Do private equity managers have superior information on public markets?☆

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Do Private Equity Managers Have Superior Information on Public Markets?

Abstract

This paper investigates whether private equity (PE) fund managers have private information about the valuations of public equity. Using cash flows from 941 buyout and venture funds, I show that PE distribution patterns predict returns in the industries of funds' specialization. Fund managers tend to sell at the industry peaks only when they have performance fees to harvest and foresee public firms' future earnings rather than discount rates. My tests distinguish timing skill from reactions to market conditions and spillover effects of PE activity on public firms. The results help better understand PE performance and have implications for manager selection.

Although private equity (PE) funds invest in private companies, their investment outcomes depend crucially on the interface with public capital markets. Whether or not the fund's exit (or entry) involves a public transaction, comparable public market valuations affect the price. Prior research shows that PE managers are causing changes in policies of the investee companies as well as the industries in which they operate, while being highly responsive to conditions in capital markets (e.g. see Bernstein, Lerner, Sørensen, and Strömberg (2016) for spillover effects and Axelson, Jenkinson, Strömberg, and Weisbach (2010) for market conditions). Yet, there is little evidence of how informed PE managers are about the valuations of public equities. Need they engender changes in their portfolio companies to justify their costly intermediation to investors or better knowledge of when to trade might be enough? In this paper, I examine whether PE managers can indeed buy low and sell high. I rely on the unique to PE contractual features to identify the private information-based market timing ability from the alternative explanations.

Participation in a PE fund requires the investors (the limited partners, or LPs) to provide a pre-specified amount of cash over a multi-year period on short notice in exchange for a stream of payouts from the fund over a finite period. The schedule of fund outlays and inflows (henceforth, fund cash flow) is *ex-ante* unknown and determined by the managers of the funds (the general partners, or GPs). In addition to fixed fees, GPs receive performance fees (carried-interest), a fraction of the fund lifetime profits, and decide when to return the capital to LPs. Such a near-absence of control over the timing of investments and divestments by investors distinguishes the PE funds from other forms of delegated asset management. The ceding of fund cash flow timing to GPs is commonly viewed as necessary given that PE funds hold non-traded assets but also as a source of liquidity risk for LPs. Recent studies have shown that GPs are extracting agency benefits from these control rights over the fund cash flow schedule (e.g. see Robinson and Sensoy, 2013).

Less understood is the potential benefit to LPs of ceding the fund cash flow timing rights. GPs oversee operations of dozens of companies as active board members (thus, may know as much as the companies' management), specialize in certain types of businesses, and at the same time, have a first-hand read on the portfolio demands of financial and corporate investors. Consequently, in this analysis I empirically focus on two closely related issues. First, I examine if GPs have an informational advantage relative to public market prices. I show that GPs do appear to learn valuable private information about the valuation of certain public equities, and that the potential gains to LPs from delegating fund cash flow timing to GPs can be 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. 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.

Second, I examine the effects of the agency relationship between LPs and GPs. I show that unless GPs have "skin-in-the-game" via positive performance fees to harvest, they appear not to be using their private information to exit the fund investments near the market peaks, but deliver inferior holding period abnormal returns nonetheless.[1] I also show that GPs with a good market timing track record, but nonetheless facing a particularly high survival risk (beyond the current fund term), are more likely to delay distributions to LPs when industry return volatility is about to rise. In these situations, GPs may want to decrease distributions because they own out-of-the-money options on the current and future funds' assets, and increasing industry volatility makes these options more valuable. These results contribute to the growing literature on PE governance, and more broadly, on optimal contracting.[2]

I conduct my analysis using a sample of 941 U.S.-focused buyout and venture funds incepted between 1979 and 2006. The data is obtained from the Burgiss database of PE funds that previous studies have found to be representative of the universe that has been available for institutional investors (e.g. Harris, Jenkinson, and Kaplan, 2014). Besides the precise amounts and dates of capital calls and distributions for each fund, I observe the quarterly net asset values as well as various characteristics including GP-affiliation and the industry of specialization. My empirical tests examine public market return (mean and variance) predictability as a function of the relative size and timing of PE fund distributions, while accounting for the time-varying supply of funds.

Taking advantage of PE contractual design, I attempt to disentangle the market timing skills (or superior information) of GPs from alternative explanations such as time-varying exit conditions or causal effects of PE activity on public companies. My identifying assumption is that, unlike the revelation of private

[1] Normally, performance fees in PE are subject to a claw-back if the fund's remaining assets' value decreases. Meanwhile, early exits may reduce the amount of asset management and monitoring fees that GPs collect from the fund, and additionally forgo a chance to improve the performance rank among peer-funds.

[2] For example, Barrot (2012) finds that the remaining fund life determines the type of venture fund investments that can run counter to LPs' objectives. Degeorge, Martin, and Phalippou (2016) find evidence consistent with some GPs "going-for-broke" with secondary buyout investments. On the other hand, the results in Fang, Ivashina, and Lerner (2015) suggest that GPs' intermediation might not be as costly. The authors find essentially no outperformance of private investments implemented by top LPs directly.

signals, these alternative explanations do not relate to how much of the personal wealth exposure to the industry valuations GPs remove over a short interval. I scrutinize this assumption via a series of placebo tests and event studies. Furthermore, I find that the predictability of public equity returns by PE fund cash flows vanishes outside the industries in which GPs specialize and relates to the earnings news across those industries.

I develop a new metric of a GP's *Timing Track Record* that conveys valuable information about a fund's future propensity to exit close to industry highs. Consistent with the skill hypothesis, these market timing track records are as important predictors of future returns as the financial incentives to GPs. To examine the robustness of these results and remove potentially confounding effects in my primary tests, I conduct simulations that allow for a better control for variation in exit conditions (e.g., time-varying expected returns by industry). My inference is robust to spatial dependence in errors over calendar-time, as well as to exclusions of particularly dramatic market episodes and certain fund groups.

There exists anecdotal and indirect evidence consistent with market timing ability of PE managers (or, at least, efforts thereof).[3] Recently, prominent PE firms have launched actively managed mutual funds citing their private investing expertise as an informational advantage.[4] Yet, to-date there is no direct support for the PE superior information-based market timing hypothesis, clear of the alternative explanations that are important for economic implications of the results. While Ball, Chiu, and Smith (2011) conclude that VCs simply react to market conditions, Lerner (1994), Kaplan and Strömberg (2008), and Guo, Hotchkiss, and Song (2011) do not disentangle private information-based market timing from reacting to the exit condition variation, time-varying expected returns, and causal effects of PE activities on public company valuations. Similarly, in the deal-level return attribution by Acharya, Gottschalg, Hahn, and Kehoe (2013) the timing of deals' onset and unwinding is explicitly discarded as a source of abnormal performance (i.e., returns are "corrected" for the industry multiple expansion and leverage).

My findings suggest that LPs' choice of a PE fund should incorporate GPs' market timing track record since the expected gains persist across funds by the same GP and correspond to 2-5% of abnormal returns

[3] Anecdotal evidence of positive informational spillovers resulting 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, among many others.

[4] For example, see "Following KKR, Blackstone Chases Retail with Mutual Fund" Forbes, July 16, 2013.

per annum. However, to the extent a given GP is at risk of not raising a next fund (e.g., due to a lack of a long and successful overall track record), the expected gains from the timing skill decrease and may turn negative as the probability of the "asset-hoarding" increases. Provided that some GPs' market timing skill would therefore require lower (or higher) premium for the funds they manage, my analysis contributes to the discussion of a few important questions in the investments literature: (i) why investors choose to allocate to PE, (ii) how they select managers, and (iii) what contract they chose with a particular manager.

As per Harris, et al. (2014), the data show that in large samples, both buyout and venture funds on average outperform public markets (on the holding period basis). My findings suggest that LPs' portfolio abnormal performance attributable to PE is likely underestimated. Even without active management by an LP, PE fund distributions near the respective industry peaks induce fluctuations in portfolio weights that result in higher Sharpe-ratios for the LP. Meanwhile, the LP may also optimize allocations in her overall portfolio based on the signals from the PE part. I deploy the PE portfolio choice framework of Bollen and Sensoy (2016) for this analysis. Thus, my results reconcile the high attention that LPs continue to pay to absolute (rather than just the holding period abnormal) returns of PE funds as documented in the survey by DaRin and Phalippou (2016).

The question of market timing connects this paper with many other studies. On the one hand, the private information channel relates to a large body of literature on initial public offering (IPO), and mergers and acquisition (M&A) waves in the context of either adverse selection (signaling) problems or some form of investor irrationality.[5] On the other hand, there is an active field that studies market timing efforts by professional investors in liquid markets such as mutual funds and hedge funds. While Griffin and Xu (2009) find that hedge funds exhibit no ability to time sectors or pick better stocks styles Agarwal, Jiang, Tang, and Yang (2013) find evidence supporting successful informed trading by institutional investors. Also, Venkatesan (2014) finds that average mutual fund manager can predict stocks' earning news and fund flows increase in that skill.

The results in this paper also suggest possibly broader roles for PE in modern capital markets. In settings such as Grossman and Stiglitz (1980), GPs' learning through private investing constitutes a "costly

[5] Ritter (1991); and Loughran and Ritter (1995) find that the new issues in the low IPO-volume periods perform better than those in the high-volume periods do. Baker and Wurgler (2000) document evidence consistent with opportunistic market timing by firms. More recently, Dittmar and Field (2015) find that firms earn positive abnormal returns in stock repurchases.

arbitrage" that improves the informational efficiency of public markets. For example, the tech-bubble of the late 1990s might have become greater if not for the deluge of PE exits trying to preempt (the GPs' carried interest being hit by) the bust. The data show that venture funds incepted between 1995 and 1998 have divested considerably more than invested during the later stage of the NASDAQ boom. Even for the funds with not fully drawn capital commitments as of the beginning of 1999, the ratio of total distributions to capital calls during the following 12 months was 7-to-1. This fact contradicts the popular wisdom that venture capitalists' (VCs') activity amplifies the valuation cycle.[6]

The paper proceeds as follows. Section 1 describes the data. Section 2 provides preliminary evidence of the market-timing skill presence among GPs, and motivates the hypotheses development and methods choice in section 3 which also reviews the closely related literature. Sections 4 and 5 report the main tests. Section 6 concludes. Additional details, robustness, and placebo tests are in the Appendix.

1. Data

PE data for this study was obtained from Burgiss, a leading provider of portfolio management software, services, and analytics to private capital investors. The dataset is sourced exclusively from about 300 investors in private capital funds (LPs) that collectively have made over 20,000 commitments to private capital funds, and includes their complete cash flow and valuation history. The underlying LP universe comprises approximately 60% pension funds (a mix of public and private), 20% endowments, and 20% other investors (such as sovereign wealth funds and funds-of funds). 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.

I limit the sample to U.S.-focused buyout and venture funds with more than 25 and 10 million in capital commitments, respectively, incepted between 1979 and 2006. In total, the sample includes 349 (592) buyout (venture) funds, of which 126 (169) continue operations as of March 2013. For each fund, I observe: (1) the primary industry sector according to the Global Industry Classification Standard (henceforth *industry*); (2) amount of capital committed; (3) strategy description; (4) dated amounts of cash inflows and outflows

[6] For example, see "Venture capital funding soars to levels last seen in dot-com bubble" by Chris O'Brien, Los Angeles Times, April 18, 2014.

as well as Net Asset Values (NAVs) reported quarterly.[7] Figure A.1 demonstrates the high variation in fund cash-flow schedules for both buyout and venture funds.

Panel A of Table 1 reports the basic summary statistics for buyout and venture subsamples. The results suggest high within-type variation in fund life duration, size, and returns. 85% of the funds are affiliated with a PE firm (GPs) with multiple funds. For each of these funds, I observe 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.

[Insert Table 1 here]

I utilize the CRSP value-weighted index as a proxy for public market equity returns. For industry returns, I use S&P500 industry sectors because these map directly to the classification in the Burgiss data and represent the widely followed benchmarks by practitioners. Results are similar if I use industry subindices of the S&P600 (small capitalization stocks). The list of industries and summary statistics for monthly total returns, price-earnings, and book-to-market ratios from January 1989 through September 2014 are reported in Panel B of Table 1. Panel A of Table 1 also reports the Public Market Equivalent (PME) measure of market-adjusted fund performance as described by Kaplan and Schoar (2005), as well as a similar indicator calculated against the industry benchmark, *PME vs. Industry*. Summary statistics for other variables of interest are reported in Table 1 Panel C. *CAY Ratio* is the cointegrated consumption-wealth ratio from Lettau and Ludvigson (2001). *VIX* is the CBOE volatility index for the S&P500. *BBB-AAA spread* and *AAA-UST spread* are, respectively, the difference between Moody's Baa and Aaa yields, and Aaa yield and 10-year constant maturity U.S. Treasury yield, *10-year yield*. The *3-month yield* is the U.S. Treasury bill rate.

2. Motivation and preliminary evidence

The information that a GP obtains through the investment cycle and public markets valuations are closely related.[8] Public markets prices reflect cash flow expectations and investor preferences, while also affecting

[7] The cash-flow information is the net of all fees allowing for accurate computation of returns to LPs. I do not know the gross-of-fees performance of investments, nor the fee terms. Fortunately, the only contractual term essential for my tests, the minimum rate of return to LPs beyond which GPs start to earn carry, has almost no variation within fund type according to other studies. For example, see Metrick and Yasuda (2010); and Robinson and Sensoy (2013). For buyouts (venture) funds this "hurdle rate" is almost always 8 (0)%.

[8] A detailed discussion of the institutional details supporting this statement is provided in Appendix A.1.

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. Bargaining over price would normally revolve around an assortment of valuation ratios of comparable publicly traded firms as indications of a fair price, even though the business characteristics might not exactly match those of the target company. Thus, GPs may be able to take advantage of superior knowledge of industry trends even when the fund portfolio companies have, in fact, relatively small exposures to these trends.

The ability of GPs to act on company-specific information is likely limited by adverse-selection concerns of prospective buyers. In fact, a need to make concessions regarding idiosyncratic returns is consistent with buyout- and venture-backed initial IPO outperformance, particularly against characteristics-matched portfolios, as documented in Brav and Gompers (1997); Cao and Lerner (2006); and Harford and Kolasinski (2013). However, this adverse selection is much less relevant with respect to the firm's industry-wide risk since those who typically buy from (sell to) PE funds are more concerned about the relative performance of the asset and not the absolute performance as do GPs.[9]

Given these institutional settings, there are several ways to think about scope for market timing on behalf of GPs. In this paper, (primarily on the identification grounds to be discussed later) I will abstract away from the analysis of the timing of decisions concerning when to launch a fund as well as what industry and strategy to adopt as its mandate. Instead, I will focus on GPs' far more discretionary decisions, namely, when to deploy and release the committed capital over the contractual life of a particular fund.

Specifically, I *define (the effects of) GPs' market timing* the excess return that a *passive 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 the *identical company* that my data allow is the return on the portfolio of public firms from the same industry as the fund specialty (henceforth, the *market*). To the extent GPs' informational advantage should dissipate beyond the area of fund specialty, poor match of the industry (as the hypothetically *identical company*) will act against me finding robust results. Conversely, finding results being stronger with benchmarks less related to fund specialization shall point on explanations other than the above-discussed private information flow in PE.

[9] GPs typically receive a fixed fee of 2% of fund size over the course of their contractual life, and 20% of the fund's *absolute profits* if they exceed a predetermined threshold. See Metrick and Yasuda (2010); and Robinson and Sensoy (2013) for details.

2.1. A simple measure of GPs' market-timing

To analyze the aforementioned market timing effects, I propose a measure of a gross return over a fund's lifetime due to selling at market highs and buying at lows. Computationally, it is very similar to the *PME* of Kaplan and Schoar (2005). However, the *Timing Track Record* (henceforth *TTR*) measures the timing component of a fund's total returns that *PME* explicitly disregards. Specifically, I define,

$$TTR = \frac{\overline{PME}}{PME}$$
$$= \frac{\sum_{t=0}^{T} D_t \cdot exp\{r_{1,T} \cdot (1-t/T)\} \big/ \sum_0^T C_t \cdot exp\{r_{1,T} \cdot (1-t/T)\}}{\sum_{t=0}^{T} D_t \cdot exp\{r_{t+1,T}\} \big/ \sum_0^T C_t \cdot exp\{r_{t+1,T}\}} \tag{1}$$

where $r_{t+1,T}$ is the market return from the cash flow date, t, until the fund's resolution (with $r_{T+1,T} := 0$), while $D_t(C_t)$ denotes the fund's distributions (capital calls). In essence, *TTR* is a ratio of two profitability indices with different discount rates. The discount rates in the denominator reflect the *investment period's* opportunity costs while those in the numerator reflect the *commitment period's* opportunity costs. Thus, a *TTR* value above one indicates that the NPV is greater if measured against the fund commitment period's opportunity cost. In other words, a TTR greater than one is consistent with value added from the market timing by GP.

To better see the intuition behind *TTR*, consider the following stylized example. Two funds, A and B, 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. For simplicity, we assume that neither fund has a portfolio company selection skill, and hence earns the market rate of return on investments, thus PME=1.0 for both funds by definition. However, fund A chooses to draw capital in equal installments over three years whereas fund B, correctly anticipating a market downturn, draws less capital initially.

Entry Timing Example

Year	r_{mkt}	**Fund A** Cash Flow	**Fund B** Cash Flow	**Fund A** NAVs
0	-	-10	-5	10
1	5.0%	-10	-5	20.50 $=10 \cdot 1.05+10$
2	-13.6%	-10	-20	27.71
3	5.0%	0	0	29.09
4	5.0%	**30.55**	**31.81**	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* equal to one, fund B creates more value for its LPs than fund A: 1.81

versus 0.55. This is reflected in a higher $\overline{PME}$ for fund B, and thus a higher *TTR* for fund B. In this way, *TTR* measures the market timing ability of the managers of fund B. Appendix A.2 provides examples with more realistic cash flows and market returns that show how *TTR* captures the timing of exits as well.

