Do Private Equity Managers Have Superior Information on Public Markets?

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Abstract

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

I. Introduction

Although private equity (PE) funds invest in private companies, their investment outcomes crucially depend on public capital markets: A fund's entry or exit valuation is affected by comparable public market prices, regardless of whether the transaction is public. Prior research shows that PE managers (general partners (GPs)) change the policies of both investee companies and the industries in which they operate (see, e.g., Bernstein, Lerner, Sorensen, and Strömberg (2016)) and that GPs vigorously respond to changes in market conditions (see, e.g., Axelson, Jenkinson, Strömberg, and Weisbach (2013)). Relatively little is known, however, about how informed GPs are regarding the valuations of public equities. Amid the growing evidence that GPs' control over PE fund cash-flow schedules extracts

agency benefits (see, e.g., Robinson and Sensoy (2013)), it remains poorly under-stood whether the fund investors also benefit from this distinctive feature of PE contracts. Because GPs oversee dozens of companies as active board members and specialize in certain types of businesses, the timing of entry and exit decisions based on this informational advantage (relative to public market prices) could create value for their fund investors.

This article shows that GPs do appear to learn important private information about the valuation of certain public equities and that the potential gains to fund investors from delegating fund investment timing to GPs are substantial. For the typical PE fund, the contribution from the timing of the industry-valuation cycle to the lifetime total return is as large as the contribution from holding the asset. Using the Burgiss sample of 941 U.S.-focused buyout and venture funds incepted between 1979 and 2006, I show that an interquartile increase in the rate of funds' distributions to investors predicts approximately 6% lower 12-month returns for the fund's primary S&P 500 sector incrementally to other predictors. I develop a simple and robust fund-level metric of a GP's timing track record that conveys valuable information about a fund's future propensity to exit close to industry highs. For tighter control of variation in exit conditions, I conduct simulations showing that this predictability vanishes outside GPs' industries of specialization and relates to the industry earnings news.

Indirect anecdotal and survey evidence is consistent with the market-timing ability of PE managers.[1] To date, however, there has been no direct support for superior information-based market timing by GPs. Ball, Chiu, and Smith (2011) conclude that venture GPs simply react to market conditions; Lerner (1994), Kaplan and Strömberg (2009), and Guo, Hotchkiss, and Song (2011) do not attempt to disentangle superior information-based market timing from reacting to entry/exit conditions, time-varying expected returns, and causal effects of PE activities on public company valuations. Acharya, Gottschalg, Hahn, and Kehoe (2013) and Jenkinson, Morkoetter, and Wetzer (2018) also do not examine this channel with deal-level samples.

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

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

The first contribution of this article is, then, novel systematic evidence of successful market-timing actions by PE GPs that are important for the price and allocative efficiency of capital markets (à la Asriyan, Fuchs, and Green (2017)). To identify this channel, I make use of PE contractual design. PE funds differ from other forms of delegated asset management in the near absence of control that PE fund investors (limited partners (LPs)) have over the timing of investments and divestments.[2] This PE contract feature allows me to disentangle GPs' superior information channel from alternative explanations, such as time-varying exit conditions and causal effects of PE on public companies. The intuition behind my tests is similar to that in the literature on private information-based self-selection in the insurance industry (Chiappori and Salanie (2000)). Although my main tests assume that the shifts in GPs' personal wealth exposure do not pertain to the alternative explanations, I take advantage of PE institutional settings to scrutinize this assumption. In particular, I run placebo tests that examine industry returns following PE exits that are comparable in size and style but happen well before or after the carry cash-out date. Hence, these placebo exits do not have a "relief from exposure" effect on the GPs' wealth. I provide extensive robustness tests that include regression discontinuity with funds' to-date performance as a forcing variable.

Identifying GPs' market-timing skill is one thing; whether LPs should care about this insight is another. LPs might ignore this timing altogether because their allocations to equities (and specific sectors within equities) can remain unchanged if they adjust their public equity holdings accordingly.[3] Given this argument, the literature on PE fund performance has focused on evaluating abnormal *holding-period returns*, that is, in comparison to similarly timed public market investments (see, among others, Kaplan and Schoar (2005), Ang, Chen, Goetzmann, and Phalippou (2018), and Stafford (2017). If the valuation ratios that GPs buy (sell) at merely reflect periods of high (low) risk premia commanded by similar investments, the incrementally higher returns from these deals represent a *normal* compensation to LPs for incurring a greater disutility from risky investments. Alternatively, GPs' market-timing decisions, as manifested by PE cash-flow patterns, could create a valuable option for fund LPs, as long as GPs' decisions reflect superior information not already embedded in market prices. In other words, the literature has remained unclear on whether LPs benefit from GPs' market timing.

Regarding this lack of clarity, my second contribution is evidence that ceding cash-flow rights to GPs *does* create economic value for fund LPs and constitutes an important dimension in the PE manager-selection process. I show that an industry-level long-short trading strategy implemented based on the signal from PE fund

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

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

distributions generates 80 basis points (bps) per quarter in the Fama–French 3-factor alpha and 0.3-higher annualized Sharpe ratios. Industry-level market timing must then create value for LPs even when total equity allocation remains constant. Therefore, some investors with PE portfolios can enhance their overall portfolio performance using the information that other investors do not have in real time.[4] These results justify using total returns to quantify variation in skill across GPs (Korteweg and Sorensen (2017)). Insofar as successful market timing by GPs increases the fund total return and produces useful information, the results of this article potentially explain the attention that LPs continue to pay to GPs' ability to generate total returns (Da Rin and Phalippou (2017)), in addition to the market-adjusted performance.

Finally, by demonstrating the pivotal effect of in-the-money carry for GPs' market-timing decisions, this article contributes to studies of the effects of investment manager compensation schemes on performance (see, e.g., Brown, Harlow, and Starks (1996)). In the PE context specifically, whereas Hüther, Robinson, Sievers, and Hartmann-Wendels (2020) document that differences in carry rules affect fund returns ex ante, my results speak to the dynamic effects thereof. Market-timing actions yield a good setting for examining this question because the counterfactual outcome is relatively well observed. My analysis also highlights why LPs cannot gain much from timing their commitments to PE funds, as recently shown by Brown, Harris, Hu, Jenkinson, Kaplan, and Robinson (2021). GPs' timing of fund cash flows significantly attenuates the effect of contractual start and end times.

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

Although my GP market-timing measure is very much in the spirit of the Grinblatt and Titman (1993) measure that naturally decomposes into the broad market, industry, stock specific, and so forth, I zoom at the industry level. On the one hand, my data do not permit a comparable asset of a finer granularity than the industry level. On the other hand, the presence of market-wide timing is eclipsed by the industry timing (gross of broad market) because, as discussed previously, such

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[4]There is a 3- to 9-month delay in the revelation of PE fund cash flows to data vendors. Thus, such a PE signal-based allocation strategy is feasible for LPs with representative enough portfolios managed by skilled GPs whose incentives can be discerned relatively well.

[5]Some exceptions include Griffin and Xu (2009), who, using 13F data, find that hedge funds exhibit no ability to pick sectors, and Chen and Liang (2007), who, using a statistical model similar to that of Henriksson and Merton (1981), find that self-described market-timing hedge funds outperform public-information–based strategies.

GP-induced changes to LP portfolios generate value even if LPs partially undo the effects by reinvesting proceeds in public equities. The preponderance of evidence suggests that, on average, GPs' broad market timing is a watered-down industry timing. Besides the long–short strategy performance results, I show that i) the predictability is 0 against the industries that comoved with the fund's focal industry the least, and ii) the predictability in the focal industry relates to its future earnings news rather than variations in the discount factors.

Why would GP market timing relate to the industry's future earnings? Ben-David, Birru, and Rossi (2019) find that corporate executives (i.e., "insiders") earn abnormal returns in trading stocks that belong to the industry of their employer and that this is likely due to better interpretations of public news about that industry (see also Kacperczyk, Sialm, and Zheng (2005), Bradley, Gokkaya, and Liu (2017)). This is one mechanism, albeit not unique to PE funds, that can explain my findings. Another (yet complementary) mechanism relates to GPs' high involvement in planning and tracking the operational performance of their investee companies.[6] It is plausible, albeit hard to corroborate with direct anecdotes, that GPs filter valuable signals from such real-time and less biased cash-flow projections from the management of dozens (hundreds) of related companies they oversee (confidentially screen).

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

Between the data description and concluding remarks, the main analysis in this article is organized in 2 interconnected blocks: Sections III and IV. The first block provides descriptive evidence consistent with market-timing actions by GPs. The second block distinguishes the superior information channel from alternative explanations. The tests in the second block can be viewed as the conditional holdings analysis of Ferson and Khang (2002), whereas the first block features the unconditional counterpart thereof. Supportive materials are organized in Appendix A and the Supplementary Material, and Appendix B summarizes key variable definitions.

