_{t=0}^{T} D_t \cdot exp\{r_{1:T} \cdot (1-t/T)\}}{\sum_0^T C_t \cdot exp\{r_{1:T} \cdot (1-t/T)\}} / \frac{\sum_{t=0}^{T} D_t \cdot exp\{r_{t+1:T}\}}{\sum_0^T C_t \cdot exp\{r_{t+1:T}\}}$, where $t = 0$ is fund inception, $r_{t+1:T}$ is continuously compounded return on the S&P500 subindex between date t and the fund's resolution, while $D_t[C_t]$ is the fund's distribution [capital call] at end of period t, and D_T equals the last most reported NAV corresponding to *SubResTime*. *SubResTime* is the first quarter when fund NAV drops below 15% of the fund total distributions up to that quarter. Specifications (3)-(4) include additional *return-predictive* covariates (see Table II of the main text). Standard errors in parentheses are clustered at *SubResTime*, */**/*** denote significance at 10/5/1%. The sample is comprised of 349 (592) U.S.-focused buyout (venture) funds.

	(1)	(2)	(3)	(4)
toDateTTR>1 × toDateIRR>Hurdle × Rush20	−0.010***	−0.010*	−0.005*	−0.009*
	(0.003)	(0.006)	(0.003)	(0.005)
toDateTTR>1 × toDateIRR>Hurdle	−0.000	0.003	0.002	0.004
	(0.003)	(0.004)	(0.002)	(0.003)
toDateTTR>1 × Rush20		0.000		0.004
		(0.004)		(0.004)
toDateIRR>Hurdle × Rush20		−0.000		0.001
		(0.004)		(0.003)
toDateTTR>1		−0.001		−0.002
		(0.004)		(0.002)
toDateIRR>Hurdle		−0.005*		−0.002
		(0.003)		(0.003)
Rush20	0.001	0.001	0.002	0.001
	(0.002)	(0.003)	(0.002)	(0.003)
Vintage fixed effects	Yes	Yes	Yes	Yes
Predictive covariates	No	No	Yes	Yes
Observations	893	893	892	892
R^2	0.212	0.218	0.444	0.445

TABLE IA-3
Return predictability and earnings news: full IV

Panel A of this table reports instrumental variable regression estimates of the following model:

$$E[Rush_{ij}] = \lambda_j^R + c_i^R + \alpha^R\big[Informed_{ij} \quad IndReturn_{ij}^{1:12} Informed_{ij} \quad IndReturn_{ij}^{1:12}\big],$$

where $Rush_{ij}$ measures the intensity of fund i distributions to LPs right before *SubResTime*; $Informed_{ij}$ is an indicator for the presence of incentives and market-timing skill; $IndReturn_{ij}$ is the mean monthly return on *Industry* over 12 months following fund i *SubResTime*, and a_j^R—vintage year fixed effects. *Informed*, *IndReturn*, and their interaction are instrumented with the *IndustryEPSsurprise* over the respective period, the propensity for the fund to be *Informed*, and their interaction. *Informed* are funds with both *toDateTTR>1* and *toDateIRR>HR* as of *SubResTime*. In specifications (1) and (3), *SubResTime* is based on 15% residual NAV threshold as opposed to 20% in specifications (2) and (4). All specifications include vintage group fixed effects, while specifications (3) and (4) also include *Predictive covariates*, c_i^R. The propensity to be *Informed* is obtained from a probit model (as reported in specification (1) of Panel B with pooled 15% and 20% *SubResTimes*) and is set to missing whenever the fund has fewer than five peers. *Mfx* denote marginal effects evaluated at means. *1st stage K-P Wald stat* is the partial F-statistic from Kleibergen and Paap (2006) Wald test—see Internet Appendix for first stage details. Standard errors in parentheses are robust to heteroskedasticity, */**/*** denote significance at 10/5/1%. The sample is comprised of 349 (592) U.S.-focused buyout (venture) funds.