The money-multiple (i.e., ratio of nominal distributions to contributions) is an absolute performance measure widely utilized by practitioners and would reflect the difference in returns to LPs from funds A and B. In fact, the money-multiples of A and B are 1.02 and 1.06, respectively. In this specific case, they are the same as *TTRs* because the cumulative market return is zero and the *PME* of each fund is 1.0. However, in practice, money-multiples also reflect differences in market returns over fund lives, as well as differences in the fund-holding period's abnormal returns. Thus, equation (1) essentially strips-out the prevailing market trend from the money-multiple, and deflates it by the gross lifetime return due to portfolio companies' selection (and nurturing) effects. In addition to its simplicity, *TTR* also benefits from a robustness to risk misspecification by virtue of its relation to *PME*.[10]

More formally, consider the following decomposition of the fund money-multiple from the *Entry Timing Example* above. For brevity, denote the life-time return on the market with r (equal to 0 in our example):

$$\begin{aligned} ln(MM) &= ln(\sum_D) - ln(\sum_C) && (2)\\ &= ln(\overline{PME}) + A\bar{r} && (3)\\ &= ln(D_4 \cdot e^{r(1-\frac{4}{4})}) + ln(C_0 \cdot e^{r(1-\frac{0}{4})} + C_0 \cdot e^{r(1-\frac{1}{4})} + C_0 \cdot e^{r(1-\frac{2}{4})}) + A\bar{r} \\ &= ln(D_4 \cdot 1) + ln(e^r C_0 \cdot e^{\frac{0}{4}r} + C_0 \cdot e^{-\frac{1}{4}r} + C_0 \cdot e^{-\frac{2}{4}r}) + A\bar{r} \\ &= ln(D_4 \cdot 1) + r + ln(C_0 + C_0 \cdot e^{-\frac{1}{4}r} + C_0 \cdot e^{-\frac{1}{2}r}) + A\bar{r}[-0.25em] \end{aligned}$$

Hence, we can express $A\bar{r}$ from 2 and as:

$$\begin{aligned} A\bar{r} &= r - ln(C_0 + C_1 + C_2) + ln(C_0 + C_1 e^{-\frac{1}{4}r} + C_2 e^{-\frac{1}{2}r}) \\ &= r - ln(\frac{C_0 + C_1 + C_2}{C_0 + C_1 e^{-\frac{1}{4}r} + C_2 e^{-\frac{1}{2}r}}) \\ &= 0 - ln(\frac{10 + 10 + 10}{10 + 10e^{-\frac{1}{4}0} + 10e^{-\frac{1}{2}0}}) = 0 \end{aligned}$$

With positive (negative) r, $A\bar{r} < (>) r$, and the magnitude in the difference is proportional to the weight

[10] See Korteweg and Nagel (2016); and Sørensen and Jagannathan (2015) for details. Robinson and Sensoy (2016) provide empirical assessment of the question by examining sensitivity of cross-sectional mean *PME* to different beta/benchmark assumption. Moreover, risk-related measurement errors will tend to cancel out in *TTR* because $\overline{PME}$ will have estimation errors positively correlated with those in *PME*.

of cash flows occurring later in the fund's life (i.e. $C_2, C_1 \gg C_0$). Thus, $A\bar{r}$ can be thought of as the average market return over the fund's life multiplied by the fund's duration. In general, we can write it as:

$$A\bar{r} = \big(ln(\mathcal{D}^{-r}) - ln(\mathcal{C}^{-r})\big)r, \tag{4}$$
$$\text{where } \mathcal{C} = \frac{\sum_0^T C_t}{\sum_0^T C_t e^{-\frac{t}{T}r}},$$
$$\text{and } \mathcal{D} = \frac{\sum_0^T D_t}{\sum_0^T D_t e^{-\frac{t}{T}r}}$$

Substituting expression (1) in (3), we can obtain an alternative formulation for *TTR* as the residual from money-multiple, PME, and the fund's duration-adjusted trend in the public benchmark:

$$ln(TTR) = ln(MM) - ln(PME) - A\bar{r} \tag{5}$$

Division of equation (5) through by fund's cash flow duration, A (or some proxy thereof), obtains the annualized measures of respective component of the fund's total return. Note however that, unlike the equation (1), the approach through equation (4) to recover $A\bar{r}$ may provide misleading results when $\mathcal{C} = \mathcal{D} = 1$. This occurs when fund cash flows comprise of just one inflow (in year 0) and one outflow (e.g. in year 5). In this case, equation (4) yields 0 with any r and the difference between the money-multiple and PME will be attributed to GPs' timing of the fund cash flows *during* the fund's contractual life (albeit there were no any interim cash flows).

2.2. *Should LPs care about TTR?*

Before examining empirical evidence concerning PE fund *TTR*s, it is important to understand whether LPs should see any difference between funds A and B in our example (or perceive both funds equally as zero-NPV projects instead). Put differently, given that LPs can "undo" the fund's *TTR* against any investable benchmark, should they appreciate the *option to not undo*?[11]

In a recent study, Bollen and Sensoy (2016) analyze portfolio choice between private and public assets while taking into account the salient features of PE fund investing. Namely, their framework explicitly models the uncertainty about the timing of fund cash flows, and random liquidity shocks that LPs face. These liquidity shocks force LPs to sell their stakes in PE funds at a haircut to fair values. The authors then

[11] *Undoing TTR* requires financing of the fund calls with short-sales of the benchmark and investing the distributions from the fund in the benchmark.

solve for expected returns that PE funds need to attain for LPs to be willing to allocate capital to them, given a range of assumptions calibrated to data.

One of the key insights from Bollen and Sensoy (2016) is that returns that LPs should expect to attain are lower than the expected net-of-fees "reported" (i.e. holding period) return of PE funds. The difference amounts to 1-2.5% per annum (depending on risk-aversion, allocation to PE, etc) and reflects the expected fire-sales of PE fund stakes by LPs due to these liquidity shocks which positively correlate with the market returns. Hence, it can be viewed as PE illiquidity cost. It is important to note that the calibration of the model effectively imposes *TTR=1* since the GPs' distribution rule does not foresee market downturns and, hence, is uncorrelated with the arrival of liquidity shocks.

A positive correlation of the GPs distribution rule with these shocks would significantly diminish this *PE illiquidity cost* per Bollen and Sensoy (2016) framework. This cost may even turn negative if instead of having static weights within the public portfolio the LPs could have those weights *dynamically rebalanced* conditional on a signal contained in the recent distributions from PE funds. Not only could LPs respond to such a signal by increasing the weight of a risk-free asset ahead of market downturns but also by changing the industry exposure within the public equity portfolio accordingly. To illustrate the latter point, consider Figure 4 which analyzes the abnormal return of a public equity portfolios built off S&P500 GICS sector indicies based on the signal from PE distributions. A public equity portfolio that is net-short the GICS sectors, in which a specific PE distributions pattern (to be discussed in detail later) has been observed before the next quarter rebalancing, delivers 80 basis points per quarter in Fama-French three-factor alpha and enjoys about 0.3 higher Sharpe-ratio than an equally-weighted GICS sectors portfolio.

Thus, I conclude that the *option to not undo TRR* should be perceived as valuable by many LPs based on fully rational grounds. In practice, a preference for market timing by GPs is consistent with LPs' continued attention to money-multiples (i.e. see 2016 survey by DaRin and Phalippou) as a measure of fund performance despite the generally high awareness of PME-like performance metrics.

2.3. Empirical analysis of TTR

I begin with a univariate analysis of fund TTRs. Panels A and B of Figure 1 plot frequency distributions of *TTRs* for the sample funds against the broad market and the respective fund industry, separately for buyout and venture subsamples. First, there is clearly a significant variation across funds, suggesting that

TTR is indeed a potentially important dimension of performance. Some 10% of funds managed to lose in excess of 20% of total return due to the timing of the interim cash flows over their lives. Whereas the 90^{th}-percentile fund (venture and buyout samples combined) has gained over 50% by timing the within fund-life industry valuation cycles. Second, the means are statistically greater than one, and are larger against the industry benchmark albeit remain economically small, corresponding to an average alpha of about 1% per year (versus 2-4% per year based on *PME*).

[Insert Figure 1 here]

Panel C of Figure 1 allows to better understand the importance of *TTR* in the cross section of fund returns by reporting the variance decomposition of money multiple (following 5) by PME-quartiles. It shows that the domination by *PME*, i.e. the holding period abnormal return, is limited to the top- and bottom-quartile funds. Whereas, for the typical fund (i.e. in the middle two quartiles) the contribution from timing is as big as from holding and the two are virtually uncorrelated (so that they are quite likely to offset each other). For 44% of funds in my sample *TTR* exceeds *PME*.

Note that *TTR* equals 1 for any cash flow schedule whenever benchmark return is constant. Thus, unlike the log-*PME*, log-*TTRs* is bounded by the benchmark's variance over the fund's life. It is therefore unsurprising to see much more extreme values for *PME* in either tail of the distribution. This is what also (at least partially) explains the notably lower dispersion of values in Panel B in comparison with Panel A (since the industry portfolio volatility is lower than the industry average), and in the venture subsample versus buyouts. What is more surprising is the non-zero and opposite-sign covariance between *TTR* and *PME* in the extreme quartiles as Figure 1C shows. It follows that for the best (worst) performing funds, both timing- and holding abnormal returns tend to be good (bad).

Proceeding with the multivariate analysis, Panel A of Table 2 reports associations of industry *TTRs* with GP characteristics that proxy for institutional quality (e.g. see Kaplan and Schoar, 2005; Robinson and Sensoy, 2016). Fund size (size-squared) is positively (negatively) related to end-of-life *TTR*. However, the size effect is insignificant when temporal variation is controlled for via vintage-year fixed effects, as per specification (2). Meanwhile, according to specifications (1)-(3) and (5), fund sequence is positively related to *TTR* when measured against the industry returns. This indicates that funds raised by GPs with more experience in a given industry are likely to better navigate industry peaks and troughs. These results attenuate significantly with *TTR*s and sequence measured against the broad market as reported in Panel B.

[Insert Table 2 here]

The positive coefficients for *PME* in specifications (3), (5), and (6) confirm the evidence from the variance decomposition analysis discussed just above. Driven by the top and bottom performance quartiles, funds with higher *PME* tend to also be better at timing the industry valuation cycles, regardless of the inception year and other covariates. This could be happening for a number of mutually non-exclusive reasons. First, very few bottom-quartile funds attain high enough absolute return for GPs to receive carried interest. Consequently, those GPs face little incentives to avoid a reduction in the funds' asset values (but would rather keep the "invested capital" base high). Second, the "selection and nurturing" skill that *PME* encompasses might be genuinely related to GPs' knowledge of the industry that also enables successful timing. It is also possible that *PME*s pick-up the effects of inherently market timing decisions that do not trigger fund-level cash flows (e.g., corporate acquisitions by the fund's portfolio company that do not require new equity injections by the fund).

Specifications (4) through (6) in Table 2 show a positive relation between a GP's previous and current funds' *TTR*. This indicates that timing ability is persistent at the GP level. The fact that all these relations are uniformly weaker when timing is measured against the broad market benchmark (Panel B of Table 2) is consistent with GPs being better informed at the industry level. In Appendix, I report extensive robustness and falsification tests for these results.[12]

2.4. To-date-TTRs

Like *PME*, *TTR* can be computed on a to-date basis by assuming the respective period to be the last, and the NAV at that date to be a liquidating distribution (see Brown, Gredil, and Kaplan (2016) for *to-date-PME*). Importantly, the mean market return for $\overline{PME}$ computation will also be date specific (so that no information beyond this date is utilized).

[12] Panel A of Table A.1 reports similar regressions but with additional control variables that proxy for possible measurement errors in *TTRs* driven by systematic risk's misspecification: industry return over the fund lifetime and its interactions with the respective variable(s) of interest. The results appear largely unchanged from those in Panel A of Table 2. The only meaningfully different coefficient is that of *PME* suggesting that the correlations between *TTR* and *PME* may indeed arise spuriously (yet unlikely to be as large). The same conclusion follows from Panel B of Table A.1 where I simulate random exits for actual fund operation dates and industry return paths across different fund risk assumptions. The tests of conditional correlations between past *TTRs* and future *PMEs*, as described in section 5.1, shall be free of this concern.

Panel A of Figure 2 compares such interim *TTR*s (measured at the fifth anniversary) with the final ones for the funds that operated for at least 9 years. By the fifth year, *TTR* would tend to reflect mostly the entry timing. Examples in Figure A.2 show that bad exit timing can offset the effect of the entry and vice versa. Nonetheless, from Panel B it appears that funds with a good timing track record as of mid-life normally further improve *TTR* in the remainder of their lives (as evident by the exponential form of the relation), and thus, tend to exhibit good exit timing.

To preclude any "mechanical" correlation between the interim and subsequent metric of timing, panels B and C of Figure 2 plot the growth in *TTR* after the fifth year on the y-axis. Besides, 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. This reveals a positive relation between the interim and subsequent *TTR* when GPs' option to receive the fraction of fund assets is in-the-money; and generally a negative relation when incentives with LPs are less well aligned. Note that the relationship is largely flat within the group of funds with *TTR* above one.

In summary, this section has developed a simple measure of GP market timing ability that can be computed at different points of a fund's life. Based on this measure, timing ability may have a significant positive value to LPs, appears more pronounced with respect to the fund industry returns than to the broad market trends, and persists over the sequence of funds run by the same GP$\times$strategy. Furthermore, the analysis in this section suggests that the contractual incentives may affect GPs' decisions to time the market. These incentives evolve dynamically (as fund asset values change) and may be very different across GPs at later stages of fund lives. I now turn to a more detailed discussion of hypotheses and the development of empirical tests that distinguish amongst alternative explanations.

3. Hypotheses and methods

3.1. Related literature

There are relatively few studies of market timing track records of institutional money managers that specialize in investing in private companies with an objective to improve the investees' value and with an explicit horizon for exit. Lerner (1994) examines the choices of venture-backed biotech firms to raise capital by IPO or through private financing during 1978-1992. He concludes that VCs can time the market by issuing before the sector declines and that experienced VCs appear more skilled in this way. More recently, Ball, Chiu, and Smith (2011) argue that the biotech sample-period of Lerner (1994) was "anomalous". Using data on 3,477 IPOs and 4,486 acquisitions of venture-backed companies over 1978-2009, they find evidence consistent with firms reacting to favorable exit conditions ("pseudo-timing") rather than attempting to take advantage of investor over-optimism. This conclusion is based on the lack of evidence that IPOs precede negative market/sector return as well as IPO returns being statistically lower than those after exits through M&A.

Kaplan and Strömberg (2008) summarize empirical evidence consistent with buyout GPs taking advantage of market timing, including the relative (mis)pricing between debt and equity. Combining the results of Kaplan and Stein (1993); Axelson et al. (2010); and Guo et al. (2011), the authors report expansion of the industry capital-to-cash-flow ratios as an important driver of the mean absolute returns for the sample of buyout deals undertaken during 1980-2006. Kaplan and Strömberg (2008) also elaborate on the much higher responsiveness of buyout leverage to the credit market conditions as opposed to that of public corporations, which may point to GPs' ability to capitalize on apparent debt mispricing.

3.1.1. Pseudo-timing

There are two alternative explanations to the market-timing skill of GPs that are also consistent with PE funds' *TTR* exceeding one and persisting (as per section 2). First, GPs do not have any superior information, but their rush-to-exit reflects the variation in the broad market and industry condition for exits, consistent with rational (yet uninformed) behavior models of Schultz (2003); and Pastor and Veronesi (2005).[13] Following Ball et al. (2011), I refer to this alternative as *Pseudo-timing*. Simply put, a "sell after market's run-ups" trading rule can be implemented without the costly help of an agent.

In fact, such investment timing by GPs may even generate utility losses to LPs since asset valuations may reflect time-varying risk premia. To see this, consider an extension of the Merton (1971) portfolio choice framework that encompasses liquid and illiquid risky assets as per Ang, Papanikolaou, and Westerfield

[13] Schultz (2003) demonstrates that mean-reversion coupled with a decision rule of issuing after market's run-ups would be observationally similar to informed trading. Pastor and Veronesi (2005) develop a model of "rational IPO waves" where issuance volume varies endogenously as a function of market conditions without any overreactions by investors or differences in cash-flow signal precisions.

(2014). The authors model illiquidity as the stochastic arrival of trading opportunities so that immediate consumption can only be financed with liquid wealth (either risky or risk-free assets). The likelihood of a suboptimally high weight of the illiquid risky asset in states of high marginal utility of consumption causes lower target allocations to risky assets overall, and the illiquid one (i.e., the PE) specifically. Therefore, if PE weights were to increase in these high marginal utility states (i.e., as a result of *Pseudo-timing*), the equilibrium expected returns required to support a given target allocation to the illiquid asset would need to be higher (and similarly with distributions in the low marginal utility states). Hence, to assess the economic value added from market timing by GPs, it is necessary to separate any such gains from the *Pseudo-timing* alternative.

3.1.2. Footprints of PE activity

The second group of alternative explanations pertains to the causal effect of PE fund operations on the behavior of public firms and investors. Several recent studies document evidence consistent with the peer firms responding to governance threats and improvements by peers by changes in investing and operating policies.[14] For example, Aldatmaz and Brown (2015) find that PE investments cause financial and operating changes in publicly listed firms in the same country-industry. Harford, Stanfield and Zhang (2016) find that LBOs predict merger waves and an increase in valuations in the industry and that the overall evidence is most consistent with causation (rather than selection). Thus, it could be that the industry cash flow prospects change *because* PE funds alter their industry participation. I call this *Footprint-on-Firms*.

Both channels, market timing and *Footprint-on-Firms*, may give rise to observationally similar event-time patterns. It could also be a *Price Distortion*. That is, the market price may temporarily decrease to absorb the increased supply of certain types of assets coming from admittedly informed investors (i.e., private equity GPs), whereas the industry down-turn fails to materialize. Note that neither *Footprint-on-Firms* nor *Price Distortion* do imply economic gains to LPs.

[14] See Berstein, Lerner, Sørensen, and Strömberg (2016); and Aldatmaz and Brown (2015) in the context of PE participation; and Gantchev, Gredil, and Jotikasthira (2016) in the context of hedge fund activism.

3.2. Hypotheses

In light of the discussion above, it appears hardly possible to identify GPs' market timing skill (that would be value-relevant for LPs) from the alternative explanations with regards to all aspects of PE fund management (e.g., launching and investing). However, one could utilize the difference in the *propensity to deploy this skill* (or information) due to changes in the contractual incentives to GPs that are induced by their fund to-date performance (which reflects not just the skill but some luck as well). Such a difference arises with respect to distribution of fund capital following exits and can be conveyed via the following table which depicts a dilemma faced by GPs of a fund that has already deployed its capital:[15]

Do GPs Want to Rush Fund's Exits?