II.   Data

PE data for this study are obtained from Burgiss. The data set is sourced from approximately 300 LPs that collectively have made over 20,000 commitments to private capital funds, and it includes their complete cash-flow and valuation histories. Harris, Jenkinson, and Kaplan (2014) compare several PE data sets and conclude that the Burgiss data set is representative of the buyout and

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[6]See, for example, "What Private-Equity Strategy Planners Can Teach Public Companies," McKinsey & Company, Oct. 2016. The attention to up-to-date projections is high in the not-for-control transaction as well: A typical term sheet requires the investee company to provide annual operating plans, updated monthly, even when the GPs do not receive a board seat (see, e.g., Lerner, Leamon, and Hardymon (2012)).

venture funds' investable universe. The data set maintains confidentiality by removing all names.

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

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

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

For public equity returns, I utilize S&P 500 Global Industry Classification Standard (GICS) subindexes, which map directly to the classification in the Burgiss data and represent benchmarks that are widely followed by practitioners. Burgiss reports GICS for 881 out of 942 in my sample. For the unclassified funds (most of which are buyout funds), I assign "Industrials" as the industry focus. Results are similar if I use S&P 600 subindexes, the small-capitalization stocks. Panel A2 of Table 1 reports the distribution of my fund sample by GICS and vintage-year group. Panel B reports the summary statistics for monthly returns, price-to-earnings ratio, and book-to-market ratio from Jan. 1989 through Sept. 2014 for respective S&P 500 subindexes. Additionally, for each fund, I observe a dummy (but not the underlying scores) indicating whether the declared industry comprises more than 50% by value of the actual investments made by the fund. Only 59% of my sample funds have such concentrated portfolios (untabulated). This does not imply, however, that the remainder of funds have investments spread over more than 2–3 industries.

TABLE 1

Summary Statistics

Table 1 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 Mar. 2013. OVERALL_SEQ and IND_SEQ report the fund chronological order of the inception date within general partner (GP) and GP industry, respectively, or 0s when the fund's GP affiliation is not available (≈15% of sample funds). VINTAGE denotes the year of fund inception. IRR is the internal rate of return. PME is the Kaplan and Schoar (2005) public market equivalent index, computed using the S&P 500 subindex corresponding to the GICS sector of the fund specialization. Panel B reports statistics for monthly returns and the price-to-earning and book-to-market ratios of these subindexes for the period Jan. 1989–Oct. 2013. Panel C reports statistics for the rest of the variables used in this study. See Appendix B for definitions.

Panel A1. Private Equity Funds

Variable	Mean	Std. Dev.	P1	P5	P25	P50	P75	P95	P99
Buyout									
OVERALL_SEQ	3.0	2.7	0.0	0.0	1.0	2.0	4.0	9.0	12.0
IND_SEQ	2.1	1.7	0.0	0.0	1.0	2.0	3.0	6.0	8.0
VINTAGE	1996	5	1982	1986	1994	1997	2000	2003	2005
LIFE (quarters)	48	11	20	30	41	48	55	65	81
FUND_SIZE ($millions)	745	955	25	60	160	400	910	2920	5000
IRR	0.165	0.227	−0.195	−0.077	0.060	0.130	0.225	0.488	1.017
MONEY_MULTIPLE	13.32	181.21	0.52	1.00	1.69	2.28	3.44	8.69	51.92
PME	1.34	0.87	0.26	0.48	0.87	1.24	1.63	2.48	3.08
Venture									
OVERALL_SEQ	3.1	2.8	0.0	0.0	1.0	2.0	4.0	9.0	13.0
IND_SEQ	2.7	2.5	0.0	0.0	1.0	2.0	4.0	6.0	11.0
VINTAGE	1993	6	1980	1982	1987	1994	1999	2001	2003
LIFE (quarters)	49	11	23	33	42	49	56	68	78
FUND_SIZE ($millions)	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	1.38	1.69	0.13	0.32	0.62	0.99	1.45	3.68	10.22

Panel A2. Funds Sample by Industry and Vintage Year

	1979–1983	1984–1986	1987–1989	1990–1992	1993–1994	1996–1998	1999–2001	2002–2006	Total
Consumer discretionary	6	7	6	7	19	30	32	9	116
Consumer staples	0	1	1	0	2	3	7	1	15
Energy	0	0	1	1	0	3	3	1	9
Financials	3	2	5	1	8	12	14	2	47
Health care	5	11	21	15	25	39	32	8	156
Industrials	16	28	37	15	17	31	31	9	184
Internet technology	27	35	39	20	48	83	95	9	356
Materials	0	0	1	0	1	4	2	1	9
Telecommunications	2	2	4	4	6	13	17	1	49
Utilities	0	0	0	0	1	0	0	0	1
Total	59	86	115	63	127	218	233	49	942

Panel B. Industry Benchmark Returns and Ratios

	Returns		Book-to-Market Ratio				Price-to-Earnings Ratio		
	Mean	Std. Dev.	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
Health care	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	Std. Dev.	P1	P5	P25	P50	P75	P95	P99
MARKET_RETURN	0.95	4.53	−10.21	−7.42	−1.74	1.54	3.92	7.53	10.20
CAY	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_TO_AAA	0.98	0.40	0.55	0.60	0.73	0.90	1.14	1.44	3.00
AAA_TO_UST	1.33	0.48	0.49	0.72	0.91	1.31	1.70	2.11	2.53
10Y_UST	5.45	2.04	1.68	2.01	3.96	5.28	7.09	8.86	9.26
3M_UST	3.56	2.46	0.02	0.04	1.13	4.14	5.33	7.64	8.43
IND_EPS_SUR	0.02	0.77	−1.43	−1.22	−0.59	0.03	0.62	1.29	1.56
IND_FRW_MULTΔ	−0.01	0.83	−1.66	−1.37	−0.61	−0.05	0.58	1.47	1.71

Summary statistics for other variables of interest are reported in Panel C of Table 1. These include equity return predictive covariates (see Appendix B). The panel also reports summary statistics for IND_EPS_SUR and IND_FRW_MULTΔ, which denote, respectively, the industry aggregate difference in reported earnings from the analyst forecast and the change in the ratio of price to "forecasted earnings." Both variables are computed by Bloomberg from the median 12-month analyst forecasts for the S&P 500 GICS subindex.

III.   Suggestive Evidence

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

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

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

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

Specifically, I define (the effect of GPs') market timing as the excess return that an outside investor would attain if he or she bought and sold an *identical company* at the *same times* as the fund GPs made capital calls and distributions. The tightest definition of an *identical company* that my data allow is the portfolio of public firms in the same industry. To the extent that GPs' informational advantage dissipates beyond the area of fund specialty, a poor match of industry (as the

identical company proxy) will act against finding robust results. Conversely, finding results to be stronger with benchmarks less related to the funds' areas of expertise would point to explanations other than private information flow in PE.

A. Market-Timing Metric

Consistent with the previously given definition of market timing, I propose a measure of gross return over a fund's life due to selling at market highs and buying at lows. Computationally, it is similar to the PME of Kaplan and Schoar (2005). However, the *timing track record* (TTR) measures the component of the fund's total returns that PME explicitly disregards:

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(1) \quad \text{TTR} = \overline{\text{PME}}/\text{PME} = \frac{\sum_{t=0}^{T} D_t \times \exp\{r_{1:T} \times (1 - t/T)\}}{\sum_{t=0}^{T} C_t \times \exp\{r_{1:T} \times (1 - t/T)\}} \Bigg/ \frac{\sum_{t=0}^{T} D_t \times \exp\{r_{t+1:T}\}}{\sum_{t=0}^{T} C_t \times \exp\{r_{t+1:T}\}}
$$

$$
= \underbrace{\frac{\sum_{t=0}^{T} C_t \times \exp\{r_{t+1:T}\}}{\sum_{t=0}^{T} C_t \times \exp\{r_{1:T} \times (1 - t/T)\}}}_{\text{EntryTiming}} \times \underbrace{\frac{\sum_{t=0}^{T} D_t \times \exp\{r_{1:T} \times (1 - t/T)\}}{\sum_{t=0}^{T} D_t \times \exp\{r_{t+1:T}\}}}_{\text{ExitTiming}},
$$

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

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

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

Consider two funds, A and B, that start at the same time with $30 in committed capital and have up to 2 years to invest. Both funds liquidate in the fourth year. Assume that neither fund has company selection or nurturing skill and earns exactly the market rate of return on investments, so PME = 1.0 for both funds. However, fund A chooses to draw capital in equal installments over 3 years, whereas fund B, having correctly anticipated a market downturn in year 2, draws less capital initially:

Entry-Timing Example

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

Although both funds have PME of 1, fund B creates potentially more value to its LPs than fund A: 1.81 versus 0.55. This is reflected in a higher $\overline{\text{PME}}$ and thus a higher TTR for fund B. In this way, TTR measures market timing by the managers of fund B.

The money multiple (i.e., $\sum D_t / \sum C_t$) is an absolute performance metric widely utilized by practitioners and would reflect the difference in returns to LPs from funds A and B. The money multiples of A and B are 1.02 and 1.06, respectively. In this example, they equal to TTRs because the cumulative market return is 0 and the PME of each fund is unity. This is, however, almost never true in practice because the market trends over fund lives and the funds' holding-period excess returns vary.