Panel A: Instrumentation of the Informed Status with its Propensity

	15%thld (1)	20%thld (2)	15%thld (3)	20%thld (4)
Informed(D) × IndustryReturn	−10.537**	−9.510**	−9.367**	−7.843*
	(4.598)	(4.382)	(4.613)	(4.265)
IndustryReturn	1.336	0.744	2.537	1.468
	(2.790)	(2.719)	(2.756)	(2.787)
Informed(D)	−0.104	−0.139	−0.088	−0.094
	(0.085)	(0.088)	(0.124)	(0.140)
Vintage year fixed effects	Yes	Yes	Yes	Yes
Predictive covariates	No	No	Yes	Yes
1st stage K-P Wald statistic	17.5	18.6	16.5	12.0
Observations	628	695	628	695

Panel B: Informed Status Probability Model

	(1)		(2)	
	β/(t-stat)	Mfx	β/(t-stat)	Mfx
Median peer PME	1.115***	0.4384	1.210***	0.4741
	(6.29)		(6.54)	
Median peer TTR	3.575***	1.4051	1.510***	0.5918
	(8.93)		(2.94)	
Industry Return since inception	0.274***	0.1075	0.040	0.0157
	(5.46)		(0.38)	
Previous fund TTR>1	0.194*	0.0763	0.330***	0.1293
	(1.69)		(2.78)	
Vintage year fixed effects	No		Yes	
Observations	1,349		1,349	
Pseudo R^2 (Baseline probability)	0.153	(42.4%)	0.211	(42.7%)

Table IA-4
Does Informed Rush sacrifice holding period returns?

This table reports OLS estimates of the following model:

$$E[HAR_{ij}] = \alpha \cdot Informed_{ij}Rush_{ij} + \alpha_0 Informed_{ij} + \alpha_1 Rush_{ij} + \lambda_j$$

where HAR_{ij} is the holding period abnormal return of fund i as measured by a natural log of the Kaplan-Schoar PME at the latest available date (henceforth, Last PME) against the fund industry and the broad market in specifications (1) and (2), respectively. In specifications (3) and (4), HAR_{ij} is a log of a ratio of Last PME (industry or market) to the respective PME as of the fund's 5^{th} anniversary. $Rush_{ij}$ – a fraction of distributions (to LPs) over the last 6 quarters before the *SubResTime* in the funds' total-to-date. $Informed_{ij}$ is the main effects and the interaction of two dummies which proxy for the presence of skill and financial incentive and are based on whether *TTR* (*IRR*) as of *SubResTime* exceeds 1 (Hurdle rate), λ_j – fund vintage-year and industry fixed effects. *TTR* measures the fund gross return to date due to selling at market peaks and buying at troughs and is defined as $\frac{\sum_{t=0}^{T} D_t \cdot exp\{r_{1:T} \cdot (1-t/T)\}}{\sum_0^T C_t \cdot exp\{r_{1:T} \cdot (1-t/T)\}} / \frac{\sum_{t=0}^{T} D_t \cdot exp\{r_{t+1:T}\}}{\sum_0^T C_t \cdot exp\{r_{t+1:T}\}}$, where $t = 0$ is fund inception, $r_{t+1:T}$ is continuously compounded return on public benchmark between date t and the fund's resolution, while $D_t[C_t]$ is the fund's distribution [capital call] at end of period t, ant D_T equals the last most reported NAV corresponding to *SubResTime*. *SubResTime* is the first fund-quarter with non-zero cash-flows when fund NAV drops below 15% of the fund total distributions up to that quarter. The sample is comprised of 349 (592) U.S.-focused buyout (venture) funds and for the purpose of this analysis is restricted to funds with *SubResTime* of at least 7 years since inception. The industry and market returns are proxied by, respectively, S&P500 subindex corresponding to the GICS Industry sector of the fund specialty and CRSP valued-weighed index. Standard errors in parentheses are clustered by fund vintage year, */**/*** denote significance at 10/5/1%.

	PME 0:T		PME 5y:T	
	industry	market	industry	market
	(1)	(2)	(3)	(4)
Rush effects:				
toDateTTR>1 × toDateIRR>Hurdle × Rush	0.068	0.034	0.415	0.362
	(0.602)	(0.624)	(0.568)	(0.536)
toDateTTR>1 × Rush	0.234	0.430	0.041	0.143
	(0.440)	(0.428)	(0.359)	(0.392)
toDateIRR>Hurdle × Rush	0.286	0.360	−0.058	0.053
	(0.399)	(0.354)	(0.398)	(0.358)
Rush	−0.514*	−0.567**	0.104	0.073
	(0.256)	(0.242)	(0.224)	(0.205)
Base effects:				
toDateTTR>1 × toDateIRR>Hurdle	0.150	0.087	−0.025	−0.066
	(0.153)	(0.159)	(0.175)	(0.160)
toDateTTR>1	−0.342***	−0.239**	−0.300***	−0.185**
	(0.099)	(0.092)	(0.086)	(0.089)
toDateIRR>Hurdle	0.659***	0.718***	0.361**	0.404***
	(0.120)	(0.112)	(0.146)	(0.132)
Vintage fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Sum(*Rush effects*)	0.074	0.257	0.502	0.631
p-value	0.757	0.422	0.000	0.001
Observations	796	796	796	796
R^2	0.383	0.433	0.271	0.279