Market Forecast: / Fund return to-date:	Negative	Positive
Above Hurdle rate	**Yes**	Not as much
Below Hurdle rate	No as much	No as much

The columns denote GPs outlook (unobservable to LPs and the researchers) on the market prices for assets similar to the fund's holdings while the rows denote the fund's observable to-date performance. Fund's net IRR above hurdle rate implies that GPs would secure performance fees if the fund were resolved at current NAVs. Consequently, when the performance fee option is in-the-money, GPs are arguably more inclined to act based on their negative outlook and, in doing so, reveal their timing skill. Clearly, such outlook has to feature a long-lived market downturn since, once distributed to LPs, the fund's capital cannot be recalled.

In reality, the market outlook is certainly not the only consideration for GPs. Clustering of fund distributions can arise for many other reasons (observable or not) – appendix A.2 provides a discussion of most obvious trade-offs. But this duality of reasons to exit is exactly what enables the identification of GPs' timing skill since the financial market conditions (i.e. *Pseudo-timing*) and the potential of causal spillovers of PE activity (i.e. *Footprint-on-Firms*) pertain to all exits, not just driven by GPs' private signal. Meanwhile, Robinson and Sensoy (2013) provide direct evidence that "carry interest"-related incentives significantly affect the distribution pattern of PE funds.

[15] Note that such a "rift in incentives" is absent with respect to entry decisions / capital calls since all GPs want to maximize the total return in a new fund, whatever it takes.

Finally, to provide further support for market timing being a skill (that LPs can measure when making commitment to specific PE funds), I interact the aforementioned incentives channel with the ex-ante observable proxy of skill. I take advantage of the analysis in section 2 and utilize past *TTR* with respect to the fund's primary industry benchmark for that purpose. Introducing the predictable skill dimension also allows me to examine whether ceding the cash flow timing rights to skilled GPs increases the expected value to LPs *unconditionally*. Alternatively, it could be that skilled GPs might be better at extracting agency benefit from the fund cash flow control rights. One situation amendable to such agency cost extraction is when GPs struggle to survive through rising a next fund due to some bad decisions (or luck) hindering the current fund's overall performance.

These considerations yield the following testable hypotheses:

H1 High rates of fund distributions to LPs predicts *lower* market returns when the value of GP's carried interest has been just removed from "at risk" (in comparison to otherwise similar distributions).

If this hypothesis holds, LPs may expect the market timing by GPs to positively contribute to PE fund returns (to the extent that GPs are expected to earn positive Carry).

H2 Risk-shifting efforts by skilled GPs is more likely to have an adverse effect on LP portfolios as compared to risk-shifting efforts of less skilled GPs.

GPs may seek to retain fund assets ahead of elevated market volatility when their survival is jeopardized. As discussed above, GPs are option-holders that want the underlying asset volatility to increase. Provided that high volatility is typically associated with low returns, these actions (when successful) would tend to result in lower Sharpe-ratios for LPs. The question is (given similar incentives) whether skilled GPs are more successful in correctly predicting such turbulent times in the industry.

If *H2* holds while *H1* fails, PE funds in general should command higher risk premium than previously estimated (e.g., Franzoni et al., 2012; Sørensen et al., 2014; Bollen and Sensoy, 2016). If both *H1* and *H2* hold, GPs' private information represents a "double-edged sword" since GPs would return the capital before an industry downturn when the fund performance has been good but will retain it through a market downturn (associated with higher volatility) when their overall performance has been bad and survival jeopardized. Thus, LPs' choice of a PE manager should incorporate GPs' market timing track record *as well as* the likelihood of subsequent fundraising difficulties that may trigger the adverse incentives to risk-shift. Note that either *H1* or *H2* imply that PE managers have superior information about public equity valuations.

Going forward, I will not differentiate between types of PE funds since it seems plausible that same logic applies to both buyout and venture partnerships while section 2 suggests qualitatively similar results.

3.3. Statistical model

I conduct most tests by estimating versions of the following equation via OLS with β as the coefficient of main interest:

$$IndustryReturn_{ij,1:12} = \beta \cdot Informed_{ij}Rush_{ij} + \gamma_1 Informed_{ij} + \gamma_2 Rush_{ij} + a_j + c_i + \varepsilon_{ij}, \qquad (6)$$

where $IndustryReturn_{ij,1:12}$ is the mean monthly *Industry Return* over the 12 months following fund i *Stopping-time*: the quarter when the NAV of fund i drops below *X%* of the total distributions prior to that,

$Informed_{ij}$ is a binary variable that subsets the funds of interest,

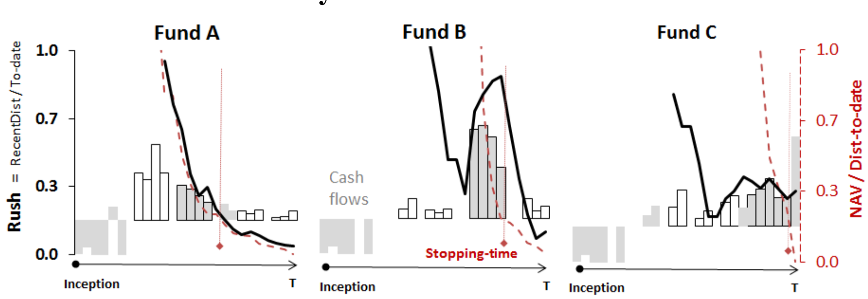
$Rush_{ij}$ - a ratio of the past few quarter distributions to the fund's total to-date,

$a_j + c_i$ - fund cohort fixed effects and *Stopping-time-i* controls, and

ε_{ij} - unobservable error term, spatially correlated across i and j.

Stopping-time and *Rush* summarize the cash flow pattern to implement the incentives-based identification scheme discussed above. Consider the *Example chart* below for intuition behind model (6) and its variables.

Key Variables' Intuition



The bars indicate cash flows for these three hypothetical funds, capital calls after inception followed by distribution (of proceeds upon the sales of fund assets) towards the end of contractual life (T). Note that if cumulative distributions exceed the cumulative capital calls by enough (based on Hurdle rate), GPs receive performance fees (i.e. "carry", usually 20% of the residual). However, until distributions are made, GPs' carry (if in-the-money) remains "at risk" as a fraction of the fund's asset value.

The dashed red lines denote 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 the values <1 are plotted), the remaining exposure to the market is large relatively to how much has been already "harvested". Hence, subsequent distributions reduce this exposure for the fund and, hence, for GPs' carry. The quarters in which these ratios cross *X%* (15% in this example) for the respective fund are denoted with vertical arrow-line and represent the *Stopping-times*, i.e. the times when remaining exposures become *relatively inconsequential* for the fund life-time results.[16]

β of model (6) amounts to a joint comparison of the public benchmark returns after *stopping-times* of the cash flow patterns like 'Fund B' having *in-the-money* carry with (i) otherwise similar patterns but *out-of-the-money* carry, and (ii) with the ones like 'Fund A' and *in-the-money* carry. *Rush* essentially summarizes the to-date distributions pattern into a single value between 0 and 1, so that 'Fund B'-like patterns are coded as more informative than 'Fund C' (where the contractual life constraint is more likely to confound timing signals).

The key *identifying assumption* is that distributions for funds A, B and C equally depend on market conditions and have the same spillover effects. The soundness of this assumption depends on the control funds (i.e. the *Rush*-amounts and *Stopping-times* where $Informed = 0$) and the control variables (measured as of *Stopping-time*). I follow Goyal and Welch (2008) to select risk-premia proxies, extending and redefining variables at the industry level where appropriate.[17] I use two control groups - "uninformed" and "random". The former comprises of actual funds incepted in the same vintage year as *Informed* but lacking either incentive or skill (as measured *before* the *Stopping-time*). To obtain the second group, I jointly model *Rush* and *Stopping-time* and simulate hypothetical exits for each *Informed* fund. This simulated control group allows tighter evidence against the *Pseudo-timing* hypothesis but cannot replace actual funds with respect to addressing the concerns about *Footprint-on-Firms*. Furthermore, I scrutinize this *identifying assumption* by examining the difference in industry returns before (and after) the *Stopping-time* (i.e. use the white bars from our *Example chart* to construct placebo *Rush*).

One convenience feature of model (6) is that point estimates and t-statistics on $(\beta, \gamma_1, \gamma_2)$ represent excess

[16] I examine a range between 5% and 25% and report tests with two: 15% and 20%. See appendix A.2 for a discussion.

[17] Industry's price-earning and book-to-market ratios, CAY ratio of Lettau and Ludvigson, VIX index, U.S. Treasury yields, corporate credit spreads, and the industry past excess return.

returns and Sharpe-ratios on a trading strategy implemented conditionally on the signal arrival (for many quarter-industries there could be none). To understand model (6) in a standard causal inference framework, one should swap *IndustryReturn* with *Rush* as the outcome variable:

$$E[Rush_{ij}] = a_j^R + c_i^R + \beta^R[Informed_{ij} IndustryReturn_{ij,1:12} \quad Informed_{ij} \quad IndustryReturn_{ij,1:12}] \qquad (7)$$

Thus, the assumption is that future *Industry returns cause Rush* which is also conditionally independent from the treatment assignment (the *Informed*-dummy). I will use this reverse-regression representation of model (6) to test for the effects of earning news and discount-rate innovations in section 5.2 via 2SLS.

4. Main results

4.1. Informed exits versus uninformed

I begin with a simple event study. Figure 3 reports the cumulative *Industry returns* from -8 to +10 quarters around the *stopping-quarter* as defined by a crossing of the 15% threshold of NAV/(total distributions to-date) for funds with high (above vintage year median) *Rush*. The solid line represents the mean of *Informed* exits, indicating where TTR-to-date>1 and IRR-to-date>Hurdle Rate. We can see that compared to all other funds with high *Rush* (the dashed line), the *Industry returns* are on average significantly lower following the *stopping-quarters* of *Informed*. Panel A reports the results for the entire sample period. Panel B shows that this clear difference remains even after excluding two years associated with particularly dramatic market declines (2001 and 2008). In addition, Panels A and B suggest that the results are unlikely to be driven by differences in the systematic risk, since the cumulative returns are similar from eight to three quarters before the stopping-time. In Figure 4, I provide additional evidence against a risk-based explanation. It follows that a quarterly rebalanced portfolio based on *Informed Rush* yields statistically significant 80 basis points per quarter over Fama-French three-factor model.

[Insert Figures 3 and 4 here]

According to Figure 3, the industry share price underperformance following *Informed Rush* fades after four to six quarters and does not revert over the 10-quarter horizon plotted. A reversion would be expected if the underperformance were driven by the *Price Distortion* alternative as the selling pressure subsided and the deterioration in the industry fundamentals failed to materialize.[18]

[18] The *Price Distortion* is also inconsistent with the pattern in Figure A.4B, which plots a similar event study as Figure 3A, but

By estimating Model (6) within the sample of actual funds, I nest the event studies of Figure 3 and A.4 in a multivariate setting. This allows for isolating the effect of GPs' timing skills from the mere responses to the variations in exit conditions over time and spillover effects (i.e., the *Pseudo-timing* and *Footprint-on-Firms* alternatives discussed in section 3). Table 3 reports these estimates. Columns (1) and (2) report the baseline specification (with controls comprising fund vintage-year fixed effects only) for the stopping-quarters corresponding to 15% and 20% NAV/(total distributions to-date) thresholds, respectively. Columns (3) and (4) expand the set of controls to include month- and industry-month covariates that previous literature considers informative about expected returns. Subsequently, I will refer to these interchangeably as *predictive covariates* or *Pseudo-timing* factors.

Panel A of Table 3 reports the results for the baseline definition of the informed group: funds with $TTR > 1$ and $IRR > Hurdle$ as of the respective stopping-time. For expositional clarity, I denote this dummy as a product of two dummies, *TTRg1*IRRgHR*. Recall that our main coefficient of interest is on its interaction with *Rush*, β. Regardless of the specification, it is significantly negative. Meanwhile, the coefficient of *Rush* itself is positive but statistically zero. Thus, the data are highly supportive of hypothesis *H1*: *Informed Rush* predicts lower *Industry returns* once the variation in exit conditions were accounted for.

[Insert Table 3 here]

The dependent variable is the subsequent 12-month average return of public firms in the primary industry of the fund. The magnitude of β tells us how much lower monthly returns would be as we increase the *Informed Rush*. The inter-quartile range for the *Rush* is approximately 0.3. This translates into 0.3% to 0.7% lower returns per month over the course of a year. Thus, the economic significance of the information in *Informed* is substantial. Ball et al. (2011) also question whether the post-exit returns are negative as possibly a stronger statement about the timing ability. Wald tests reject the null of $\beta + \gamma_1 + \gamma_2 = 0$ at 5% confidence level in all specifications but (4).

Interestingly, the magnitudes of the β estimates are 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

for the funds that did not "rush to exit" (*Rush*<vintage median). It appears that when *Informed* and incentivized GPs procrastinate with trimming remaining exposures (as manifested by low *Rush*-values), the industry share price performance tends to improve. However, the industry 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 stopping-quarter.

by the publicly observable signals about expected returns. This fact suggests that GPs tend to not return the capital when market observables point to relatively high risk-premia (consistent with results in Robinson and Sensoy, 2013). Nonetheless, it follows from specifications (3) and (4) that the exit decisions by skilled and incentivized GPs appear to contain a significant information component that appears missing in the public information set.

Next, Panel B of Table 3 breaks down the *Informed*-dummy definition into its constituents, $TTR > 1$ and $IRR > Hurdle$, and examines the effect of each interaction with Rush separately. In this case, *TTRg1*Rush* measures the predictive effect of *Rush* by funds that appear skilled but likely do not have as much "skin-in-the-game". For them, 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 *TTRg1*IRRgHR*Rush* (now truly a triple-interaction) appear even stronger than in Panel A, although the magnitudes are not formally comparable between the two panels. Besides providing further evidence on the significance of GP agency, this result suggests that *TTR-to-date* is indeed a good proxy of GPs' market timing skill since it *predicts* funds' propensity to sell at industry highs.

These results are robust to variable construction and the inference methods. Specifically, Panel A (B) of Table A.2 reports standard errors on β-estimates in Panel A (B) Table 3 but computed under a variety of assumptions about the error dependency in Model (6). I follow Conley (1999) to model the spatial correlation between the return intervals arising from the proximity of *Stopping-times*, I also consider clustering by vintage year (as in Kaplan and Schoar, 2005) as well as clustering in two dimensions simultaneously. As follows from Table A.2, the standard errors clustered by *stopping-time* tend to be largest (and, thus, reported in Table 3) while estimated βs remain significant at 5% confidence level with each of the 7 inference methods considered. In addition, to make sure that results are not driven by a non-representative group of funds, I replace *Rush* with a dummy variable that takes a value of one whenever *Rush* exceeds 0.2 (which also happens to be the sample median). This yields a total of 205 funds (i.e. just under the quarter of the sample) that satisfy all three conditions (*TTR-to-date*> 1, *IRR-to-date*>*Hurdle*, and *Rush>0.2*). Table A.3 reports the results which remain qualitatively similar and statistically significant despite neglecting most of the variation in *Rush*.[19] Next section provides additional evidence via simulations.

[19] As Figure B.1 demonstrates, the latter can be characterized as having a "well behaved" distribution, not driven by few outliers.

Finally, I scrutinize the assumption about the equality in the industry spillover effects across funds in relation to the *Footprint-on-Firms* alternative. For that, I examine whether *Informed Rush* outside the stopping-quarter periods is associated with future *Industry returns*. That is, when there is less difference in the GPs' market timing incentives between *Informed* and the control groups. Results of this placebo test are reported in Table A.4 and show no statistically or economically significant relation.

The evidence presented in this section strongly supports hypothesis *H1*. This suggests that GP industry timing skill is present and likely beneficial for LP portfolios and that delegating cash flow timing rights to GPs could be optimal for LPs. Overall, the results so far are hard to rationalize with *Footprint-on-Firms* effects being non-zero as far as PE exits are concerned.

4.2. Informed Rush *versus random*

There are several limitations to the control group constructed from actual funds. First, it would be interesting to further examine whether PE funds rushing to exit predict industry returns on average, unconditionally on GP skill and incentives. Second, the control group may be "contaminated" by funds whose GPs, in fact, do have timing skill and enough incentives. Finally, the funds in the control group might be inherently different across many important dimensions.

Accordingly, I also estimate Model (6) using random (hypothetical) stopping-times and *Rush* amounts in place of the control group exits.[20] I obtain these by simulating residuals from a simultaneous equations model (the *auxiliary model*) of ln(Stopping-time) and Φ^{-1}(Rush) for all funds in my sample as linear functions of Vintage×Industry fixed effects, fund size, PME-to-date, IRR-rank-to-date, follow-on fund start dates and investments activity.[21]

[20] Note that the dependent variable in Model (6) is essentially stock returns. These resemble a random walk-up to some variation in risk premia. Hence, once risk premia are controlled for and *Footprint* effects of PE exits are ruled out, there should be no difference under the null hypothesis of Model (6) between the sample *Rush/stopping-times* from their random combinations. In other words, neither actual nor simulated exits should explain the future stock returns (residual to the risk-premia) under the null hypothesis of Model (6). It is important to highlight that the economic question of interest makes these two estimators particularly good complements as they mitigate the vulnerability of assumptions that each one requires. That is, with a control group comprising hypothetical exits we need to assume-away *Footprint-on-Firms*, while with a control group comprising actual funds we need to assume-away their differences with respect to the exit-conditions/risk-premia variation.

[21] The procedure is asymptotically equivalent to the *Simulated Method of Moments*, accounts for uncertainty of the auxiliary model parameter estimates, and involves three steps: (i) estimating a model of "fund fixed effects" for stopping-time and *Rush*, (ii) independently simulating 1,000 blocks of up to 100 random exits per fund under this model (the random draws are made with respect to stopping-time and rush innovations [from bivariate Normal] and the covariance matrix thereof [from Wishart]), and (iii) pool Model (6) (*main model*) estimates over these *independent simulations*. See Appendix B.1-B.2 for discussion and details.

4.2.1. Refining the baseline estimates

Table 4 reports the simulation-based estimates of *Industry returns* predictive regressions reported in the previous section. As in Table 3, specifications (1) and (2) correspond to the stopping times under 15% and 20% thresholds for the baseline model, whereas specifications (3) and (4) also include additional *Pseudo-timing* controls. The point estimates and standard errors in Panel A (B) of Table 4 are the simulation-based counterparts of Panel A (B) of Table 3.[22] They support the conclusion that the industry market timing is indeed statistically present among GPs and that both ingredients (incentive and skill) are necessary.