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

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

$$(2) \qquad \ln(\text{TTR}) = \ln(\text{MM}) - \ln(\text{PME}) - \bar{r} \times \text{FUND\_DURATION}.$$

The Supplementary Material derives equation (2) and shows its equivalence to equation (1).

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

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

Finally, although a level of 1 is a natural reference, the realized TTR can also be compared with a TTR derived from a hypothetical cash-flow schedule between the dates that the fund was active. It is also evident that, insofar as capital calls and distributions span changes in the portfolio weights, TTR can be viewed as a particularly scaled measure of covariance between the holding weight change and the subsequent return, as in Grinblatt and Titman (1993).

B.   Empirical Analysis of Timing Track Records

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

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

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

1.   Relations with Fund Characteristics

Table 2 reports regression results of TTRs computed against the fund's focal industry on GP characteristics that proxy for institutional quality (e.g., Kaplan and Schoar (2005), Robinson and Sensoy (2016)). Fund size is positively related to end-of-life TTR, whereas the size squared loads negatively. However, coefficients on

FIGURE 1

Timing Track Records: Univariate Analysis

Figure 1 summarizes the distributional properties of the sample timing track records (TTRs), which measure a fund's gross return due to selling near the market peaks and buying near the troughs. The left (right) side of Graph A shows the frequency distributions of TTRs for buyout (venture) funds using the complete history of the fund cash flows. Lines and text indicate the sample means and a 2-sided test for their equality to 1 (i.e., the null hypothesis of no abnormal returns due to timing; ** and *** indicate statistical significance at the 5% and 1% levels, respectively). Graph B reports the variance decomposition of end-of-life money multiples adjusted for the trend in the industry into the selection (as measured by log PME) and timing as measured by log TTR. "Full Sample" indicates all funds (buyout and venture); the other 3 columns report results by subsample based on the relative rank of the fund's public market equivalent (PME) within fund type (venture or buyout) and vintage year. Graph C breaks down the variation in TTR into 2 sources, entry and exit (per equation (1)), similarly for the full sample and subsamples. Table 1 describes the sample, and Appendix B defines the variables.

Graph A. TTRs by Fund Type

Graph B. Variance Decomposition of Funds' Total Returns

Graph C. Variance Decomposition of Funds' TTRs
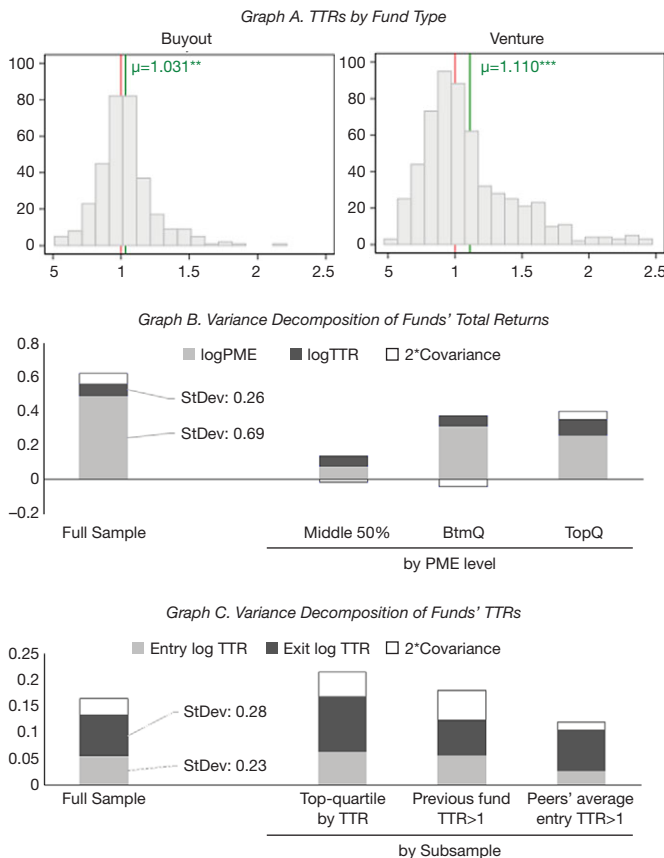
size become insignificant when temporal variation is controlled for via vintage-year fixed effects, as per specification 2. According to specifications 1–3 and 6, TTR positively relates to the fund's ordinal sequence in a given GP × INDUSTRY. This indicates that funds run by GPs with more experience in the industry tend to better navigate industry peaks and troughs.

The positive coefficients on PME in specifications 3, 5, and 6 of Table 2 corroborate the variance decomposition analysis discussed previously. Funds with a higher PME also tend to be better at timing the industry-valuation cycles, even when the inception year and other covariates are controlled for. This pattern may

TABLE 2

Timing Track Records: Associations and Persistence

Table 2 reports regression estimates of the log of funds' end-life timing track records (TTRs) on a set of fund/general partner (GP) characteristics. TTR measures the gross return due to selling near the market peaks during the fund lifetime and buying near the troughs. Table 1 describes the sample, and Appendix B defines key variables. The explanatory variables are all in logs: FUND_SIZE (FUND_SIZE_SQ), the size (size squared) of the fund dollar amount of capital committed; IND_SEQ, the chronological order of the fund inception date within same the GP and industry; and PME, the fund's Kaplan and Schoar (2005) public market equivalent (PME); PREV_FUND_TTR, the GP's previous fund TTR. Specifications 2–6 include fund vintage fixed effects. Table IA-3 in the Supplementary Material reports additional specifications and robustness. Standard errors in parentheses are clustered by GP. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	1	2	3	4	5	6
FUND_SIZE	0.515***	0.082				
	(0.162)	(0.150)				
FUND_SIZE_SQ	−0.014***	−0.003				
	(0.004)	(0.004)				
IND_SEQ	0.057***	0.049***	0.040**			0.055**
	(0.021)	(0.018)	(0.017)			(0.024)
PME			0.040***		0.059***	0.054***
			(0.015)		(0.020)	(0.020)
PREV_FUND_TTR				0.135**	0.115**	0.107**
				(0.052)	(0.051)	(0.049)
Vintage-year fixed effects	No	Yes	Yes	Yes	Yes	Yes
No. of obs.	756	756	756	404	404	404
R^2	0.025	0.387	0.386	0.431	0.449	0.457

arise as a result of a number of reasons that are not mutually exclusive. First, very few bottom-quartile funds attain a high enough absolute return for GPs to receive carried interest. Consequently, these GPs have little incentive to avoid a reduction in the funds' asset values. Second, the selection and nurturing skill (that PME encompasses) can genuinely relate to GPs' knowledge of the industry, which enables successful timing of its cycles as well. It is also possible that PMEs pick up the effects of inherent market-timing decisions that do not trigger fund-level cash flows. These could be mergers and acquisitions by the fund's portfolio companies that did not require new equity injections from the fund. Specifications 4–6 show a positive relation between a GP's previous and current funds' TTRs. This indicates that timing ability is persistent at the GP level.

In the Supplementary Material, I report robustness and falsification tests for the results in Table 2 and the univariate analysis reported earlier. Specifically, Panel A of Table IA-3 in the Supplementary Material reports similar regressions but with additional control variables that proxy for possible measurement errors in TTRs. The results are largely unchanged from those in Table 2. Panel B of Table IA-3 reports analysis based on simulated fund cash flows under various assumptions about individual fund risk (as indicated by the subpanel headers) while keeping the fund start dates and the industry returns fixed to the actually realized values. The key takeaways from this analysis are described next.

The average fund delivers 70%–80% of the feasible gains from timing (measured by the interdecile range of simulated TTRs). The unconditional probability that a fund's TTR will exceed that of a random cash-flow schedule is 52%–53%. Even though neither of these magnitudes strikes as very large economically, each one is statistically different from 50%. As for the multivariate relations reported in Table 2, none holds with the simulated TTRs on average across replications.

Perhaps the only exception is the coefficient on PME, which came back at 0.02–0.03 with a *t*-statistic of 1.5 in simulations. Although both are a factor of 2–3 smaller than with the actual fund TTRs and PMEs, I conduct additional analysis in the Supplementary Material. It shows i) a positive association between TTRs and PMEs in settings that are more robust to risk heterogeneity and fund-life overlaps and ii) weaker associations of TTR with PME computed against the broad market and with the fund's ordinal sequence unconditionally on industry.

Just like PME, TTR can be computed on a to-date basis by assuming a particular date to be the last and the NAV as of that date to be a liquidating distribution. Graph A of Figure 2 compares such interim TTRs (measured at the fifth anniversary) with the final TTRs for the funds that operated for at least 9 years. Importantly, the mean market return for $\overline{\text{PME}}$ computation is also date specific, so no information beyond that date is utilized. It appears that funds with good TTRs as of midlife tend to further improve it by the end of their lifetime.