TABLE IA-5
Risk shifting evidence

This table reports simulation-based estimates of abnormal volatility of *Industry returns*. *Industry returns* are of S&P500 subindex corresponding to the GICS Industry sector of the fund specialty. The estimation methodology is described in section IA-2 of this appendix. In short, I (1) estimate an *auxiliary model* model of fund fixed effects for *SubResTime* and *Rush*, (2) independently simulate 1,000 blocks of up to 100 random exits per fund under this model, and (3) pool *main model* estimates over these independent simulations. The *main model* is:

$$E[IndustryVolty_{ij,h}] = \beta \cdot Informed_{ij}Rush_{ij} + \gamma_1 Informed_{ij} + \gamma_2 Rush_{ij} + \lambda_j,$$

where $IndustryVolty_{ij,h}$ annualized standard deviation of monthly returns {-6 to -0} and {-12 to -8} quarters of fund i actual (i.e. $Informed_{ij} = 1$) or simulated *SubResTime*; $Rush_{ij}$ – actual or simulated fraction of distributions over the last 6 quarters in the funds' total-to-date, λ_j – "fund fixed effects" estimates from the *auxiliary model*. The estimation is over funds with actual stopping-time of at least 8 years that as of the 5th anniversary had (i) a POSITIVE track record of market timing as measured by $TTR > 1$ or (ii) where the firm faces high survival risk as measured by net-of-fees IRR in the bottom tercile among type×vintage peers (*Btm*) and/or no successor fund raised up until at least the 6th quarter before *SubResTime* (*NoNext*). *TTR* measures the fund gross return to date due to selling at market peaks and buying at troughs. Specifications (1) and (3) report results for the volatility over the {-6 to 0 quarters} window from the stopping-quarter which corresponds to *Rush* measurement period. Specifications (2) and (4) report results for the {-12 to -8 quarters} window which corresponds to at least the sixth year of the fund operations. Note that high values of *Rush* indicate that relatively few distributions to LPs have been made before *quarter-6* from the stopping. Besides the main terms of *Informed* constituents: (TTR>1), ($Btm|NoNext = 1$), ($Btm|YesNext = 1$), ($Top|NoNext = 1$) and their interaction, control variables include *Rush* and the projections of fund fixed effect (from the *auxiliary model*). In Specifications (3) and (4) control variables also include the levels of VIX index as the fund stopping-quarter and the {-12 to -8 quarters} or {-6 to 0 quarters} window respectively. Standard errors in parentheses are clustered at *SubResTime*, */**/*** denote significance at 10/5/1%.

	-6:0q (1)	-12:-8q (2)	-6:0q (3)	-12:-8q (4)
TTR>1 × Btm|NoNext × Rush	0.025	0.075**	0.007	0.064**
	(0.027)	(0.038)	(0.022)	(0.030)
TTR>1 × Top|NoNext × Rush	0.007	−0.010	0.012	−0.010
	(0.020)	(0.025)	(0.016)	(0.019)
TTR>1 × BtmYes|Next × Rush	0.006	−0.015	0.001	−0.007
	(0.012)	(0.017)	(0.009)	(0.015)
Btm|NoNext × Rush	−0.001	−0.009	0.006	−0.010
	(0.012)	(0.015)	(0.007)	(0.012)
Top|NoNext × Rush	−0.006	0.018	−0.006	0.007
	(0.011)	(0.019)	(0.007)	(0.016)
Btm|YesNext × Rush	0.006	0.016*	0.000	0.002
	(0.006)	(0.008)	(0.004)	(0.008)
TTR>1 × Rush	−0.006	−0.006	0.003	−0.003
	(0.007)	(0.008)	(0.005)	(0.007)
Rush, Informed fixed effects	Yes	Yes	Yes	Yes
Fund fixed effects	Yes	Yes	Yes	Yes
VIX levels	No	No	Yes	Yes
# of Actual funds	596	596	596	596
Pseudo funds per 1 Actual	94.6	94.6	94.5	94.1
# of independent simulations	1000	1000	1000	1000

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