[Insert Table 4 here]

Meanwhile, Panel C of Table 4 depicts what we could not learn with the control group comprising actual funds – whether aggregate PE distributions are informative of future *Industry returns*, unconditionally on the GPs' situation. The coefficient on *ActualFund*Rush*, although negative, is economically small (about 0.15% per month) and far from being significant statistically.

In addition, note that unlike in Table 3, the point estimates with additional *Pseudo-timing* controls are very close to those with just the baseline fixed effects, particularly, for the 15% threshold case where the effect is stronger (specifications (1) and (3)). This is because the (projections of) fund fixed effects with respect to *Stopping-time* and *Rush* absorb much of the (co)variation in these controls and *Rush*. In other words, to the extent the expected industry returns tend to change slowly, controlling for the fund fixed effects obtained from the *auxiliary model* is sufficient. Further, in Figure B.3A, I show that, consistent with a knowledge-based explanation, the return predictability vanishes as one moves to sectors that did not correlate with the funds' primary industry in the recent past. Additional tests are reported in Figure B.2.

4.2.2. Informed "Stays"

I now turn to the tests of hypothesis *H2* that questions whether GP skills might also hurt LP interests through more "asset-hoarding" ahead of high volatility times. These tests will determine whether GPs acted as out-of-the money option holders by delaying the exercise in the anticipation of higher asset volatility.[23] Note that even though LPs may also benefit from the option value of a distressed equity claim, it appears

[22] Note that in each case the control group is formed only of the pseudo exits that correspond to the informed funds.

[23] 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.

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 change the dependent variable in Model (6) 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 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$\times$industry and other fund- and firm-level covariates (as per the *auxiliary model* in Table B.1). 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 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$\times$vintage-year peers (*Btm*/*Top*), and (ii) whether a successor fund has been raised (*NoNext*/*YesNext*).[24] To not engage more than three-level interaction terms, I define three non-overlapping groups of interests: *BtmNoNext*, *BtmYesNext*, and *TopNoNext*. In addition, to preclude a look-ahead bias and unrealistic assumptions, I measure *TTR* and *IRR* as of the *fifth* anniversary of the respective fund and constrain the sample to funds with actual stopping-times of 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, *BtmNoNext*-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 *Bt-*

[24] 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 (2016).

mYesNext-funds' GPs. On 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 *TopNoNext*-funds completes the analysis by highlighting the role of current performance with respect to the risk-shifting incentives. There should be zero effects to the extent performance fees in the current fund reduce GPs risk-appetite and/or high current performance rank significantly increases the odds of fundraising success (e.g. see Barber and Yasuda, 2016).

Table 5 reports the results for the stopping-quarter defined based on 15% NAV/"total distributions to-date" threshold. All specifications include the projections of fund fixed effect (see appendix Appendix B) 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.

As discussed above, interpretations would be ambiguous if the coefficients of $Informed \times$ Rush were different from zero in {-6 to 0}-window, either statistically or economically. This is clearly not the case as specifications (1) and (3) suggest—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 *H2*.

[Insert Table 5 here]

Specifications (2) and (4) of Table 5 support *H2*. 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 stark difference when both conditions are satisfied. A positive and significant coefficient of *TTRg1*BtmNoNext*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 *TTRg1*TopNoNext*Rush* "speak" against the effects on *TTRg1*BtmNoNext*Rush* being driven by some unaccounted time variation (i.e., when many funds had no successor by mid-life). Thus, we can conclude that *Informed* GPs who have incentives to "hoard" fund assets appear to be significantly more likely to "hoard" their fund assets through periods of high turbulence in the industry.

Meanwhile, the effectively zero coefficients on *TTRg1*BtmYesNext*-terms indicate that poorly performing GPs (*Informed* or not) but with a successor fund, nonetheless, do not exhibit such risk-shifting behaviors. This suggests that expected flows from future funds do restrain managers from "destroying value" (consistent with the framework of Chung et al., 2012). However, given that *H1* holds as well, these "future fund flows" alone appear not enough to induce a first-best action with respect to the LPs' objective.

To sum up for section 4.2, I confirm that (i) hypothesis *H1* hold: if (and only if) the GPs have good timing track record and have *in-the-money* carry at stake, do their fund distributions predict *Industry returns*. Also, I find support for hypothesis *H2* that risk-shifting by *Informed* GPs is more hazardous for LPs' performance. Both hypotheses are consistent with GPs possessing superior information about public equities not reflected in the market prices.

5. Additional results

In this section, I conduct tests to better illuminate the channel and trade-offs that GP market timing entails. I begin by examining whether portfolio gains that LPs experience due to the market timing by *Informed* GPs come at the cost of inferior holding period returns of their funds.

5.1. 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 PME) to be negatively correlated with those from buying (selling) near the industry troughs (peaks). Although the results in 2 suggest that this correlation seems to be positive, they do not provide evidence of the relation between the extent of exits' clustering as measured by *Rush* (*Informed* and not). Moreover, we want to learn the abnormal holding period returns by funds where *Informed* GPs apparently refrained from exiting 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 from the overall performance maximization standpoint).

A replacement of the industry returns subsequent to the stopping-times with the funds' holding period abnormal performance in model (6) yields the required tests. Table 6 reports the estimates.[25] As in Panel B of Table 3, *Informed*-dummy is broken into its constituents, $TTR > 1$ and $IRR > Hurdle$. To zoom at GPs' portfolio company selection and nurturing effects, I add industry fixed effects to vintage fixed effects while there is no purpose to condition on the risk-premia covariates at the stopping time anymore (dropping industry fixed effects leaves the estimates largely unchanged and key takeaways intact).

[Insert Table 6 here]

The differences across specifications in Table 6 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* ≈ 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*.

Meanwhile, the significantly negative coefficient on $TTRg1$ 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).

In specifications (3) and (4), I focus on holding period returns specifically during the periods of exits

[25] For brevity, I only report results for the stopping-quarter definition based on 15%-NAV-to-Distributions threshold. The results are similar with a threshold between 10 and 20%.

(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 results regarding the sensitivity of the funds' PME growths during the resolution period to *Rush* are interesting. The main-effect coefficient is no longer even negative while the interactions with just $TTRg1$ and just *IRRgHR* 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 *auxiliary model* in section 4.2). Nonetheless, 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*. Thus, the positive association of *Rush* with holding period returns appears stronger economically and statistically during the later periods of fund lives when most divestments occur.

5.2. What are GPs informed about: cash flows or discount rates?

Previous sections provide evidence of public equity returns predictability by the patterns of PE fund distributions to their investors. This predictability appears to originate from private information that GPs learn while managing their funds rather than belong to the public markets information set E_t. In this section I test what channels within the PE information cycle (see Appendix A) are responsible for this advantage.

As per Campbell and Shiller (1988), we can attribute the unexpected asset returns to (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 ($\equiv N_{DR,t+1}$):

$$\begin{aligned} r_{t+1} - E_t r_{t+1} &= (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j r_{t+1+j} \\ &= N_{CF,t+1} - N_{DR,t+1} \end{aligned}$$

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 required log rate of return for the period.

In this section, I study whether GPs are able to foresee $N_{CF,t+1}$ and/or $N_{DR,t+1}$. As discussed earlier, both channels could be at play because of GPs' potential involvement in the operational management of the portfolio companies and their special position in the capital market that enables them to observe portfolio demands of various public and private investors. To accomplish such tests, one could simply replace future returns in (6) with $N_{CF,t+1}$ and then with $N_{DR,t+1}$. However, there are no proxies of cash-flow news that would be uncorrelated with discount-rate news (and vice-versa). For example, even though the information on realized earnings are readily available, analysts' forecasts thereof likely depend on the expected returns. Similarly, forward price-earnings ratio also reflects the expected cash flows, and hence, their innovations.

To attain a stronger evidence regarding the links of *Informed Rush* to a particular channel (cash flows or discount rate) in the realized industry returns, I swap the future industry returns with *Rush* as the dependent variable in Model (6) (see section 3.3 for additional discussion). I then instrument the Industry returns with, respectively, proxies of industry cash-flow news or discount-rate news. Treating the proxy for the other channel as the included instrument enables me to better absorb the unrelated variation while ensuring that the returns' channel of interest correlates with *Rush* strongly enough. I proxy for cash-flow news by *Industry EPS Surprise* and *Industry ForwardPE*Δ, respectively. Both are computed from EPS estimates for the respective S&P500 GICS Industry sector subindex: 12-month trailing values and analysts' consensus forecasts for the next two fiscal years as obtained from Bloomberg.

Table 7 reports the results. The coefficients of $Informed \times IndRet$ and *IndRet* are essentially reverse regression estimates of the coefficients of $Informed \times Rush$ and *Rush* in Model (6), as discussed in section 3.3. Although their magnitudes are now less convenient to interpret, the basic intuition remains unchanged—a significantly negative coefficient indicates that Rush preempts a period of lower returns in the industry. All specifications include industry expected returns covariates to proxy for $E_t r_{t+1}$.[26]

Specifications (1) and (3) use actual fund exits as the control group, corresponding to the approach in Table 3, while specifications (2) and (4) report simulation-based analysis of the question, as described in section 4.2. First-stage regression results are summarized by the partial F-statistic (via Kleibergen-Paap Wald test) and show no evidence of the instruments' weakness in either case.

[Insert Table 7 here]

In specifications (1) and (2), the excluded instruments are *Industry EPS Surprise* and its interaction with *Informed*-dummy, while *Industry ForwardPE*Δ and its interaction with *Informed*-dummy are added to the first and second stage regressions along with other covariates and the fund group fixed effects. Significantly negative coefficients of $Informed \times IndRet$ indicate that skilled GPs foresee the industry cash flow news that cause the industry returns to fall. The point estimates suggest that aggregate earnings surprise that would

[26] Industry 5-year CAR, P/E, B/M; CAY-ratio CBOE VIX, BAA-AAA spread, AAA-UST spread, 10-year, and 3-month UST.

trigger a 10% fall in the industry index is preceded by 25-38 percentage points higher *Informed Rush*.

Specifications (3) and (4) use the terms with *Industry ForwardPE*Δ as excluded instruments while including *Industry EPS Surprise* in the set of other covariates, and hence, test whether GPs foresee innovations in the discount rates that investors require given the industry cash flows. Although the point estimates on $Informed \times IndRet$ and IndRet are negative according to specification (3), they are far from being significant statistically, so as their sum (untabulated test). Furthermore, these coefficients are not even negative (while also insignificant) according to specification (4), which uses hypothetical exits as the control group which should better absorb funds' heterogeneity and variations in $E_t r_{t+1}$.

Thus, it appears that the GPs' forecasting edge is limited to the cash-flow process in the industry of specialization while their public and capital market activities do not seem to yield important insights about swings in the marginal investor's risk preferences. It is also consistent with the predictability of returns vanishing outside the native industry as reported in section 4.2.1.

6. Conclusion

In this paper, I provide evidence consistent with PE fund managers (GPs) being more informed about certain publicly traded firms' valuations than marginal investors in public markets. This can create value for the private equity fund investors beyond the ways that have been analyzed in the literature. Learning through the private investment/divestment process appears to be the source of this knowledge which enables GPs to have some ability to time industry peaks and troughs. This knowledge appears to persist and pertain to the industry cash flow fundamentals as measured by public firms' aggregate earnings news.

However, while such a market-timing yields economically significant benefits for the funds' investors (LPs), it is not always concordant with the GPs' objectives. The incentives are adverse if the current fund's return is below the performance fee hurdle and the GPs are unable to raise a subsequent fund. In these cases, skilled GPs are likely to delay fund distributions ahead of elevated industry volatility periods. Hence, the results in this paper have strong implications for managers and contract choice by LPs. Investing with highly reputable GPs that are less likely to face fundraising difficulties reduces the *ex-ante* probability of the asset hoarding with more adverse consequences for LPs. Conversely, fund terms should contain more provisions protecting against the asset hoarding in general (i.e. at a cost of limiting the potential gains from more delegation) if the likelihood for such adverse incentives to emerge is relatively high.

My tests isolate GPs' market-timing skills from reactions to time-varying market conditions and causal effects of private equity funds activity spillovers on public firm policies. However, this informed trading by GPs is unlikely to go completely unnoticed by other investors in capital markets. If so, private equity funds may have a positive causal effect on the informational efficiency of the capital market, providing a channel for how private information gets impounded into the public market prices.

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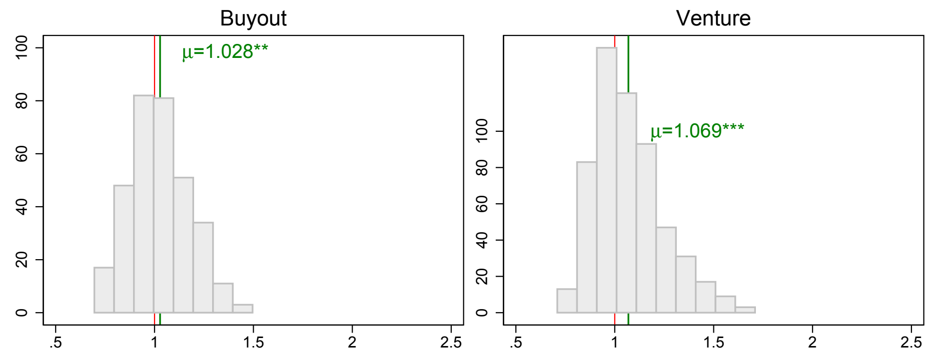
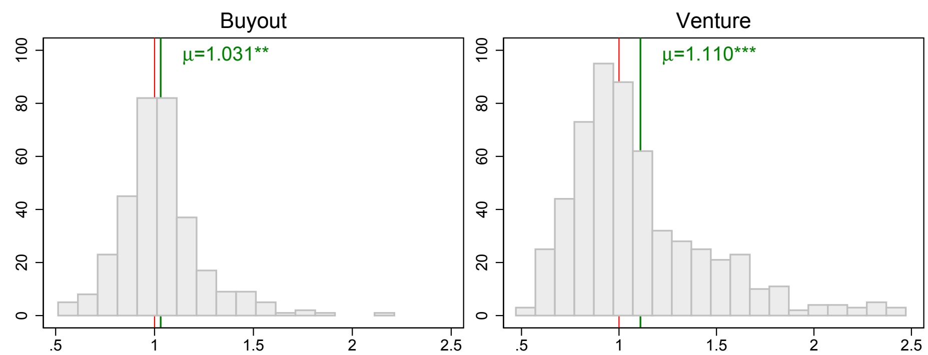
Figure 1. This figure plots Timing Track Record (*TTR*) values for the sample private equity funds. *TTR* is defined in section 2 and measures the gross-return due to selling near the market peaks during the fund life-time and buying near the troughs. Panel A left (right) chart shows the frequency distributions 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% diffrence 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*). Panel C provides a variance decomposition of end-of-life money-multiples adjusted for market-trend (i.e. $\overline{PME}$ per the text) into the selection (as measured by Kaplan-Schoar PME) and timing as measured by *TTRs* by PME quartile within the strategy (venture or buyout) and vintage year.

Panel A: Broad market *TTR*s



Panel B: Industry TTRs



Panel C: Funds total-return variance decomposition

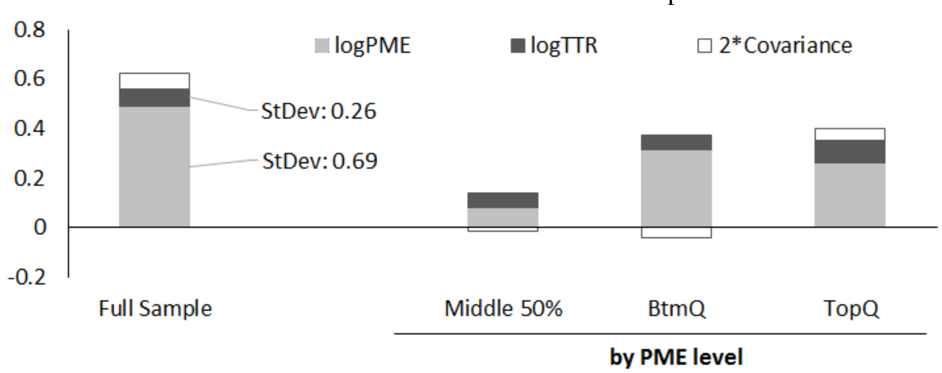
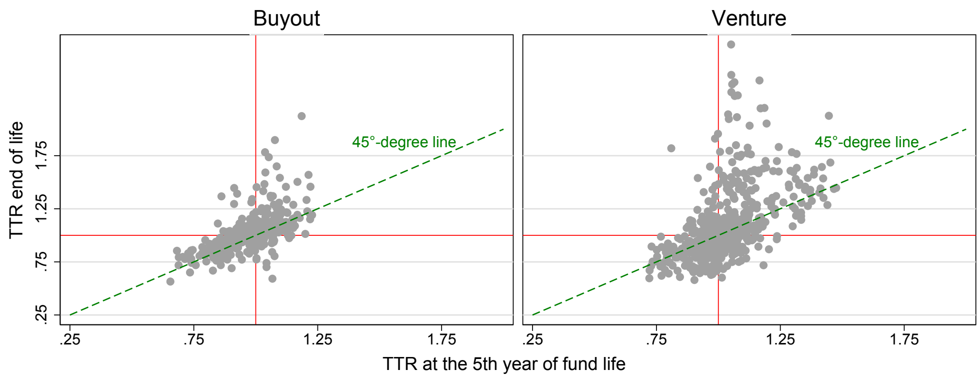
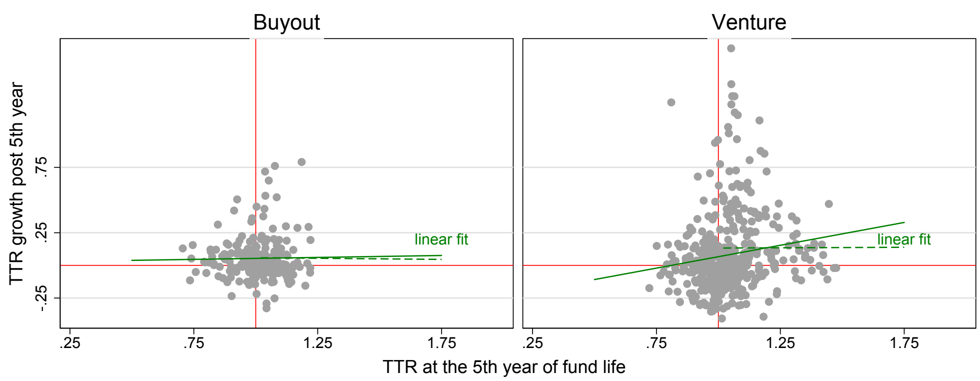


Figure 2. This figure compares private equity funds Timing Track Record (*TTR*) as of the 5^{th} year since fund inception with those values upon fund resolution (Panel A) and the post 5^{th}-year growth conditional on the fund's 5^{th}-year IRR being above [below] the Hurdle rate (8% for buyouts and 0% for venture funds) in Panel B [C]. *TTR* is defined in section 2 and measures the gross-return due to selling near the market peaks during the fund life-time and buying near the troughs. Industry returns and cash flows beyond the $5th$-year do not affect the computation of *TTR*) as of the 5^{th} year. Observations are two-side censored at 2.5% level based on the 5^{th}-year *TTR* across all panels.