To preclude a spurious correlation between the interim and final values of TTR, Graphs B and C of Figure 2 plot the growth in TTR after the fifth year on the *y*-axis. Graph B limits the sample to funds with net-of-fees IRR exceeding the hurdle rate as of the fifth anniversary, whereas Graph C covers the complement set. The charts reveal a positive relation between the interim and final TTRs when GPs' option to receive the fraction of fund assets is in the money (Graph B) and a negative to flat relation when incentives for GPs are less well aligned (Graph C). However, the relation is mostly flat among funds with a TTR above 1, suggesting that the variation in magnitude is less predictive than the sign of its log.
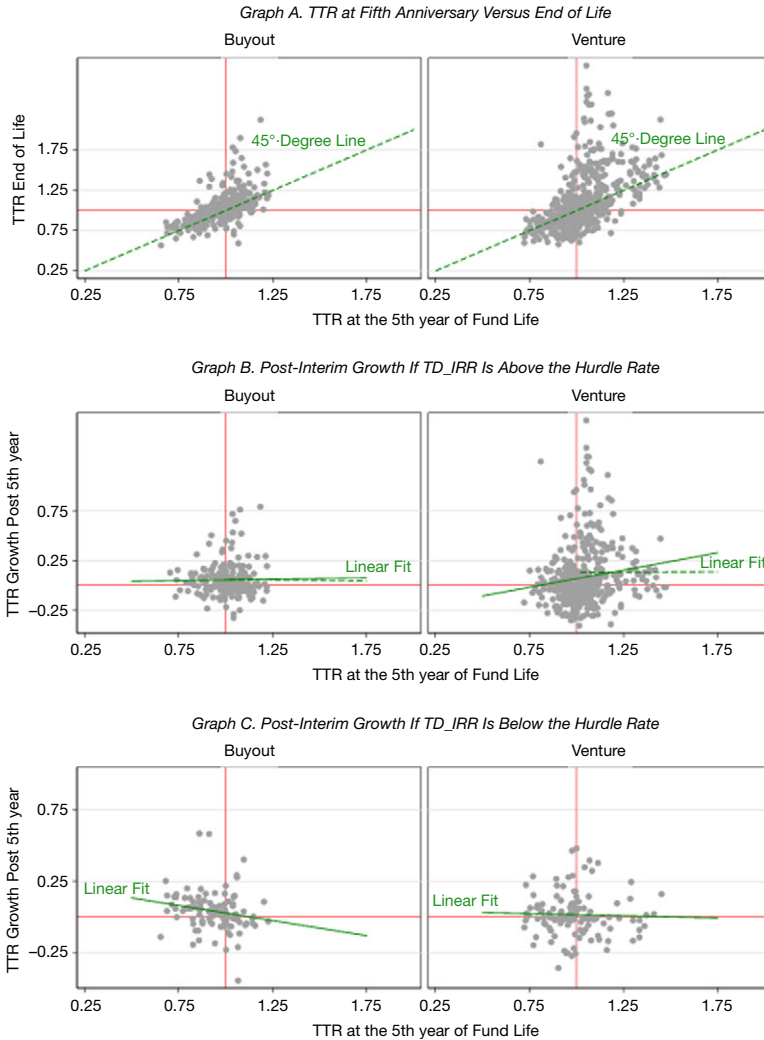
2.   Entries Versus Exits

I now examine the entry and exit contribution to the fund's overall TTR, as implied by equation (1). I begin with the variance decomposition of log TTR in Graph C of Figure 1. To preclude a mechanical relation between exit and entry TTRs, I measure $r_{1:T}$ over the first 6 years for computing the entry TTR and start with the fourth year in computing the exit TTR. The graph shows that the exit TTR has a higher variance than the entry TTR and that the covariance between the two is positive. The graph also shows that the covariance is larger for funds with higher overall TTR in the current vintage and higher previous fund TTRs, but it is smaller when the average vintage peer exhibits good entry timing.

In untabulated analyses, I find that the average entry TTR is just below 1, at 0.997 (0.982) for venture (buyout) funds, as opposed to being statistically greater than 1 for both subsamples with regard to exits (1.071 on average). Table 3 reports multivariate analyses of these TTR components.[8] Specifically, in Panel A (B), I regress the log of entry (exit) TTR on the overall to-date TTR as of the fund's fifth anniversary and other variables. I examine the relations with the indicator for whether the declared industry comprises more than half of the fund investments (DECLARED_IND>50%; see Section II), the peers' average entry (exit) log TTR,

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

FIGURE 2

Sample Fund TTRs: Fifth Anniversary Versus Final

Figure 2 compares the sample funds' TD_TTR as of the fifth year since inception with their end-of-life timing track records (TTRs) (Graph A) and reports the post–fifth-year growth conditional on the fund's fifth-anniversary internal rate of return (IRR) being above (below) the hurdle rate (8% for buyouts and 0% for venture funds) in Graph B (Graph C). TTR measures funds' gross return due to selling near the market peaks and buying near the troughs. Table 1 describes the sample, and Appendix B defines the variables. Results are reported separately by buyout and venture subsamples in, respectively, the left-hand-side and right-hand-side plots.

Graph A. TTR at Fifth Anniversary Versus End of Life

Graph B. Post-Interim Growth If TD_IRR Is Above the Hurdle Rate

Graph C. Post-Interim Growth If TD_IRR Is Below the Hurdle Rate

and the indicator for whether the GP had an overall TTR greater than 1 in the previous fund (PREV_FUND_TTR>1).

The regressions reveal several interesting patterns. First, both entry and exit TTRs strongly and positively relate to the overall TTR, even if measured at a fund's midlife, with the coefficient being nearly twice as high for the entry case. Second, the portfolio concentration in the primary industry positively associates with both

TABLE 3

Timing Track Records: Entry Versus Exit

Table 3 reports regression estimates of the log of funds' entry timing track records (TTRs) in Panel A and exit TTRs in Panel B on a set of fund/general partner (GP) characteristics. TTR measures the gross return due to selling near the market peaks during the fund's lifetime and buying near the troughs, which can be broken down to the entry (exit) components due to the pattern of capital calls (distributions), as shown in equation (1). Table 1 describes the sample, and Appendix B defines key variables. The explanatory variables are as follows: TTR_5Y, the log of overall fund to-date TTR measured as of the end of the fifth year since inception; DECLARED_IND>50%, a dummy taking the value of 1 if a single industry represents more than 50% of the fund investments made during its lifetime, and 0 otherwise; PEER_TTR, the log of the average entry TTR in Panel A (exit TTR in Panel B) computed across the fund's strategy × vintage peers (excluding the fund itself); and PREV_FUND_TTR>1, a dummy taking the value of 1 if the GP's previous fund TTR exceeded 1, and 0 otherwise. Specifications 4–6 include fund vintage fixed effects. Standard errors in parentheses are clustered by GP. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	1	2	3	4	5	6
Panel A. Entry TTRs						
TTR_5Y	0.685***					
	(0.067)					
DECLARED_IND>50%		0.024*			0.012	0.019
		(0.014)			(0.010)	(0.012)
PEER_TTR			0.946***			0.710***
			(0.032)			(0.109)
PREV_FUND_TTR>1				−0.038**		−0.026*
				(0.015)		(0.015)
Vintage-year fixed effects	No	No	No	Yes	Yes	Yes
No. of obs.	941	941	886	802	941	756
R^2	0.237	0.002	0.582	0.564	0.559	0.594
Panel B. Exit TTRs						
TTR_5Y	0.398***					
	(0.067)					
DECLARED_IND>50%		−0.004			0.026*	0.029*
		(0.018)			(0.014)	(0.016)
PEER_TTR			0.953***			0.237**
			(0.063)			(0.111)
PREV_FUND_TTR>1				0.014		0.014
				(0.019)		(0.019)
Vintage-year fixed effects	No	No	No	Yes	Yes	Yes
No. of obs.	941	941	884	802	941	754
R^2	0.057	0.000	0.261	0.497	0.474	0.505

components, although the relation is statistically weak and not robust to vintage-year fixed effects (specifications 4–6). For exit TTR, vintage fixed effects turn the coefficient from 0 to significantly positive. For entry TTR, vintage fixed effects attenuate the previously significant positive coefficient on DECLARED_IND>50%. Interestingly, vintage fixed effects also have a different effect on the magnitude of the very strong association between the fund's entry and exit track records with those of its peers. For entry, the coefficient attenuates from 0.946 to 0.71, much less so than it does for exits, from 0.953 to 0.237. Finally, the correlation with the past fund TTR indicator is only weakly positive for the exit TTR and actually negative for the entry TTR. This result stands in contrast to the strongly positive relation for the overall TTRs reported in Table 2, which also holds with the dummy-variable definition. These patterns are consistent with a fund entry TTR being stronger associated with vintage-year and peer characteristics than its exit TTR, perhaps reflecting tighter contractual constraints on GPs with regard to investing of funds' capital in comparison to divesting of funds' assets. Investment period start and duration are subject to less discretion by GPs than are the individual

investments' holding periods. Nevertheless, it appears that both exit and entry TTRs are complementary indicators of GPs' timing skill.