Panel A: Interim versus Final



Panel B: Post-interim growth if *above* Hurdle



Panel C: Post-interim growth if *below* Hurdle

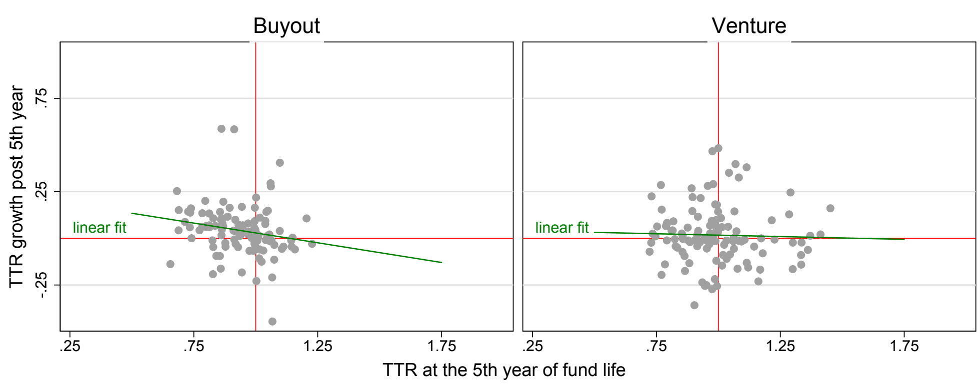
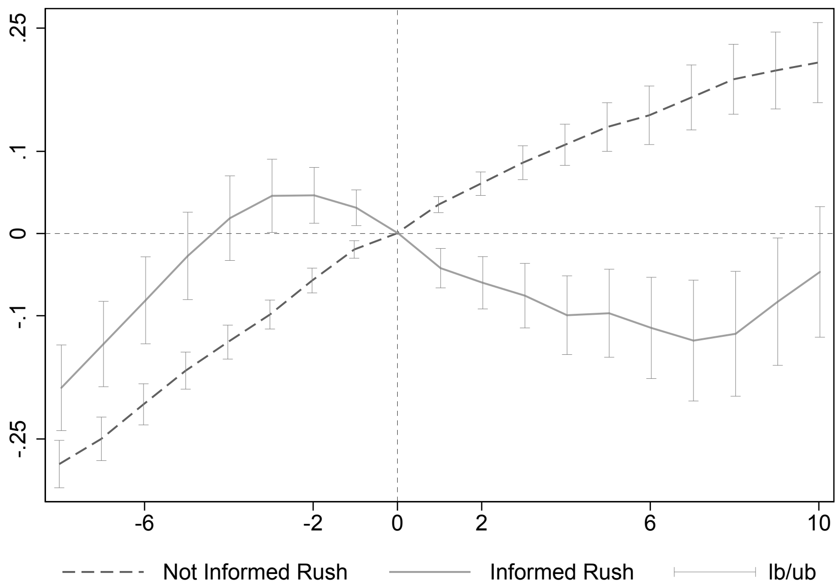


Figure 3. This figure plots cumulative *Industry returns* around the *stopping-time* for funds with a clustering of exits (henceforth, *Rush*) above the median for the respective vintage year. *Rush* is defined as a fraction of distributions over 6 quarters before the *stopping-time* in the fund total-to-date. The *stopping time* is defined as the distribution quarter at which NAV dropped below 15% of the fund total distributions to-date. The *Industry returns* are those of S&P500 subindex of the GICS industry sector that the fund specializes in. The solid line (*Informed Rush*) line is the mean across funds that as of the stopping-quarter meet two criteria: (a) positive track record of market timing as proxied by to-date-$TTR > 1$ (section 2), (b) the fund to-date performance enables GPs to receive carried interest (if the fund were to resolve immediately) as proxied by net-of-fees to-date-*IRR* above the hurdle-rate. The dashed line comprise of funds that do not meet these two criteria. Panel A reports results for the full sample. Panel B excludes stopping times that occurred in 2001 and 2008. The bars denote 95% confidence intervals.

Panel A: Full Sample of Exits: 1990-2013



Panel B: Excluding Extremes: 2001 and 2008

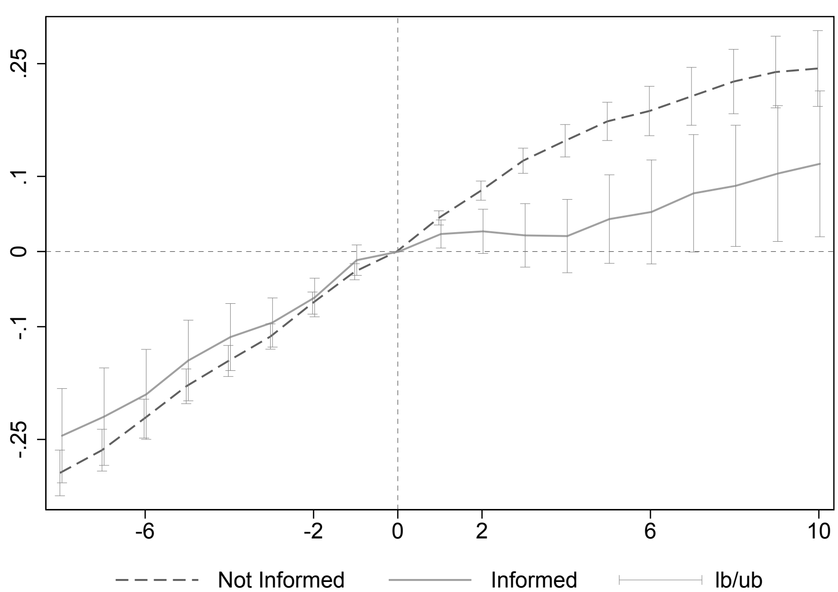
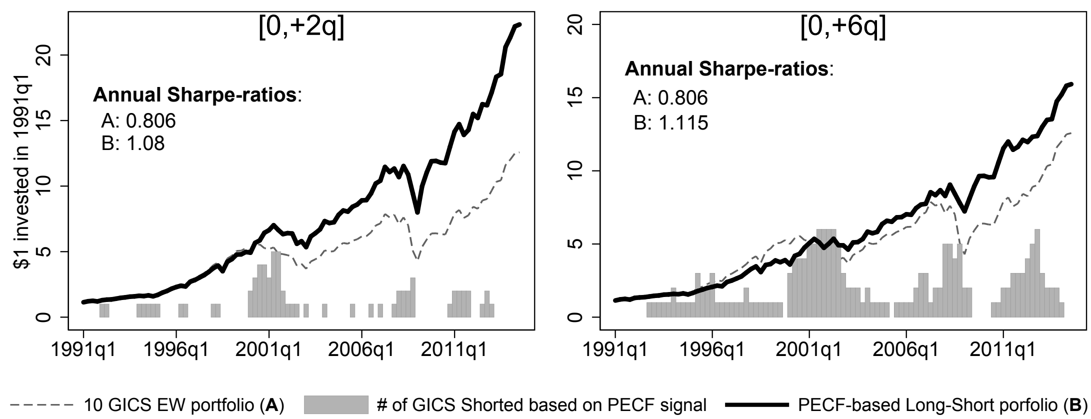


Figure 4. This figure reports performance of a portfolio that is rebalanced quarterly based on *Informed Rush* signal (portfolio *B*) in comparison to an equally-weighted 10 GICS sector portfolio (*A*), also rebalanced quarterly. Portfolio B sells Industry sectors where two or more *Treated* funds exhibited above-median *Rush* at their *stopping-time* over the past 3 or 7 quarters (i.e. [0,+2q] or [0,+6q] observation window respectively) and buys the remaining sectors (equally-weighted). *Rush* is defined as a fraction of distributions over 6 quarters before the *stopping-time* in the fund total-to-date distributions. The median is computed over all funds of the same type (venture or buyout) incepted in the same year. The *stopping time* is defined as the distribution quarter at which NAV dropped below 15% of the fund total distributions to-date. *Treated* funds satisfy the following criteria: (a) positive track record of market timing as proxied by $TTR > 1$ (section 2), (b) the fund to-date performance enables GPs to receive carried interest (if the fund were to resolve immediately) as proxied by net-of-fees *IRR* above the hurdle-rate. Panel A reports cumulative returns since 1999Q1 through 2013Q1 for both portfolios (A&B), their Sharpe-ratios and the number of sectors shorted in B end of each quarter. Panel B 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. Standard errors in parentheses are robust to autocorrelation, */**/*** denote significance at 10/5/1% confidence level.

Panel A: Cumulative Returns by Holding Period Window



Panel B: Abnormal Return Estimates

	[0,+2q]			[0,+6q]		
	B-rf	B-rf	B-A	B-rf	B-rf	B-A
alpha	0.014***	0.011***	0.008***	0.014***	0.011**	0.008**
	(0.005)	(0.003)	(0.003)	(0.005)	(0.004)	(0.004)
mktrf	0.664***	0.734***	−0.187***	0.472***	0.541***	−0.379***
	(0.092)	(0.066)	(0.054)	(0.083)	(0.082)	(0.073)
smb		−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)
N	95	95	95	95	95	95

Table 1. 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 data is not available (Ĩ5% of sample funds). IRR stands for internal rate of return. PME vs Market (Industry) denotes Kaplan and Schoar (2005) Public Market Equivalent Index versus broad market (S&P500 subindex corresponding to the GICS Industry Sector of the fund specialty). 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 as described in section 1.

Panel A: Private Equity 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 ($mln)	745	955	25	60	160	400	910	2920	5000
	IRR	0.165	0.227	-0.195	-0.077	0.060	0.130	0.225	0.488	1.017
	Money Multiple	13.32	181.21	0.52	1.00	1.69	2.28	3.44	8.69	51.92
	PME vs Market	1.34	0.92	0.29	0.51	0.90	1.22	1.61	2.29	3.87
	PME vs Industry	1.34	0.87	0.26	0.48	0.87	1.24	1.63	2.48	3.08
Venture	Overall Sequence	3.1	2.8	0.0	0.0	1.0	2.0	4.0	9.0	13.0
	Industry Sequence	2.7	2.5	0.0	0.0	1.0	2.0	4.0	8.0	11.0
	Vintage Year	1993	6	1980	1982	1987	1994	1999	2001	2003
	Life in Quarters	49	11	23	33	42	49	56	68	78
	Fund Size ($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 Market	1.46	2.13	0.12	0.25	0.59	0.94	1.39	3.99	12.40
	PME vs Industry	1.38	1.69	0.13	0.32	0.62	0.99	1.45	3.68	10.22

Panel B: Industry Benchmarks

GICS Sector	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

Table 2. This table reports linear regression model estimates of the log of funds' end-life *TTRs*. *TTR* is defined in section 2 and measures the gross-return due to selling near the market peaks during the fund life-time and buying near the troughs. 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. Table A.1 reports additional specifications and robustness checks. Standard errors in parentheses are clustered at GP-level, */**/*** denote significance at 10/5/1% confidence level.

Panel A: TTR versus Industry

	(1)	(2)	(3)	(4)	(5)	(6)
$ln(Size)_i$	0.515***	0.082				
	(0.162)	(0.150)				
$ln(Size)_i^2$	−0.014***	−0.003				
	(0.004)	(0.004)				
$ln(IndSequence)_i$	0.057***	0.049***	0.040**			0.055**
	(0.021)	(0.018)	(0.017)			(0.024)
$ln(PME)_i$			0.040***		0.059***	0.054***
			(0.015)		(0.020)	(0.020)
$ln(TTR)_{i-1}$				0.135**	0.115**	0.107**
				(0.052)	(0.051)	(0.049)
Vintage FE	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 FE	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 3. 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. As discussed in section 3.3, a negative β-estimate from the following model identifies market timing skill by GPs:

$$E[IndustryReturn_{ij,1:12}] = \beta \cdot Informed_{ij}Rush_{ij} + \gamma_1 Informed_{ij} + \gamma_2 Rush_{ij} + a_j + c_i ,$$

where $IndustryReturn_{ij,1:12}$ is a mean monthly return on S&P500 GICS industry sector of the fund specialty over 12 months following the fund *i stopping-time*, $Rush_{ij}$ – a fraction of distributions (to LPs) over the last 6 quarters in the funds' total-to-date, a_j – vintage-year fixed effects. In Panel A, $Informed_{ij}$ is a single dummy based on whether *TTR* (*IRR*) as of stopping quarter exceeds 1 (Hurdle-rate) while Panel B breaks it into the constituent dummies. *Stopping-times* in odd (even) numbered specifications are fund-quarter when fund NAV drops below 15 (20)% of the fund total distributions up to that quarter. Specifications (3)-(4) include *return-predictive* covariates, same in both panels. See Table A.4 for placebo tests. Standard errors in parentheses are clustered at stopping-quarters (see Table A.2 for other inference methods), */**/*** denote significance at 10/5/1%.

Panel A: $Informed \equiv (TTR > 1) \times (IRR > HR)$

	15%thld (1)	20%thld (2)	15%thld (3)	20%thld (4)
TTRg1*IRRgHR*Rush	−0.025***	−0.023***	−0.013***	−0.013**
	(0.007)	(0.008)	(0.005)	(0.005)
TTRg1*IRRgHR	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)
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 FE	Yes	Yes	Yes	Yes
Observations	893	941	892	940
R^2	0.218	0.234	0.446	0.464

Panel B: $Informed \equiv (TTR > 1) + (IRR > HR) + (TTR > 1) \times (IRR > HR)$

	15%thld (1)	20%thld (2)	15%thld (3)	20%thld (4)
TTRg1*IRRgHR*Rush	−0.031**	−0.026**	−0.022**	−0.021***
	(0.012)	(0.010)	(0.010)	(0.008)
TTRg1*IRRgHR	0.006	0.005	0.006*	0.005
	(0.005)	(0.004)	(0.003)	(0.003)
TTRg1*Rush	0.001	−0.004	0.008	0.004
	(0.009)	(0.007)	(0.008)	(0.006)
IRRgHR*Rush	0.010	0.010	0.004	0.009
	(0.009)	(0.009)	(0.007)	(0.007)
TTRg1(d),IRRgHR(d), Rush	Yes	Yes	Yes	Yes
Vintage FE	Yes	Yes	Yes	Yes
Predictive covariates	No	No	Yes	Yes
Observations	893	941	892	940
R^2	0.225	0.239	0.446	0.466

Table 4. This table reports simulation-based estimates of predictive regressions of *Industry returns* by *Rush*, a fraction of distributions over the last 6 quarters in the funds' total-to-date. *Industry returns* are of S&P500 subindex corresponding to the GICS Industry sector of the fund specialty. The estimation methodology is described in section 4.2 and Appendix B. In short, I (1) estimate a model of fund fixed effects for stopping-time and *Rush* (henceforth *auxiliary model*) Table B.1, (2) independently simulate 1,000 blocks of up to 100 random exits per fund under this model (henceforth *independent simulations*), and (3) pool *main model* estimates over these *independent simulations*. The *main model* is:

$$E[IndustryReturn_{ij,1:12}] = \beta \cdot Informed_{ij} Rush_{ij} + \gamma_1 Informed_{ij} + \gamma_2 Rush_{ij} + a_j + c_i \quad ,$$

where $IndustryReturn_{ij,1:12}$ is a mean monthly *Industry Return* over 12 months following fund *i* actual or simulated *stopping-time*, depending on whether $Informed_{ij} = 1$ for the actual funds of interest or $Informed_{ij} = 0$ otherwise; $Rush_{ij}$ – actual or simulated fraction of distributions over the last 6 quarters in the funds' total-to-date, a_j – "fund fixed effects" estimates from the *auxiliary model*. Panel A [B] includes funds that as of stopping-time have (i) a positive track record of market timing as measured by *TTR* defined in section 2 and [or] (ii) net-of-fees IRR in excess of the contractual Hurdle-rate. Panel C includes all funds. Stopping-times in odd (even) numbered specifications are fund-quarter when fund NAV drops below 15 (20)% of the fund total distributions up to that quarter. Specifications (3)-(4) include *return-predictive* covariates, c_i, as in Table 3. Standard errors in parentheses are clustered at stopping-quarters, */**/*** denote significance at 10/5/1%. Figures B.2-B.3 report additional tests.

	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 ≡ $(TTR > 1) \times (IRR > HR)$				
TTRg1*IRRgHR*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 ≡ $(TTR > 1) + (IRR > HR) + (TTR > 1) \times (IRR > HR)$				
TTRg1*IRRgHR*Rush	−0.032***	−0.026**	−0.034***	−0.027***
	(0.012)	(0.012)	(0.010)	(0.010)
TTRg1*Rush	0.008	0.002	0.012	0.005
	(0.009)	(0.007)	(0.007)	(0.006)
IRRgHR*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(dummies)	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Benchmark valuations	No	No	Yes	Yes
CAY-ratio, CBOE VIX	No	No	Yes	Yes
Spreads & Yields	No	No	Yes	Yes

Table 5. 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 4.2.2 and Appendix B. In short, I (1) estimate a model of fund fixed effects for stopping-time and *Rush* (henceforth *auxiliary model*, Table B.1), (2) independently simulate 1,000 blocks of up to 100 random exits per fund under this model (henceforth *independent simulations*), and (3) pool *main model* estimates over these *independent simulations*. The model is:

$$E[IndustryVolty_{ij,h}] = \beta v \cdot Informed_{ij} Rush_{ij} + \gamma_{v1} Informed_{ij} + \gamma_{v2} Rush_{ij} + a_j,$$
$$Informed \equiv (TTR5y > 1) + SurvivalRisk + \ (TTR5y > 1) \cdot SurvivalRisk \qquad ,$$

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 *stopping-time*; $Rush_{ij}$ – actual or simulated fraction of distributions over the last 6 quarters in the funds' total-to-date, a_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 (section 2) or (ii) where the firm faces high survival risk as measured by net-of-fees IRR in the bottom tercile among type$\times$vintage-year peers (*Btm*) and/or no successor fund raised up until at least the 6th quarter before the stopping quarter (*NoNext*).