It is noteworthy that the DECLARED_IND>50% dummy reflects GPs' discretion about how much to concentrate investments in the fund's focal industry. Therefore, another interesting angle is the dummy's relation with the difference between TTRs computed against the focal industry and that against the broad market returns. This analysis is reported in Table IA-5 in the Supplementary Material and suggests that funds with more concentrated portfolios deliver 1.5%–3% higher entry TTRs if measured against the industry benchmark. However, this relation is not statistically significant among venture funds. It is also attenuated for exit TTRs, as follows from Panel B of the table. The panel suggests that venture funds are unconditionally better at timing their industry peaks (rather than market-wide peaks) if vintage fixed effects are accounted for. Given that the carry role is more salient in venture fund compensation (see, e.g., Chung, Sensoy, Stern, and Weisbach (2012)), these results point to the potential importance of carry-related incentives for exit timing, as do the post-interim trends in TTR depicted in Figure 2. Section IV explores the incentives margin in great detail.

IV.   Detecting Superior Information

I begin by reviewing explanations for TTR exceeding 1 and persisting that do not imply value creation by GPs. I then develop and conduct tests that detect superior information-based market timing regardless of whether these alternative explanations hold.

A.   Identification Challenge

First, fund cash flows may simply reflect the broad market and industry conditions for entry and exit. Schultz (2003) shows that mean reversion coupled with a decision rule of issuing after a market's run-ups is observationally similar to informed trading. Pástor and Veronesi (2005) model "rational IPO waves," whereby issuance varies endogenously as a function of market conditions without any overreactions by investors or differences in signal precision. Following Ball et al. (2011), I refer to this alternative as *pseudo-timing.* Although pseudo-timing can be implemented without the costly intermediation of a GP, it can also generate utility losses to LPs. In a portfolio-choice framework featuring both types of risky assets (liquid and illiquid), pseudo-timing by GPs commands a higher expected return on the PE portfolio (Ang, Papanikolaou, and Westerfield (2014), Bollen and Sensoy (2016)). This happens because consumption can only be financed with liquid wealth, and such contra-cyclical PE cash-flow patterns increase (reduce) the weight of illiquid wealth in states of high (low) marginal utility. It therefore can be argued that delegating cash-flow timing rights to GPs offers little benefit if pseudo-timing is all they do.[9]

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[9]Because LPs know their liquidity needs better, co-investing strictly dominates committing to commingled funds. See N. Munk, "Rich Harvard, Poor Harvard" (*Vanity Fair*, Aug. 2009) and A. Ang, "Liquidating Harvard" (Columbia Business School case study). For certain LPs, even

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

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

We also know that the current fund's profit is not the only objective that GPs maximize (Metrick and Yasuda (2010), Chung et al. (2012)), and fund distributions can be a signaling device. In particular, PE funds often "rush" to make distributions from a current fund to mitigate reputational concerns with LPs and secure a follow-on fund (i.e., to "grandstand," as per Gompers (1996)). Although this grandstanding alternative should actually counteract pseudo-timing in aggregate, it induces heterogeneity in cash-flow patterns across funds because some GPs experience less pressure to make premature distributions. Therefore, the variation across fund TTRs, as well the by-GP and within-fund persistence in TTRs reported in Section III, could be explained by a combination of pseudo-timing and grandstanding.

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

1.   Ideal Setup

To test for the presence of superior information-based market timing, I utilize differences in the *propensity to deploy* this skill (or information) due to shifts in contractual incentives to GPs. The differences are induced by the fund to-date performance, which reflects a great deal of luck (Korteweg and Sorensen (2017)), and the finite-life feature of the PE fund contract. The idea can be conveyed via the following diagram that depicts a dilemma faced by the GPs of a fund that has

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pseudo-timing may create value, however, provided that it does not jeopardize the holding period returns (see Section 3.1 of the Supplementary Material). These LPs are, for some reason, unable to implement such countercyclical investment strategies at a lower (than hiring a PE GP) overall cost.

already deployed its capital. These predictions arise from a standard setup for optimal stopping under uncertainty, a brief review of which is given in the Supplementary Material.

Do You Want to Rush Your Fund's Exits?

Market Outlook Fund Return to Date	Negative	Positive
Above hurdle rate	**Yes**	Not as much
Below hurdle rate	Not as much	Not as much

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

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

$$(3) \quad \text{MARKET\_RETURN}_{i,t+1} = \gamma \mathbb{I}(\text{EXIT})_i + \alpha \mathbb{I}(\text{EXIT}|\text{IRR\_ABOVE\_HR})_i \\ + \mathbb{E}[\text{MARKET\_RETURN}_{i,t+1}|\text{PUBLIC\_DATA}_t] + e_{i,t+1},$$

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

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

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

$$
\begin{aligned}
\text{(4)} \quad \text{MARKET\_RETURN}_{i,t+1} = {}& \boldsymbol{\gamma} \mathbb{I}(\text{EXIT})_i \\
& + \boldsymbol{\alpha} \mathbb{I}(\text{EXIT}|\text{IRR\_ABOVE\_HR}, \text{SKILL})_{i,t-1} \\
& + \boldsymbol{\alpha_1} \mathbb{I}(\text{EXIT}|\text{IRR\_ABOVE\_HR})_i \\
& + \alpha_0 \mathbb{I}(\text{EXIT}|\text{SKILL})_{i,t-1} + \mathbb{E}_t^P[\text{MARKET}_{i,t+1}] + \varepsilon_{i,t+1}.
\end{aligned}
$$

Controlling for the proxy of GP skill increases the estimates' efficiency because the variance of $\varepsilon_{i,t+1}$ should be lower than that of $e_{i,t+1}$ from the model in equation (3) if the proxy is indeed relevant. In addition, this specification provides for a nested test of whether all PE exits are informative conditional on aligned incentives (i.e., $\boldsymbol{\alpha_1} < 0$ so as $\boldsymbol{\alpha}$) and absorbs the variation in exiting times due to GP heterogeneity via coefficient α_0. The latter can emerge as a result of grandstanding, as discussed in Section IV.A, whereby less reputable GPs might be forced to markedly divest the current fund before raising a new one.

In tests for adverse selection in the insurance industry setting, omitted heterogeneity is a potent concern because it can correlate with *both* ex ante choices and ex post outcomes. I argue that applying the same identification idea to PE exits mitigates such concerns markedly because it is hard to see how predetermined characteristics of GPs may predict public market returns. Meanwhile, conditional on the change in a GP's market outlook relative to the current valuations, the prediction for a higher rush to exit holds regardless of how risk averse the GP is.

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

2. Feasible Proxies

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

In practice, a PE fund-distribution process spans many years via dozens of installments, and it often is never fully completed with respect to a small fraction of assets (see the Supplementary Material for details). I therefore approximate the $\mathbb{I}(\text{EXIT})_i$ indicator with a continuous variable that reflects a fraction of the fund distributions that occurred shortly before the fund assets became *small* in

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

[11]In addition to using net IRR level as a proxy for accrued carry (see Section II for discussion).

comparison to the fund total distributions to date (henceforth, SR_TIME, short for "Substantially Resolved"). The fraction is closer to 1 (0) when most of the fund divestments took place on the eve of (long before) SR_TIME. Hence, it measures the extent to which GPs were "rushing" to exit ahead of that quarter. The chart that follows provides the intuition for how the combination of this rush and SR_TIME maps to $\mathbb{I}(\text{EXIT})$.
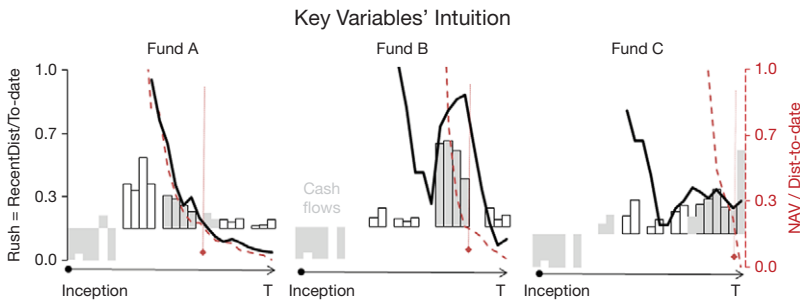
The bars in the chart indicate cash flows for 3 hypothetical funds. Capital calls are negative, followed by a positive distribution toward the end of contractual life (T). The dashed lines indicate the ratio of fund NAVs to the total distributions to date, with values reported on the right-hand side of the y-axis. When this ratio is high (only values below 1 are plotted), the remaining exposure to the market is large relative to the already "harvested" amount. Subsequent distributions reduce this exposure for the fund and, hence, for GP carry. The quarters in which these ratios cross 15% are marked with a vertical arrow line and indicate SR_TIME, that is, when remaining exposures become inconsequential for the fund lifetime results. In this example (and in the actual tests), I use a 6-quarter window to compute RUSH, plotted with a solid black line.[12] Accordingly, the distributions that contribute to the numerator of RUSH as of SR_TIME are highlighted in gray, whereas the distributions indicated with white bars only contribute to the denominator of RUSH (i.e., total distributions to date).

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

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[12]I find similar magnitudes with 4- and 8-quarter windows. This approach reduces differences between exit-venue choices (i.e., trade sale vs. IPO). See the Supplementary Material for more discussion. For NAV thresholds, I examine a range between 5% and 25% and report tests for 15% and 20%. Because the funds are nearly fully resolved, possible NAV manipulations are unlikely to meaningfully affect the measurement.