The stopping quarter is the first quarter with non-zero distributions to LPs when a fund's NAV drops below 15% of the fund's total distributions up to that quarter. 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: ($TTRg1$), ($BtmNoNext = 1$), ($BtmYesNext = 1$), ($TopNoNext = 1$) 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 stopping-quarters, */**/*** denote significance at 10/5/1%.

	-6:0q (1)	-12:-8q (2)	-6:0q (3)	-12:-8q (4)
TTRg1*BtmNoNext*Rush	0.025	0.075**	0.007	0.064**
	(0.027)	(0.038)	(0.022)	(0.030)
TTRg1*TopNoNext*Rush	0.007	−0.010	0.012	−0.010
	(0.020)	(0.025)	(0.016)	(0.019)
TTRg1*BtmYesNext*Rush	0.006	−0.015	0.001	−0.007
	(0.012)	(0.017)	(0.009)	(0.015)
BtmNoNext*Rush	−0.001	−0.009	0.006	−0.010
	(0.012)	(0.015)	(0.007)	(0.012)
TopNoNext*Rush	−0.006	0.018	−0.006	0.007
	(0.011)	(0.019)	(0.007)	(0.016)
BtmYesNext*Rush	0.006	0.016*	0.000	0.002
	(0.006)	(0.008)	(0.004)	(0.008)
TTRg1*Rush	−0.006	−0.006	0.003	−0.003
	(0.007)	(0.008)	(0.005)	(0.007)
Rush, Informed(dummies)	Yes	Yes	Yes	Yes
Fund FE	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

Table 6. This table reports OLS estimates of the following model:

$$E[HAR_{ij}] = \beta \cdot Informed_{ij}Rush_{ij} + \gamma_1 Informed_{ij} + \gamma_2 Rush_{ij} + a_j$$

where HAR_{ij} is the holding period abnormal return of fund i as measured by a natural log of 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 stopping-time in the funds' total-to-date, $Informed_{ij}$ denote dummy variables based on whether *TTR* (*IRR*) as of stopping quarter exceeds 1 (Hurdle-rate), a_j – fund vintage-year and industry fixed effects. Stopping-time 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 includes funds with stopping-times 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:				
TTRg1*IRRgHR*Rush	0.068	0.034	0.415	0.362
	(0.602)	(0.624)	(0.568)	(0.536)
TTRg1*Rush	0.234	0.430	0.041	0.143
	(0.440)	(0.428)	(0.359)	(0.392)
IRRgHR*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:				
TTRg1*IRRgHR	0.150	0.087	−0.025	−0.066
	(0.153)	(0.159)	(0.175)	(0.160)
TTRg1	−0.342***	−0.239**	−0.300***	−0.185**
	(0.099)	(0.092)	(0.086)	(0.089)
IRRgHR	0.659***	0.718***	0.361**	0.404***
	(0.120)	(0.112)	(0.146)	(0.132)
Vintage FE	Yes	Yes	Yes	Yes
Industry FE	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 7. This table reports instrumental variable regression estimates of *Rush* on next 12 months *Industry returns*:

$$E[Rush_{ij}] = a_j^R + c_i^R + \beta^R[Informed_{ij}IndustryReturn_{ij,1:12} \quad Informed_{ij} \quad IndustryReturn_{ij,1:12}],$$

where *Rush* is a fraction of distributions over the last 6 quarters in the funds' total-to-date; *Industry returns* is a mean monthly return on S&P500 GICS industry sector of the fund specialty over 12 months following the fund *i stopping-time*; $Informed$ is a dummy that proxies for incentives and market-timing skill of the fund's GP (as per Panel A of Table 3 and section 3.3).

In specifications (1) and (2), the excluded instruments are *Industry EPS Surprise* and its interaction with *Informed*-dummy, while *Industry ForwardPE*Δ and its interaction with *Informed*-dummy are added to the 1st and 2nd stage regressions along with the other return-predictive covariates (see Table 3) and the 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 *Industry ForwardPE*Δ as excluded instruments while including *Industry EPS Surprise* in the set of other covariates and, thus, test whether GPs foresee innovations in the discount-rates for the industry cash-flows. *Industry EPS Surprise* and *Industry ForwardPE*Δ are computed from EPS estimates for the respective S&P500 GICS industry sector subindex: 12-month trailing values and the next two fiscal year analysts' consensus forecasts.

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 (for *Informed* funds only) as the control group (reported are the pooled estimates across 1,000 simulations, the methodology is described in section 4.2 and Appendix B). Standard errors in parentheses are robust to heteroskedasticity and autocorrelation, */**/*** denote significance at 10/5/1%.

	(1)	(2)	(3)	(4)
Informed× IndRet	−3.825**	−2.465**	−1.194	0.846
	(1.733)	(1.042)	(2.968)	(2.569)
IndRet	0.315	0.097	−1.517	0.300
	(1.249)	(.228)	(1.842)	(0.343)
Informed	0.012	0.017	−0.032	−0.025
	(0.023)	(0.038)	(0.026)	(0.015)
Excluded Instrument	Industry EPS Surprise		Industry Forward PEΔ	
Included Instruments	Forward PEΔ		EPS Surprise	
Included Inst.×Informed	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 stat.	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 Discussion and Data

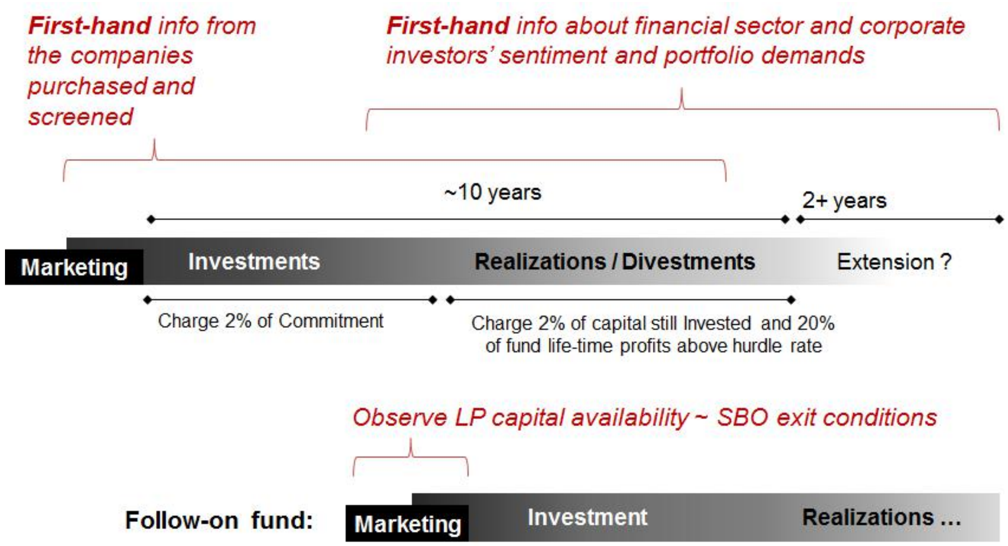
A.1. Private Information Cycle

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 private equity 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, GPs, closely monitor and exert influence on the acquired company activities, normally through active membership on the board of directors. See Gompers and Lerner (1999), Kaplan and Strömberg (2008), Metrick and Yasuda (2010) for detailed accords on private equity business models. Sorensen (2007), Acharya, Gottschalg, Hahn and Kehoe (2008), Hochberg, Ljungqvist, and Lu (2010), Hochberg, Ljungqvist, and Vissing-Jørgensen (2014), Gompers, Kovner, and Scharfstein (2010), Ewens and Rhodes-Kropf (2013) among others suggest a micro-foundation for GPs impact on portfolio companies that relates to entrepreneur rational self-selection, institutional network effects as well as financial, operational and "managerial" engineering.

The company would typically be one of many investments the funds undertake which, in turn, is a small portion of candidates that would get screened during the approximately 5-year investment period. Unlike for portfolio investors in public companies, the information set of the fund GPs would 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 in possession of the management. GPs tend to specialize in certain industries and types of businesses. This makes the signals about business fundamentals obtained through the monitoring and prospective investments due diligence quite complementary. This complementarity potentially makes GPs' information sets even better than that of a individual company's management as well as that of investors in public markets.

Both funds, 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 than 2 years after the original investment while some - after 10 years. 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 private equity fund or group of investors (financial investors) or (ii) an operating firm, possible private too, that is strategically interested in the production capacity of the target's assets (strategic investors). Transactions with non-financial buyers constitute the most frequent type of exits and often referred to as "trade-sales". The IPO route typically fetches the highest return on investment, yet other exit routes (except bankruptcy) are on average profitable as well. For example, see Ball et al (2011) for a comprehensive venture deals sample and Degeorge et al (2013) for buyouts.

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. For example, see Brown et al.(2016). 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 companies fundamentals, on the one hand, and investor portfolio demands, on the other (Including signals about fellow private equity firms capital growth trend as it relates to prospective competition among financial buyers for the current portfolio companies). These largely non-public information flows that GPs regularly participate in both, buyout and venture, can be summarized via the following scheme.



A.2. Which PE Exits Are Informative?

The traditional route in the literature has been to compare IPO exits with other exits.[27] However, this cross-sectional approach may not be the best for examining GP market-timing ability.

A.2.1. 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.[28] 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 may be as informative about GPs' expectations as sales through an IPO.

A.2.2. Agency costs considerations

The assumption that GPs take first-best actions for LPs is a strong one. Robinson and Sensoy (2013) find that PE funds' distributions cluster too much around "waterfall" dates for that assumption to be realistic. However, the conditional revelation of the GP's private signal could result precisely from the agency relationship. Continuing with the previous example of a seven-year buyout fund, assume that it has performed well enough for GPs to have a substantial performance fee 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.[29]

In contrast, there is hardly any benefit to GPs from exiting investments before the industry downturn if the performance to-date is poor. Asset liquidation would amount to suboptimal early-exercise of an option

[27] For example, Lerner (1994), and Ball et al. (2011).

[28] Just the wealth transfer from outside creditors (that overestimate the true collateral value) may exceed how much the second fund "overpays." Further, the portfolio company improvement may yet to be fully realized by the first fund.

[29] Chung, Sensoy, Stern, and Weisbach (2012) show that much of GPs' wealth derives from fees in funds not yet raised.

(to earn carry and improve performance rank) and reduce asset management fees.[30] 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). This would also be consistent with the framework of Chung et al. (2012) as well as the empirical finding by Aragon and Nanda (2011) in the context of hedge funds.

A.2.3. When do 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 (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.

[30] Some funds have the basis for asset management fees switching from committed to invested capital after the investment period elapses. See Robinson and Sensoy (2013).

A.2.4. Potential power drains

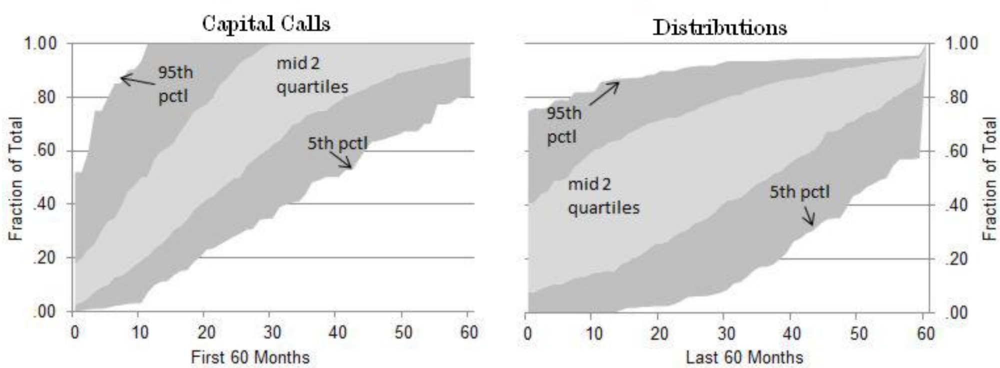
Even if the incentives to act on the timing signal are in place, the signal may not arrive or some GPs may not notice it (e.g., because of lower skill). In addition, GPs might be too diversified or could hedge their undesired exposures elsewhere. However, finance professionals are often legally prohibited to undertake any personal investing activities potentially jeopardizing best actions in the interests of clients or their employers. There is little evidence suggesting how strong and common such clauses are but GP risk-aversion combined with basis risk could also limit these hedging activities.

Prior research suggests that persistence in GP performance is particularly strong amongst the worst performing funds (e.g., see Kaplan and Schoar (2005); Phalippou and Gottschalg (2009); and Harris et al. (2014)) The substantial heterogeneity of PE fund returns is a statement about the high total risk of these funds, but also allows for considerable heterogeneity in GP skill levels. Gervais and Strobl (2012) study the industrial organization of asset management and show that in equilibrium, high-skill and low-skill managers pool into opaque funds, while medium-skill managers separate into transparent funds. It is hard to find a less transparent example of delegated money management than PE.

Figure A.1. 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. For example, according to the left-chart, a quarter of buyout funds by the 30^{th} month since inception would call 61% of its capital or less while another quarter would be fully invested by that time. From the right-chart 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 reports this analysis for the venture subsample.

Panel A: Buyout



Panel B: Venture

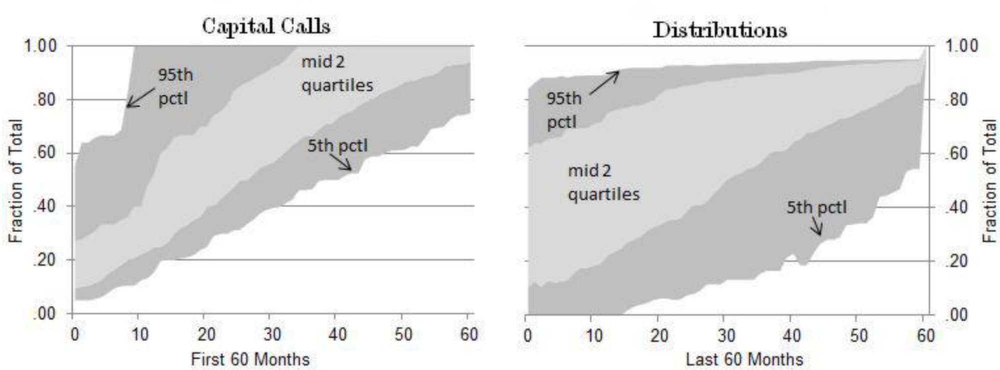


Figure A.2. Timing Track Records: Examples

This figure plots pair-wise comparisons of *Timing Track Record* (TTR) values for 8 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 section 2, in this case the fund money-multiple equals *TTR* and reflects the gross-return due to selling near the market peaks during the fund life-time and buying near the troughs. Formally, *TTR* is determined according to the following formula:

$$TTR = \frac{\sum_{t=1}^{T} Distrib_t \cdot e^{r_{1,T} \cdot (1-t/T)}}{\sum_1^T CCalls_t \cdot e^{r_{1,T} \cdot (1-t/T)}} \Big/ \frac{\sum_{t=1}^{T} Distrib_t \cdot e^{r_{t,T}}}{\sum_1^T CCalls_t \cdot e^{r_{t,T}}},$$

where $r_{t,T}(r_{1,T})$ is market return from cash flow date(fund inception) until fund resolution. 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 combines timing of both, entry and exit.

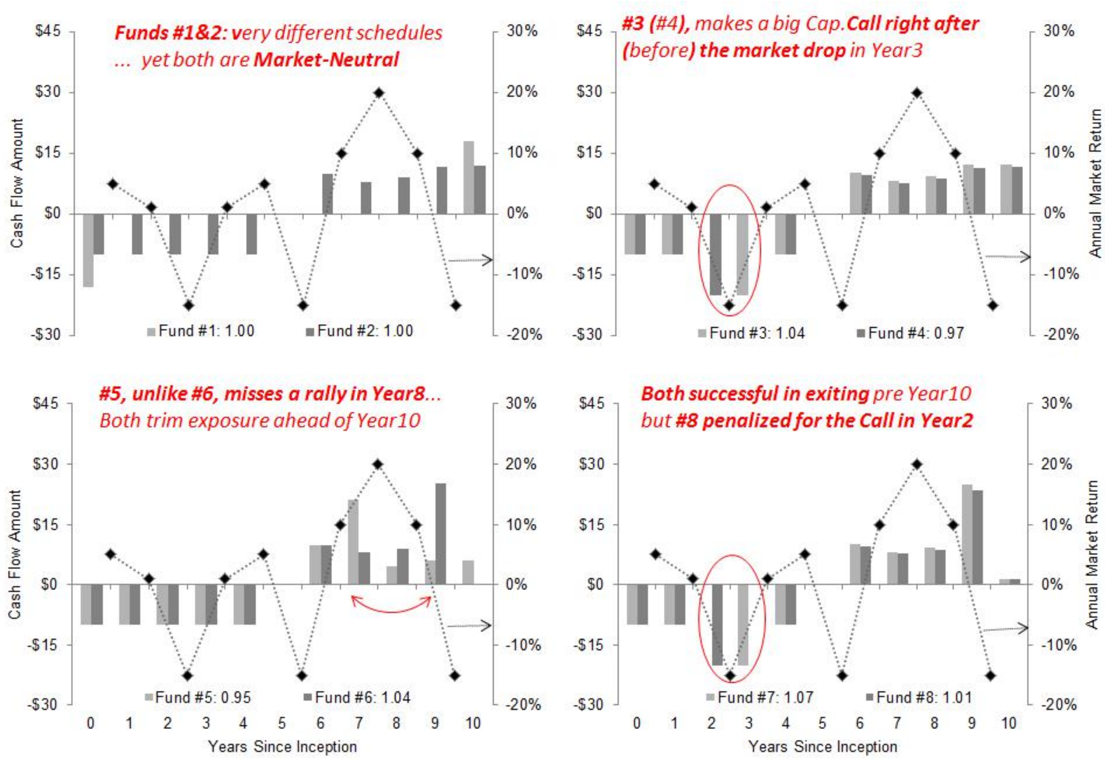
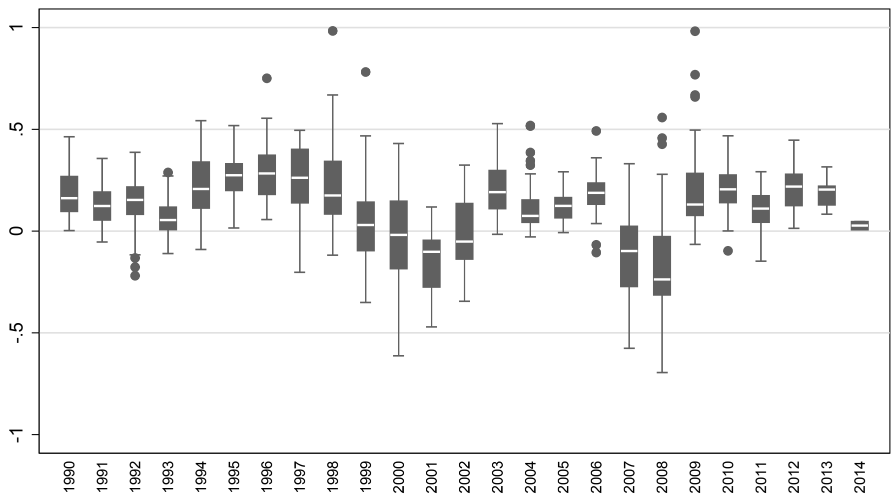


Figure A.3. Industry Returns and Fund Inceptions
This figure reports intertemporal distributions of *Industry returns* in Panel A and the sample private equity funds in Panel B. Each observation in the box-plot of Panel A represents a 12-month return of S&P500 GICS industry sector subindex. The increment 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 market peaks during the fund life-time and buying near the troughs as per Equation (1) (section 2).