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

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

B.   Test Results

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

1.   Informed Rush Versus Uninformed

Table 4 reports feasible estimates of the models in equations (3) and (4) via the following regression:

$$(5)\qquad \text{IND\_RET}_{ij}^{1:12} = \alpha \times \text{INFORMED}_{ij}\text{RUSH}ij + \gamma_0 \times \text{INFORMED}_{ij}$$
$$+\gamma_1 \times \text{RUSH}_{ij} + \text{CONTROLS}_{ij} + \varepsilon_{ij},$$

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

INFORMED$_{ij}$ is a dummy that denotes the fund group of interest. In Panel A of Table 4, these are funds that satisfy both TD_TTR > 1 and TD_IRR > HR at SR_TIME, as coded by the interaction of the respective dummies. Funds that don't satisfy either of the criteria are considered "uninformed" and serve as the control group. Hence, the identifying assumption in this setup is that informed exits have the *same* footprint-on-firms, as do uninformed exits.

Panel A of Table 4 shows that the main parameter of interest, the coefficient on the interaction between INFORMED and RUSH (also referred to as *informed rush*), α, is significantly negative across all specifications. The magnitude of α indicates how much lower of a monthly return is expected if informed rush increases from 0 to 1. The interquartile range for RUSH of approximately 0.3 translates into a return that is 0.3% to 0.7% lower per month for 12 months.

The magnitude of α estimates is about twice as large in specifications 1 and 2 of Table 4 as compared with those in specifications 3 and 4, indicating that substantial variation in informed rush could be explained by publicly observable signals about

TABLE 4

Informed Rush Versus Uninformed

Table 4 reports predictive regressions of the industry returns by informed rush, a proxy for the carried interest "cashed in" by general partners (GPs) with a positive track record of market timing in the past:

$$\mathbb{E}\left[\text{IND\_RET}_{ij}^{1:12}\right] = a \times \text{INFORMED}_{ij} \times \text{RUSH}_{ij} + \gamma_0 \times \text{INFORMED}_{ij}$$
$$+ \gamma_1 \times \text{RUSH}_{ij} + \beta c_i + \lambda_j,$$

where $\text{IND\_RET}_{ij}^{1:12}$ is the mean monthly industry return over 12 months following the fund i SR_TIME, and RUSH_{ij} measures the intensity of the fund's distributions to limited partners (LPs) right before. Table 1 describes the sample, and Appendix B defines key variables. In Panel A, INFORMED_{ij} is a single indicator variable denoting funds with both TD_TTR > 1 and TD_IRR>HR as of SR_TIME based on a 20% (15%) residual net asset value (NAV) threshold in even (odd) specifications. In Panel B, INFORMED_{ij} is a set of 3 indicator variables: for TD_TTR>1 and TD_IRR>HR separately, and the interaction thereof. Panel C examines the interaction of the informed fund definition from Panel A with the fund's portfolio actual industry concentration: DECLARED_IND>50%P takes the value of 1 if a single industry represents more than 50% of the fund investments made during its lifetime, and 0 otherwise. In all panels, specifications 3 and 4 include predictive covariates (c_i) in addition to the vintage-year fixed effects (λ_j). Standard errors in parentheses are robust to heteroscedasticity and autocorrelation. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Table IA-6 in the Supplementary Material reports inference results using other methods. Table IA-2 reports placebo tests.

	Threshold			
	15%	20%	15%	20%
	1	2	3	4
Panel A. INFORMED≡TD_TTR>1×TD_IRR>HR				
TD_TTR>1 × TD_IRR>HR × RUSH	−0.025***	−0.023***	−0.013***	−0.013**
	(0.007)	(0.008)	(0.005)	(0.005)
TD_TTR>1 × TD_IRR>HR	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)
Predictive Covariates				
IND_CAR			−0.219	−0.224
			(0.306)	(0.276)
IND_PE			−0.005**	−0.005**
			(0.002)	(0.002)
IND_BM			−0.037***	−0.023**
			(0.013)	(0.011)
CAY			0.549***	0.521***
			(0.132)	(0.123)
CBOE_VIX			0.040	0.036
			(0.028)	(0.028)
BAA_TO_AAA			0.009	0.009
			(0.007)	(0.007)
AAA_TO_UST			−0.030***	−0.029***
			(0.006)	(0.005)
10Y_UST			−0.009***	−0.010***
			(0.002)	(0.002)
3M_UST			−0.003***	−0.003**
			(0.001)	(0.001)
Vintage-year fixed effects	Yes	Yes	Yes	Yes
No. of obs.	894	942	893	941
R^2	0.218	0.234	0.446	0.464
Panel B. INFORMED ≡ TD_TTR>1 × TD_IRR>HR + TD_TTR>1 + TD_IRR>HR				
TD_TTR>1 × TD_IRR>HR × RUSH	−0.031**	−0.024**	−0.022**	−0.021***
	(0.013)	(0.011)	(0.010)	(0.008)
TD_TTR>1 × RUSH	0.006	0.001	0.008	0.004
	(0.009)	(0.006)	(0.008)	(0.006)
TD_IRR>HR × RUSH	0.001	0.001	0.004	0.009
	(0.009)	(0.009)	(0.007)	(0.007)
TD_TTR>1 × TD_IRR>HR	−0.002	−0.004	0.006*	0.005
	(0.004)	(0.004)	(0.003)	(0.003)
TD_TTR>1	−0.000	0.002	−0.002	−0.000
	(0.003)	(0.003)	(0.003)	(0.002)

TABLE 4 (continued)

Informed Rush Versus Uninformed

Panel B. INFORMED ≡ TD_TTR>1 × TD_IRR>HR + TD_TTR>1 + TD_IRR>HR (continued)

TD_IRR>HR	0.002 (0.003)	0.004 (0.003)	−0.003 (0.003)	−0.003 (0.003)
RUSH	0.002 (0.006)	0.000 (0.006)	0.003 (0.006)	0.001 (0.005)
Controls	Same as in the respective column of Panel A			
No. of obs.	894	942	893	941
R^2	0.064	0.064	0.446	0.466

Panel C. Interaction with Portfolio Composition, INFORMED ≡ TD_TTR>1 × TD_IRR>HR

DECLARED_IND>50% × INFORMED × RUSH	−0.004 (0.012)	−0.004 (0.014)	−0.002 (0.009)	−0.001 (0.010)
INFORMED × RUSH	−0.022*** (0.008)	−0.020** (0.009)	−0.012* (0.006)	−0.012* (0.007)
DECLARED_IND>50% × RUSH	0.004 (0.006)	−0.003 (0.006)	0.003 (0.005)	−0.003 (0.006)
DECLARED_IND>50% × INFORMED	0.004 (0.004)	0.005 (0.005)	0.004 (0.003)	0.003 (0.004)
INFORMED	−0.000 (0.003)	−0.000 (0.004)	0.001 (0.002)	0.001 (0.003)
DECLARED_IND>50%	−0.003 (0.002)	−0.002 (0.002)	−0.003 (0.002)	−0.001 (0.002)
RUSH	0.002 (0.005)	0.004 (0.005)	0.005 (0.004)	0.008 (0.005)
Controls	Same as in the respective column of Panel A			
No. of obs.	893	941	892	940
R^2	0.219	0.237	0.447	0.466

expected returns (and/or exit conditions predictive of returns). This fact suggests that GPs tend not to distribute capital back to LPs when observables point to elevated risk premia (consistent with the results of Robinson and Sensoy (2013)). Nonetheless, as follows from specifications 3 and 4, the exit decisions by skilled and incentivized GPs contain a significant component that appears to be missing in the public information set.

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

Panel C of Table 4 examines whether the return predictability strengthens when the actual portfolio of the fund is more concentrated in the focal industry, as suggested by the exit TTR analysis in Table 3. I interact the INFORMED dummy as defined for Panel A with a dummy indicating whether the focal industry comprises more than 50% of the actual investments made by the fund. The panel shows that

RUSH by incentivized and skilled GPs with more concentrated portfolios is not more informative of the future return in the focal industry than similar RUSH by holders of more dispersed portfolios. The coefficients on RUSH interactions with DECLARED_IND>50% are negative but far from being statistically significant, individually or jointly.[13]

I carefully examine the sensitivity of inference to different types of dependency in ε_{ij}. I follow Conley (1999) in modeling the spatial correlation between the return intervals arising from the proximity of SR_TIME; I also cluster by vintage year, as in Kaplan and Schoar (2005), and in 2 dimensions simultaneously. As shown in Supplementary Material Table IA-6, i) the standard errors reported in Table 4 tend to be the largest, and ii) estimated αs remain negative at the 5% (or better) confidence level for each of the 7 inference methods considered.

Next, I scrutinize the claim that fund heterogeneity does not drive the results in Table 4. First, I examine if clustering of fund distributions at least a year away from SR_TIME also results in the predictability of industry returns. The alternative explanation (i.e., that the inherent heterogeneity across funds makes their distribution patterns potentially incomparable) predicts α to be different from 0 away from SR_TIME as well. However, these placebo tests, reported in Supplementary Material Table IA-2, reveal no statistically or economically significant coefficients.