Panel A: Industry Returns



Panel B: Funds by vintage and TTR group

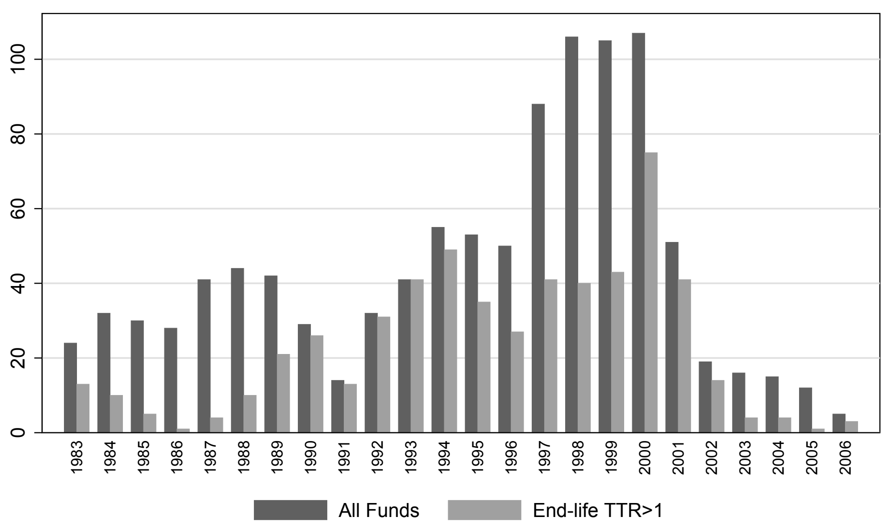
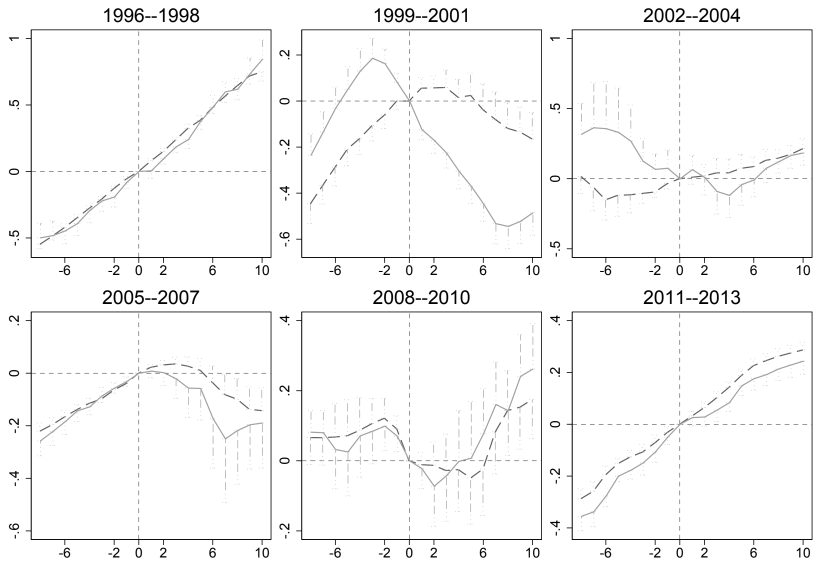


Figure A.4. Timer's Rush and Industry Returns: Additional Event Studies

This figure plots cumulative *Industry returns* around the *stopping-time* for funds that had *Rush* above (below) the fund vintage year median in Panel A (Panel B). *Rush* is a fraction of distributions over 6 quarters before the *stopping-time* in the fund total-to-date. The stopping time is defined as the distribution quarter at which NAV dropped below 15% of the fund total distributions to-date. The *Industry returns* is S&P500 subindex of the GICS sector that the fund specializes in. The light-gray (*Treated*) line is the mean across funds that as of the stopping-quarter meet two criteria: (a) positive track record of market timing as proxied by $TTR > 1$ (section 2), (b) the fund to-date performance enables GPs to receive carried interest (if the fund were to resolve immediately) as proxied by net-of-fees *IRR* above Hurdle-rate. The dark-gray line comprise of funds that do not meet these two criteria. Panel A reports results for funds with above-median *Rush* the full sample by stopping-year triplets while Panel B pools across all stopping times and below-median *Rush* (See Table 3 for above-median *Rush*). The bars denote 95% confidence interval.

Panel A: High Rush by Exit Year



Panel B: Full Sample: What if No Rush?

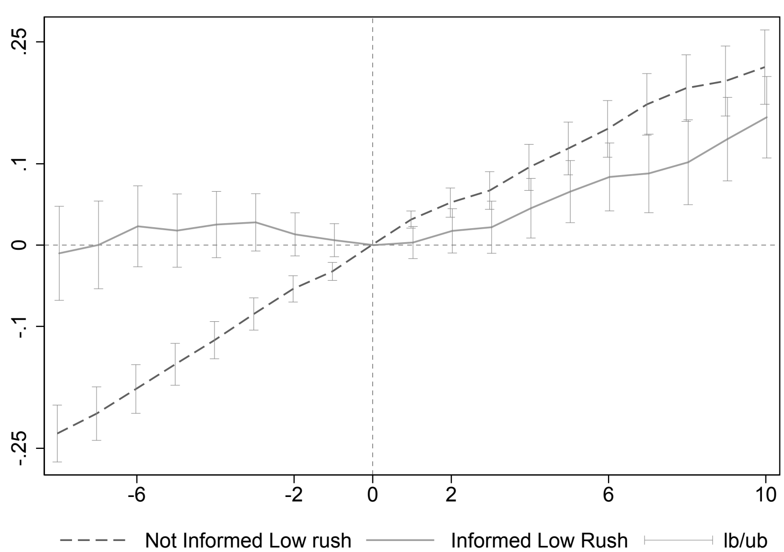


Table A.1. TTR Cross-Section: Robustness and Placebo

This table reports linear regression model estimates of the log of funds' end-life *TTRs*. *TTR* is defined in section 2 and measures the gross-return due to selling near the fund industry peaks during the fund life-time and buying near the troughs. The industry returns are proxied by those of GICS Sector index corresponding to the fund specialty. The explanatory variables are: $ln(Sequence)_i$ - 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*; the respective industry return over the fund life-time (*Trend*) and its interaction with the respective variables of interest. Panel A reports regression estimates using actual values of *TTR*. Panel B reports the corresponding coefficients from simulations based on hypothetical exit schedules but actual funds' operation dates and industry return paths. The exit schedules 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) is specified relatively to the industry. 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.

Table A.1. 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 FE	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

Table A.1. Panel B: TTRs based on Random Exit Schedules - Mean(SD) Coefficient Across 1,000 Simulations

$\alpha = 0bp$, $\sigma_i = 0\%$, $\beta = 1.0$

	(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)

$\alpha = 0bp$, $\sigma_i = 40\%$, $\beta = 1.0$

	(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)

$\alpha = 250bp$, $\sigma_i = 40\%$, $\beta = 1.0$

	(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)

$\alpha = 250bp$, $\sigma_i = 40\%$, $\beta = 1.5$

	(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. *Informed Rush* versus Uninformed, robustness checks (1)

This table reports standard errors (SEs) computed under different assumptions for the coefficient on *TTRg1*IRRgHR*Rush* from Table 3, 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 Stopping-time, 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 Thomson (2011).

Panel A: Informed $\equiv (TTR > 1) \times (IRR > HR)$

	Fund FE		Fund FE+PseudoTiming	
	15%thld	20%thld	15%thld	20%thld
	(1)	(2)	(3)	(4)
cluster by Exit quarter (Table 3A)	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 $\equiv (TTR > 1) + (IRR > HR) + (TTR > 1) \times (IRR > HR)$

	Fund FE		Fund FE+PseudoTiming	
	15%thld	20%thld	15%thld	20%thld
	(1)	(2)	(3)	(4)
cluster by Exit quarter (Table 3B)	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.3. *Informed Rush* versus Uninformed, robustness checks (2)

This table reports predictive regressions of *Industry returns* by *Informed Rush* just as Table 3 but uses 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. *Informed Rush* is a proxy for the carried interest "cashed-in" by GPs with a positive track record of market timing in the past, as measured by *TTR* (section 2). As discussed in section 3.3, a negative β-estimate from the following model identifies market timing skill by GPs::

$$E[IndustryReturn_{ij,1:12}] = \beta \cdot Informed_{ij}Rush20_{ij} + \gamma_1 Informed_{ij} + \gamma_2 Rush20_{ij} + a_j ,$$

where $IndustryReturn_{ij,1:12}$ is a mean monthly *Industry Return* over 12 months following the fund *i stopping-time*, a_j – fund vintage-year fixed effects. In Panel A, $Informed_{ij}$ is a single dummy based on whether *TTR* (*IRR*) as of stopping quarter exceeds 1 (Hurdle rate) while Panel B breaks it into the constituent dummies. Stopping-times in odd (even) numbered specifications are fund-quarter when fund NAV drops below 15 (20)% of the fund total distributions up to that quarter. Specifications (3)-(4) include additional *return-predictive* covariates, same in both panels. Standard errors in parentheses are clustered at stopping-quarters, */**/*** denote significance at 10/5/1%.

	(1)	(2)	(3)	(4)
TTRg1*IRRgHR*Rush20	−0.010***	−0.010*	−0.005*	−0.009*
	(0.003)	(0.006)	(0.003)	(0.005)
Rush20	0.001	0.001	0.002	0.001
	(0.002)	(0.003)	(0.002)	(0.003)
TTRg1		−0.001		−0.002
		(0.004)		(0.002)
IRRgHR		−0.005*		−0.002
		(0.003)		(0.003)
TTRg1*IRRgHR20	−0.000	0.003	0.002	0.004
	(0.003)	(0.004)	(0.002)	(0.003)
TTRg1*Rush20		0.000		0.004
		(0.004)		(0.004)
IRRgHR*Rush20		−0.000		0.001
		(0.004)		(0.003)
TTRg1*IRRgHR				
Vintage FE	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 A.4. Do Exits Cause Downturns?

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 3. The empirical model, the dependent variable (mean *Industry Return* 12-months forward return), and all other controls as the same as in the respective specification of Table 3A. Specifications (3)-(4) have predictive covariates added but otherwise are identical to (1)-(2). *Informed* funds group is the same as in 3A but *Rush* and return measurement period are defined differently. Recall that under the *Footprint-on-firms* alternative, exits per se should have impact on Industry performance rather than the extent they remove GPs carried interest exposure to adverse market moves (see section 3.3 for details). Specifically, here I look at a 4-quarter period with maximum cumulative distributions *outside* the (-18,12)-months window around the stopping time defined by 15% threshold (i.e. before 15%, after 15%). Also, I now measure rush amounts in \$ so that they are more proportional to the industry market capitalization (and hence, potential impact). To have magnitudes and distributions close to those of actual *Rush*, I define *MaxRush* as the probit function of $log(\$mln/10)$. Standard errors in parentheses are clustered at stopping-quarter level, */**/*** denote significance at 10/5/1%.

$Informed \equiv (TTR > 1) \times (IRR > HR)$, *Rush* outside exit period

	before15%	after15%	before15%	after15%
	(1)	(2)	(3)	(4)
TTRg1*IRRgHR*MaxRush	−0.001	−0.001	−0.002	−0.000
	(0.005)	(0.005)	(0.005)	(0.005)
TTRg1*IRRgHR	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 FE	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

Appendix B. Simulation-related Supplements and Discussions

B.1. Setup

In this section I provide additional details about the simulations-based estimation method used section 4.2. The method involves three steps.

First, I estimate models of expected $ln(stopping - time)$ and $\Phi^{-1}(Rush)$ for all funds in our sample as linear functions of: (i) Vintage-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.[31] I treat the two equations as Seemingly Unrelated Regressions as per Zellner (1964), but the main model estimates are essentially unchanged if I allow simultaneity in the stopping-time and *Rush* and use IV-estimates of the expected values (untabulated). I utilize the pseudo-panel structure of *Rush* and stopping-time observations per fund where the pattern of fund distribution permits so.[32]. Besides the expected values, I also obtain the covariance matrix of the residual $ln(stopping - time)$ and $\Phi^{-1}(Rush)$.

Table B.1 reports the *auxiliary model* of fund fixed effects that I estimate as two Seemingly Unrelated Regressions (Zellner, 1964). The fact that under the null hypothesis of Model (6), stopping-time and *Rush* do not predict *Industry returns* should relieve possible concerns about simultaneity in the formations of the dependent variables or other sources of endogeneity.[33,34] It is insightful to think about this *auxiliary model* as simply a density-mass filter for possible *Stopping-time – Rush* combinations.

The number of observations in Table B.1 reflects that for funds where 15% and 20% thresholds were not crossed simultaneously, I have repeated observations of *Rush*, stopping-time, and the covariates. I make use of this data structure to increase the estimates' precision. Most of the explanatory power for both equations comes from vintage×industry fixed effects.[35] Nonetheless, all other variables that I include significantly explain the stopping time and have signs consistent with the economic intuition. Specifically, fund log-size

[31] 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.

[32] Namely, when a fund reaches 15% and 20% threshold of residual NAV to total distributions-to-date is different

[33] See Appendix B for a discussion of the implications for *main model* estimates arising from possible endogeneity.

[34] I functionally transform both dependent variables to ensure that any simulated *stopping-time* is positive, while simulated *Rush* is between zero and one.

[35] I consolidate the buckets as described in Appendix B to have at least nine funds sharing the same vintage-industry dummy.

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 much less success in explaining *Rush* with R^2 being only 0.132.[36] Fewer explanatory variables are significant statistically, although the signs of all coefficients are economically intuitive.

The fitted values by fund-threshold for both stopping-times and *Rush* represent the projections of fund fixed effects on the set of these covariates that I will use in place of a_j dummies in estimating Model (6) in each of the *independent simulations*. 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 exclude fund-type dummy (i.e., venture or buyout) among other covariates that add more noise than explanatory power. Importantly, I treat the residual covariance matrix estimate as randomly drawn from a population.[37]

Second, I draw a sample of 100 random bivariate normal shocks from a covariance matrix that is itself randomly drawn each time 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 first-step estimates and for heteroskedastic error term in the unobserved population, essential in the third step.[38] The same shocks are merged to each fund-threshold in the sample. Adding fund-threshold-specific estimates of expected $ln(stopping-time)$ and $\Phi^{-1}(Rush)$ and reverting the functional transformations, I obtain the simulated (aka placebo) 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.

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

[36] This is consistent with the findings in Robinson and Sensoy (2011) that fund age and calendar time (quarterly) fixed effects explain less than 8% of the aggregate PE cash-flow variation.
[37] Thus, although the sample correlation between the residuals is -0.19, its value is stochastic over the simulated samples.
[38] See also a discussion in Section 3.

month 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 1 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 2013, this placebo exit is truncated so that the forward mean return is computed over at least 4 months. Hence, some of the funds post 2003 vintage will tend to have notably fewer than 100 placebo exits. The results are robust to dropping these funds (untabulated).

The log (inverse-probit) transformation in the first step insures that simulated stopping-times (*Rush*) are all positive (between 0 and 1). Although consistency of the third step will not depend on whether the distribution of actual stopping-times and *Rush* are close to the simulated ones, it is useful to examine this question as it may affect inference. Figure B.1 reports comparisons of univariate distributions and bivariate relations of actual stopping-times and *Rush* (Actual Funds) vis-a-vis those of placebo exits (Simulated Funds) for a simulated sample. It appears that simulated bivariate distributions tend to have more weight in tails which is unlikely to bias-down the parameter variance estimates.

Third, I compare how subsequent *Industry Returns* associate with *Rush* of actual funds of interest (denoted by *Informed*-dummy) as opposed to that in placebo exits corresponding to these funds via Model 6 (*main model*): $E[IndustryReturn_{ij,1:12}] = \beta Informed_{ij} Rush_{ij} + \gamma_1 Informed_{ij} + \gamma_2 Rush_{ij} + a_j$. The panel subscript j denotes a given actual fund ($Informed_{ij} = 1$) and the placebo exits($Informed_{ij} = 0$) corresponding to this fund. In Section 4.4.2 I study different groups of actual funds, subsetting the control group accordingly each time (rather than re-simulating it).

My estimation is asymptotically equivalent to the following just-identified *Simulated Method of Moments*:

$$
\begin{aligned}
E\Big[Z1_j\Big(StopTime_j - f(fund\,characteristics, performance, fundraising; \theta_t)\Big)\Big] &= 0 \\
E\Big[Z2_j\Big(Rush_j - g(fund\,characteristics, performance, fundraising; \theta_r)\Big)\Big] &= 0 \\
E\Big[Z3_{ji}\Big(IndER(\theta_{t,r},\Sigma) - \boldsymbol{\beta} TreatRush(\theta_{t,r},\Sigma) + \gamma_1 Treat + \gamma_2 Rush(\theta_{t,r},\Sigma) + FundFE\Big)\Big] &= 0 \qquad \text{(B.1)} \\
E\left[\begin{pmatrix} StopTime(\theta_{t,r},\Sigma)_{ji} \\ Rush(\theta_{t,r},\Sigma)_{ji} \end{pmatrix} \perp FundFE(j)\right] &= 0 \\
E\left[\begin{pmatrix} StopTime(\theta_{t,r},\Sigma)_{ji} \\ Rush(\theta_{t,r},\Sigma)_{ji} \end{pmatrix}\begin{pmatrix} StopTime(\theta_{t,r},\Sigma)_{ji} \\ Rush(\theta_{t,r},\Sigma)_{ji} \end{pmatrix}' \perp FundFE(j)\right] &= W_2(\Sigma,1)
\end{aligned}
$$

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) $FundFE$ 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: $\big(StopTime_j - E_j[StopTime]\big)$ and $\big(Rush_j - E_{j)}[Rush]\big)$;

(vi) $StopTime(\theta_{t,r},\Sigma)$, $Rush(\theta_{t,r},\Sigma)$ – simulated values of stopping-time and *Rush* under the parameters θ_t, θ_r and Σ, equal to the sample stopping times and *Rush* for the actual funds: $StopTime_j$ and $Rush_j$;

(v) $IndER(\theta_{t,r},\Sigma)$ – mean *Industry Return* over 12 quarters following the stopping month according to $StopTime(\theta_{t,r},\Sigma)$ and fund j inception month.

B.2. Robustness

Although consistency of moment-based estimations does not depend on distributional assumptions (provided the moment restrictions are valid), simulating stopping-time and rush-amount shocks from a randomly drawn covariance matrix is important for correct inference in such a situation. One way to think of this procedure is that it allows for error-term heteroskedasticity and clustering under Model 6, which is certainly possible 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.[39]

To insure that β 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 Model (6) over 1,000 samples of identical data for actual funds augmented with different simulated pseudo exits (henceforth *independent simulation*).

The estimates (confidence intervals) for β that I report in Tables 4 and 5 in the main text and in Figures B.2 and B.3A are (based on) equally weighted means of β_s ($avar(\beta)_s$) over these 1,000 *independent simulation*.[40] In essence, I run Fama-Macbeth (1973) procedure which is asymptotically equivalent and typically as efficient as panel Least-Squares methods.[41]. While the aggregation of point estimates is standard, my choice for the variance reflects the fact that β-estimates across our *independent simulation* must be perfectly correlated asymptotically.[42,43]

Besides β and the asymptotic variance-based confidence interval, Figure B.2 plots the range for β_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 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.

Figure A.3 plots *Industry return* ranges by exit year (Panel A) and by-vintage distribution of funds with $TTR > 1$ (Panel B). It motivates a question if our timing skill estimates might be solely driven by a few clusters of funds or exits. In each chart/panel of B.2, Case 1 corresponds to the baseline estimates of β (as reported in Table 4B). Cases 2 through 10 in Panel A exclude the following (groups of) vintage years: 1993 – 1992 – 1990 – 2001 – 1993&1992 – 1990&2001 – 1990&1993&2001 – 1990&1992&2001 –

[39] Note that similar ideas underlie imputations via the Gibbs sampler and some Bayesian inference methods.
[40] Each $avar(\beta)_s$ estimate is robust to error clustering at exit quarter.
[41] See Skoulakis (2008)
[42] A GLS version of Ferson and Harvey (1999) yields almost identical point estimates in the cases I reviewed (untabulated).
[43] This variance estimator can also be viewed as obtained through a parametric bootstrap, e.g. see Efron and Tibshirani (1994).

1990&1992&1993&2001. In Panel B, cases 2 through 10 add the following year dummies: 2007 – 1999 – 2000 – 2008 – 2007&1999 – 2000&2008 – 2000&2007 – 2000&2007&1999 - - 2000&2007&2008 – 2000&2007&1999&2008. The estimates are virtually unchanged across all cases in both panels. Hence, the results are not driven by a few calendar clusters.

Next, in Figure B.3 Panel A I examine how the predictability changes when I assign non-native *Industry returns*. For each month I compute 5-year rolling pairwise correlations for 10 GICS sectors portfolios so that for each fund-month the Industry portfolios are ranked by correlation proximity to the native-industry (Case 1). Clearly, if the effect I estimate has to do with GPs' expertise, the strongest predictability should be with respect to the native industry. That is what we observe for both threshold specifications, 15 and 20% on left and right charts respectively. The coefficients decay towards zero almost monotonically.

Finally, I seek to address concerns about the parameter-dependence of the null hypothesis that the estimation features. Panel B of Figure B.3 plot β estimates over *independent simulations* when actual fund stopping month and *Rush* are replaced by 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 C 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 4B, but somewhat higher for the 20% threshold case where with asymptotic variance estimate we can reject at 10% level.

There is not much subjectivism with the simulation framework I propose. Once could have simply taken covariance matrix of stopping-times and *Rush* (rather than residuals) to parametrize the simulations and end-up having near-uniform bivariate distribution which would make a_j fixed effects pointless (beyond controlling for the fund inception date). The only way one can shrink this covariance matrix is by including relevant covariates that nonetheless leave enough within-variation to identify the coefficients of interest in the *main model*. By the same line of arguments, it is not that important whether we neglect possible endogenity in the *auxiliary model* since the covariance of residuals shall pick it up.

The suggested estimation approach is highly attractive computationally and immediately yields convenient model diagnostics and null hypothesis verification tools. They all suggest good finite sample properties of the β and $var(\beta)$ estimates reported in Section 4.4.2 of the main text.

B.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 (i.e. logistic) instead of a mixture of normals that my simulations imply. Even though the interpretation of coefficients would be less intuitive as in Model 6, it may be worth close consideration given its wide usage and well developed asymptotic properties.[44]

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 (unlike OLS that I run).[45] Finally, by-passing 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 even for the stopping-times that do not exceed the actual.[46] The discussion in Section 3 suggests high importance of the variation in *Rush* for timing signal extraction and so do the findings in Robinson and Sensoy (2013, 2016).

[44] The dummy *Informed* and mean *Industry Return* would have to switch sides since the dependent variable needs to be binary.
[45] For example, see Wooldrich (2002).
[46] 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.

Table B.1. The Model of Fund Fixed Effects for *Stopping-time* and *Rush*

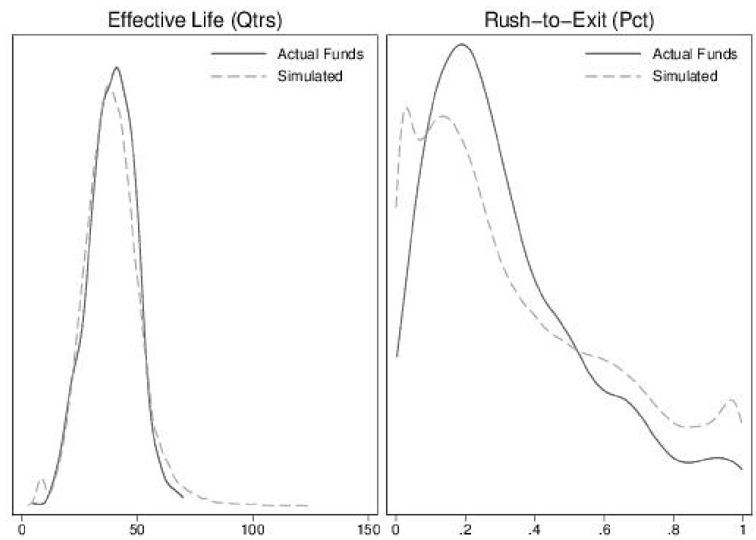
This table reports a model of funds' stopping-time and rush amounts estimated as *S*eemingly *U*nrelated *R*egressions for all funds in my sample. The dependent variables are (1) the natural logarithm of number of quarters since the fund's inception when a threshold of the NAV to total distributions 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; *PME-to-date* – Kaplan-Schoar PME against S&P500 subindex corresponding to the fund GICS Industry sector specialty; *TopTercl IRR-to-date* – dummy that equals 1 if the fund IRR is in the top tercile over the fund-type×vintage-year peers; *Follow-on Raised* – dummy that equals 1 if at least one more fund by the same GPs have started investments 2 years after the current fund inception date; *Follow-on w/n 6 qtrs* – dummy that equals 1 if another fund by the same GPs starts investments within 6 quarters from the current fund stopping-quarter; *Follow-on CapCalled* – capital called by the last-most follow-on fund by GPs as a fraction of committed (0 if no follow-on exists); *Industry-Year FE* – the fund specialty GICS industry-sector×vintage-year fixed effects. I include two observations per fund where 15% and 20% thresholds were not crossed simultaneously and the resulting stopping-times are different. This the *auxiliary model* to obtain the fitted values of "fund fixed effects" (with respect to the stopping times and rush amounts) and parametrize random exit simulations (via the covariance matrix of *SUR* residuals) – see section 4.2 and Appendix B for discussions and details. */**/*** denote significance at 10/5/1%.

	$ln(Stopping-time)$		$\Phi^{-1}(Rush)$	
	Coefficient	SE	Coefficient	SE
$ln(Size)$	0.017***	(0.006)	−0.092***	(0.023)
PME-to-date	−0.036***	(0.004)	0.128***	(0.016)
TopTercl IRR-to-date (d)	−0.165***	(0.014)	−0.151***	(0.052)
Follow-on Raised (d)	−0.056**	(0.024)	0.122	(0.086)
Follow-on w/n 6 qtrs (d)	−0.110***	(0.021)	0.143*	(0.075)
Follow-on CapCalled (%)	0.063***	(0.016)	−0.054	(0.057)
Industry-Year FE	Yes		Yes	
Observations	1242			
R^2	0.442		0.132	

Figure B.1. Actual Exits versus Simulated

This figure reports comparisons of stopping-times (*Effective Life*) and fractions of distributions over 6 quarters preceding it in the fund total distributions to-date (*Rush-to-Exit*) for actual and simulated exits. The simulation proceeds as follows. I draw a sample of 100 random bivariate normal shocks from a covariance matrix that is itself randomly drawn each time from Wishart distribution parametrized by the the covariance matrix of residual $ln(stopping-time)$ and $\Phi^{-1}(Rush)$ from the *fund fixed effect* model reported in Table B.1. The sample correlation between the residuals is -0.19. The same shocks are merged to each fund-threshold in the sample. Adding fund specific estimates of expected $ln(stopping-time)$ and $\Phi^{-1}(Rush)$ and reverting the functional transformations, I obtain simulated (i.e. placebo) values of stopping-time and *Rush* for each fund 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. Panel A reports kernel density estimates of *Effective Life* (left-hand chart) and *Rush-to-Exit* with solid (dashed) line being a separate estimate over the actual (simulated) values. Panel B plots local polynomial regressions estimates of *Effective Life* and *Rush-to-Exit* relations for actual and simulated values on the left- and right-hand charts respectively.

Panel A: Univariate Distributions



Panel B: Bivariate Relations

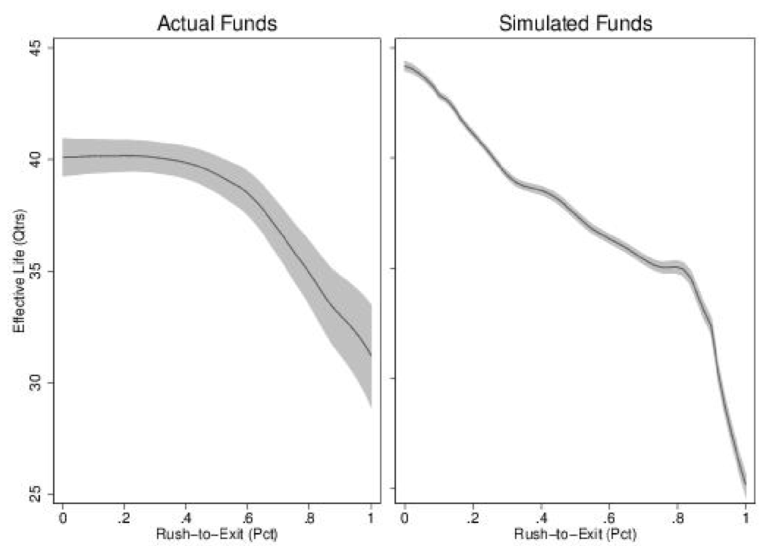
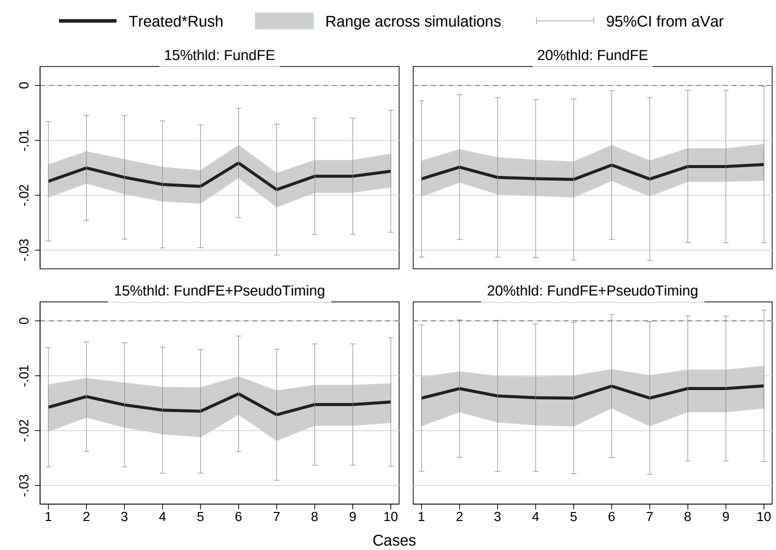


Figure B.2. Robustness

This figure reports robustness tests for the simulation-based estimates of predictive regressions of *Industry returns* by *Rush* reported in Table 4A. Top-left (right) and bottom-left (right) correspond to specifications 1 (2) and 3 (4) respectively. In both panels, *Case 1* corresponds to the baseline estimates of β tabulated in 4A. 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: ’93 – ’92 – ’90 – ’01 – ’93’92 – ’90’01 – ’90’93’01 – ’90’92’01 – ’90’92’93’01. While in Panel B, *Cases 2 through 10* include all vintages but augment the model with a dummy denoting the actual fund stopping-quarters falling in the following years: ’07 – ’09 – ’00 – ’08 – ’07’09 – ’00’08 – ’00’07 – ’00’07’09 – ’00’07’08 – ’00’07’09’08.

Panel A: Exclude Selected Vintage Years



Panel B: Dummy-out Selected Exit Years

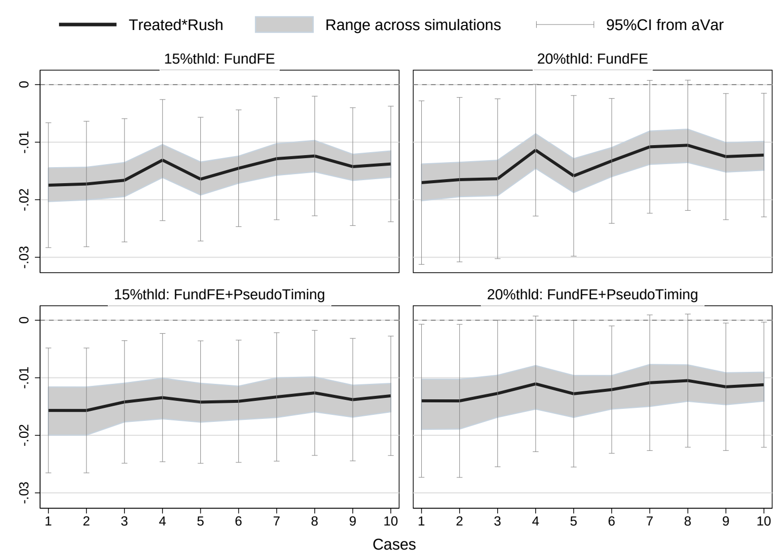
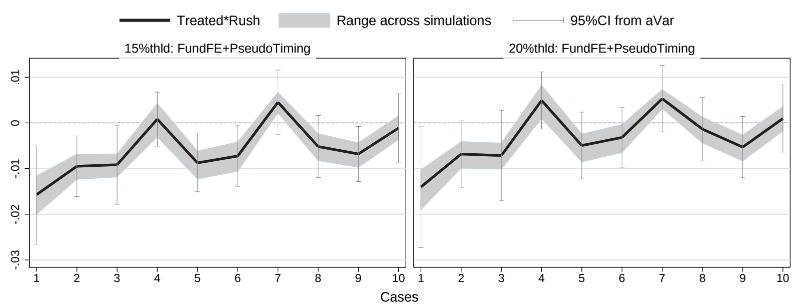


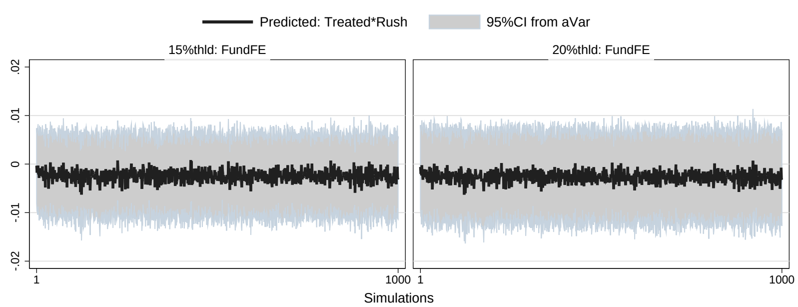
Figure B.3. Placebo Tests

This figure reports placebo tests for the simulation-based estimates of predictive regressions of *Industry returns* by *Rush* reported in Table 4. Left (right)-hand charts correspond to specification 3(4). *Case 1* of Panel A corresponds to the baseline estimates of β tabulated in Panel A of Table 4. *Cases 2 though 10* replace the fund native GICS industry sector returns, as measured by S&P500 subindex, with those of the correlation proximity-ranked sector so that 10 corresponds to the sector with the lowest correlation of monthly returns over the 5-year rolling window as of the actual stopping-quarters. 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. Panel B plots β estimates and 95% confidence intervals over these *independent simulations* if the actual funds stopping-times and distributions were replaced by the expected ones from the *fund fixed effect* model reported in Table B.1. Panel C plots the fraction of placebo exits that have t-statistic lower than that of the actual funds by each *independent simulation* (100 bivariate draws) as well as the mean value across them.

Panel A: Proximity-ranked Industries



Panel B: Fund Fixed-Effect Predictions



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