Second, I implement the fuzzy regression discontinuity design with the fund distance of TD_IRR from the hurdle rate as a forcing variable. Naturally, the difference determines the assignment of the INFORMED indicator, whereas GPs have limited ability to manipulate performance via NAV reports when the funds are substantially resolved. Table IA-8 in the Supplementary Material reveals that the inclusion of the third-order polynomial of the forcing variable does not move the point estimate on α from -0.013 in specification 3 of Table IA-8 and barely increases the standard error estimate. Table IA-8 also shows that α estimates remain well within the baseline standard deviation when the sample heterogeneity is reduced. For example, when IRRs are within 2.5% from the hurdle, α is estimated at -0.011, although the standard error increases to 0.016 as the sample shrinks to just 108 funds. It is noteworthy that the carry approximation error embedded in my data should be particularly costly for the power in such discontinuity-based tests.

Third, I conduct event studies to mitigate price-distortion concerns. Figure 3 reports the cumulative industry returns around SR_TIME based on the 15% NAV threshold for funds with RUSH above the vintage-year median. The solid line represents the mean returns around informed exits, defined as satisfying both TD_TTR > 1 and TD_IRR > HR.[14]

Graph A of Figure 3 reports the results for the entire sample period, whereas Graph B shows that a clear difference remains even after excluding 2 years with particularly dramatic declines (2001 and 2008). The figure indicates that the

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[13]In an untabulated analysis, I find that DECLARED_IND>50% × RUSH has a *t*-statistic of -1.5 if used in place of the INFORMED dummy in equation (5).

[14]The sample median RUSH is 0.2. In total, 205 funds (i.e., just under a quarter of the sample) satisfy all 3 conditions: TTR > 1, IRR > HR, and RUSH > 0.2. The Supplementary Material shows that a regression analysis with a binary RUSH definition yields results very close to Table 4 and reports additional event studies.

FIGURE 3

Informed Rush and Industry Returns: Event Studies

Figure 3 plots the cumulative return on the industry portfolio around SR_TIME for funds with RUSH above vintage-year medians. RUSH measures the intensity of funds' distributions to limited partners (LPs) right before SR_TIME, based on a 15% net asset value (NAV) threshold. The medians are computed by fund type (venture or buyout) and vintage year. The solid line (informed rush) is the mean across funds that have incentives and market-timing skill, as measured by both td_TTR>1 and td_IRR>HR as of SR_TIME. The dashed line denotes all other funds. Graph A reports results for the full sample. Graph B excludes SR_TIME that occurred in 2001 and 2008. The bars denote 95% confidence intervals. Table 1 describes the sample, and Appendix B defines the variables.
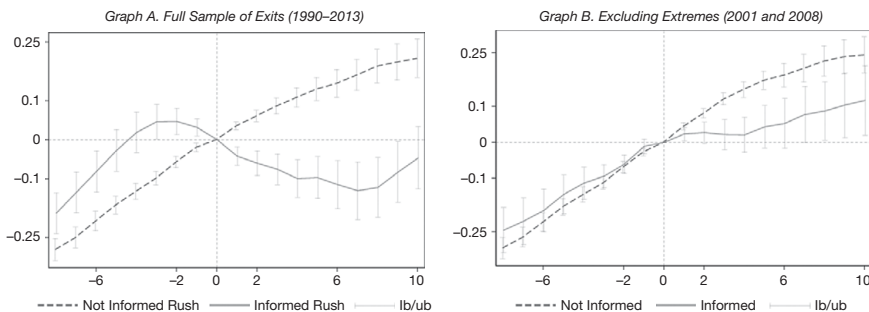
industry returns' dip following an informed rush does not revert back over the 10-quarter horizon. A reversion would be expected if the underperformance were driven by price distortion, whereby selling pressure was not followed by a deterioration in the industry fundamentals.

Finally, I run a calendar-time portfolio analysis with the fund industry sectors. Figure 4 and Supplementary Material Table IA-1 show that a quarterly rebalanced portfolio based on informed rush yields a statistically significant 80 bps per quarter over the Fama–French 3-factor model and 30%–40% higher annualized Sharpe ratios than those of the equal-weighted portfolio of industries. It is therefore highly unlikely that differences in future risk realizations across industries are responsible for the inference about α from the regression in equation (5). These results also prove that industry timing is more salient than market-wide timing, regardless of whether the portfolio of industries is value weighted or equal weighted.

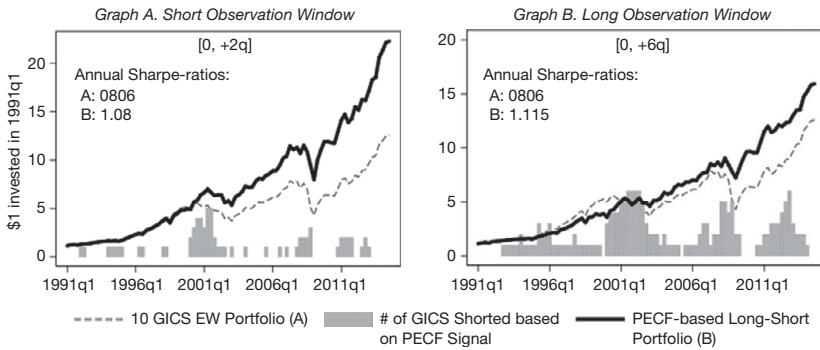## 2.   Informed Rush Versus Random

To obtain stronger evidence against the pseudo-timing alternative, I also estimate the regression in equation (5) with random (hypothetical) SR_TIME and RUSH as a control group. In particular, I seek to mitigate concerns that the residual variation in RUSH examined in Section IV.A.2 merely reflects nonlinear and interaction effects of predictive covariates.

I jointly model RUSH and SR_TIME and simulate multiple hypothetical exits for each actual fund.[15] The resulting permutations enable fund fixed effects that

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[15]The procedure is asymptotically equivalent to the simulated method of moments; accounts for the uncertainty of *auxiliary model* parameter estimates; and involves three steps: i) estimating a model of fund fixed effects for SR_TIME and RUSH, ii) independently simulating 1,000 blocks of 100 random exits per fund and estimating the main model (i.e., equation (5)) within each block, and iii) pooling the main-model estimates over these independent simulations. See the Supplementary Material for details.

FIGURE 4

Calendar-Time Portfolios: Cumulative Returns

Figure 4 compares cumulative returns and Sharpe ratios for two portfolios. Portfolio A is an equal weighted 10 S&P 500 Global Industry Classification Standard (GICS) sector portfolio. Portfolio B sells GICS sectors for which 2 or more informed funds exhibited above-median RUSH right before their SR_TIME over the past 3 or 7 quarters (i.e., [0, +2q] or [0, +6q] observation window, respectively) and buys the remaining sectors (equal weighted). Informed funds are funds with incentives and market-timing skill, as measured by both TD_TTR>1 and TD_IRR>HR as of SR_TIME, based on a 15% net asset value (NAV) threshold. RUSH measures the intensity of funds' distributions to limited partners (LPs) right before SR_TIME. The medians are computed by fund type (venture or buyout) and vintage year. Table 1 describes the sample, and Appendix B defines the variables. Supplementary Material Table IA-1 reports the abnormal return estimates of Portfolio B and B minus A against the Fama–French 3-factor model.

Graph A. Short Observation Window — [0, +2q]
Annual Sharpe-ratios:
A: 0806
B: 1.08

Graph B. Long Observation Window — [0, +6q]
Annual Sharpe-ratios:
A: 0806
B: 1.115

$1 invested in 1991q1

- - - - - 10 GICS EW Portfolio (A)   ▧ # of GICS Shorted based on PECF Signal   ——— PECF-based Long-Short Portfolio (B)

reflect a rich set of fund characteristics and the variation in exit conditions during the times they have operated (see Table A1). Because these absorb significant variation in risk premia over time, the inference should be less sensitive to the inclusion of predictive covariates and, hence, to the omission of some potentially relevant predictors.

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

To begin, Panel A of Table 5 shows what we could not learn when the control group comprised actual funds: whether aggregate PE distributions predict future industry returns unconditionally on GP incentives. Consistent with results in Ball et al. (2011), the coefficient on ACTUAL_FUND × RUSH, although negative, is economically small and statistically insignificant. However, the estimates in Panels B and C, in which I limit the actual fund groups to match the INFORMED dummy definitions used in Table 4, strongly support the presence of selection on superior information in PE fund exits.

As in Table 4, specifications 1 and 2 of Table 5 correspond to SR_TIME under the 15% and 20% thresholds for the fixed-effects-only model, whereas specifications 3 and 4 also include predictive covariates. Unlike in Table 4, the point estimates with predictive covariates included are very close to those with just the fixed effects: between 0.014 and 0.017 for α. This result means that the projections of fund fixed effects for SR_TIME and RUSH indeed absorb much of their

TABLE 5

Actual Rush Versus Random

Table 5 reports simulation-based estimates of predictive regressions of the industry returns by informed rush, a proxy for the carried interest "cashed in" by general partners (GPs) with a past track record of market timing:

$$\mathbb{E}\left[\text{IND\_RET}_{ij}^{1:12}\right] = \alpha \times \text{INFORMED}_{ij} \times \text{RUSH}_{ij} + \gamma_0 \times \text{INFORMED}_{ij}$$
$$+ \gamma_1 \times \text{RUSH}_{ij} + \beta c_i + \lambda_j,$$

where $\text{IND\_RET}_{ij}^{1:12}$ is the mean monthly industry return over 12 months following fund i's SR_TIME, and RUSH_{ij} measures the intensity of fund i distributions to limited partners (LPs) right before. Table 1 describes the sample, and Appendix B defines key variables. The estimation proceeds in 3 steps: i) Estimate a model of fund fixed effects for SR_TIME and RUSH (auxiliary model; Table A1), ii) independently simulate 1,000 blocks of 100 random exits per fund under the auxiliary model, and iii) pool the main-model estimates over these independent simulations. In all panels, the INFORMED_{ij} indicator equals 1 for actual funds and 0 for the simulated funds, even (odd) specifications report results for SR_TIME based on a 20% (15%) residual net asset value (NAV) threshold, and specifications 3 and 4 include predictive covariates (c_i) in addition to fund fixed effects (λ_j) that reflect expected SR_TIME and RUSH from the auxiliary model. Panel A includes all actual funds in the sample, along with the corresponding simulated funds. Panel B includes actual funds with both TD_TTR>1 and TD_IRR>HR and the corresponding simulated funds. Panel C includes actual funds with either TD_TTR>1 or TD_IRR>HR. Standard errors in parentheses are robust to heteroscedasticity and autocorrelation. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Threshold			
	15%	20%	15%	20%
	1	2	3	4
Panel A. INFORMED ≡ All Actual Funds				
ACTUAL_FUND × RUSH	−0.006	−0.007	−0.005	−0.005
	(0.004)	(0.005)	(0.005)	(0.004)
No. of actual funds	893	941	893	941
Pseudo-funds per 1 actual	95.0	94.3	94.9	94.2
Panel B. INFORMED≡TD_TTR>1×TD_IRR>HR				
TD_TTR>1 × TD_IRR>HR × RUSH	−0.017***	−0.017**	−0.016***	−0.014**
	(0.006)	(0.007)	(0.006)	(0.007)
No. of actual funds	373	387	373	387
Pseudo-funds per 1 actual	95.8	95.3	95.7	95.3
Panel C. INFORMED ≡ TD_TTR>1 + TD_IRR>HR + TD_TTR>1 × TD_IRR>HR				
TD_TTR>1 × TD_IRR>HR × RUSH	−0.032***	−0.026**	−0.034***	−0.027***
	(0.012)	(0.012)	(0.010)	(0.010)
TD_TTR>1 × RUSH	0.008	0.002	0.012	0.005
	(0.009)	(0.007)	(0.007)	(0.006)
TD_IRR>HR × RUSH	0.006	0.007	0.006	0.007
	(0.005)	(0.007)	(0.005)	(0.006)
No. of actual funds	756	791	756	791
Pseudo-funds per 1 actual	83.4	82.5	83.3	82.4
Applies to Each Panel				
No. of independent simulations	1,000	1,000	1,000	1,000
RUSH, INFORMED(D)	Yes	Yes	Yes	Yes
Fund fixed effects	Yes	Yes	Yes	Yes
Predictive covariates	No	No	Yes	Yes

joint variation with pseudo-timing factors, alleviating the concerns of regression and factor misspecification.

I scrutinize the robustness and statistical properties of this simulation-based estimator. Specifically, I verify i) that α-estimates are largely insensitive and statistically robust to the exclusion of various permutations of vintage and exit years (see Figure A1), and ii) that although fitted values of the informed rush never predict returns, the actual size of the tests based on asymptotic standard errors is close to the nominal size (Graphs A and B of Figure A2). By contrast, in Graph C of Figure A2, I show that the return predictability vanishes for industries that did not correlate with the funds' primary industry in the recent past.

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

3. Predictability Sources

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

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

$$(6) \quad r_{t+1} - \mathbb{E}_t r_{t+1} = (\mathbb{E}_{t+1} - \mathbb{E}_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - (\mathbb{E}_{t+1} - \mathbb{E}_t) \sum_{j=1}^{\infty} \rho^j r_{t+1+j}$$

$$= N_{C,t+1} - N_{D,t+1},$$

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

Given GPs' potential involvement in the operational management of their portfolio companies and their special position in the capital market as firsthand observers of the portfolio demands of large public and private investors, both $N_{C,t+1}$ and $N_{D,t+1}$ can be at play. To account for the correlation between these sources of returns while maintaining the identification framework outlined in Section IV.A, I use 2-stage least squares (2SLS) to estimate the following equation:

$$(7) \quad \mathbb{E}\big[\text{RUSH}_{ij}\big] = \alpha^R \big[\text{INFORMED}_{ij} \quad \text{IND\_RET}_{ij}^{1:12} \times \text{INFORMED}_{ij} \quad \text{IND\_RET}_{ij}^{1:12}\big].$$

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

I use the industry unexpected earnings to proxy for $N_{C,t+1}$ and changes in the ratios of index values to the earnings forecasts to proxy for $N_{D,t+1}$. Both variables are computed from analyst estimates aggregated to the respective S&P 500 subindex (see Section II). Accordingly, the instruments' validity hinges on i) this proxy of cash-flow and discount-rate news being indeed related to the industry return realizations tightly enough and ii) RUSH being unrelated to cash-flow and discount-rate news through other channels.

Table 6 reports the results. First-stage regression results are summarized by the Kleibergen–Paap Wald test statistics, the levels of which suggest that the excluded

instruments are indeed relevant. All specifications include predictive covariates (Appendix B). Specifications 1 and 3 use the actual fund exits as a control group, corresponding to the approach in Table 4, whereas specifications 2 and 4 use hypothetical fund exits, as in Table 5.

In specifications 1 and 2 of Table 6, the excluded instruments are IND_EPS_SUR and its interaction with the INFORMED dummy, whereas IND_FRW_MULTΔ and its interaction with INFORMED are added to the first- and second-stage regressions, along with other covariates. Significantly negative coefficients of INFORMED × IND_RET indicate that skilled GPs foresee the industry cash-flow news that causes the industry returns to fall. These estimates suggest that the industry earnings surprise that triggers a 10% drop in the industry return causes a 25- to 38-percentage-point higher informed rush over the preceding 6 quarters.

Specifications 3 and 4 of Table 6 use the terms with IND_FRW_MULTΔ as excluded instruments while including IND_EPS_SUR in the set of other covariates. Hence, these tests show whether GPs foresee innovations in the discount rates that investors require beyond the variation in the industry earning news. Although the point estimates on INFORMED × IND_RET and IND_RET are negative according to specification 3, they are far from being significant statistically. Furthermore, these coefficients are not even negative (and still insignificant) according to specification 4, which uses hypothetical exits as the control group.

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

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

V.   Conclusion

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

My tests isolate GPs' likely superior information from reactions to time-varying market conditions and certain causal effects of PE activity spillovers on public firm policies. However, such informed trading by GPs is unlikely to go completely

TABLE 6

What Are GPs Informed About?

Table 6 reports instrumental-variable regression estimates of the following model:

$$\mathbb{E}\big[\text{RUSH}_{ij}\big] = \lambda_j^R + \beta c_{ij}^R + \alpha^R \Big[\text{INFORMED}_{ij}\text{IND\_RET}_{ij}^{1:12} \times \text{INFORMED}_{ij}\text{IND\_RET}_{ij}^{1:12}\Big],$$

where RUSH_{ij} is a fraction of distributions over the last 6 quarters in fund's i total to date, INFORMED_{ij} is an indicator for the presence of incentives and market-timing skill (both TD_TTR > 1 and TD_IRR > HR), IND_RET_{ij} is the mean monthly return on a publicly traded industry benchmark over 12 months following fund i's SR_TIME, and a_j^R represents the vintage-year fixed effects. Table 1 describes the sample, and Appendix B defines key variables. In specifications 1 and 2, the excluded instruments are IND_EPS_SUR and its interaction with the Informed dummy, whereas IND_FRW_MULTΔ and its interaction with the Informed dummy are added to the first- and second-stage regressions, along with predictive covariates and fund cohort fixed effects. Therefore, specifications 1 and 2 test whether general partners (GPs) foresee the industry cash-flow news and act accordingly. Specifications 3 and 4 treat the terms with IND_FRW_MULTΔ as excluded instruments while including IND_EPS_SUR in the set of other covariates, and they therefore test whether GPs foresee innovations in the discount rates at the industry level. IND_EPS_SUR and IND_FRW_MULTΔ are computed from 12-month earnings-per-share (EPS) forecasts for the respective S&P 500 Global Industry Classification Standard (GICS) subindex. Specifications 1 and 3 use other sample funds as the control group and fund-inception-year fixed effects, whereas specifications 2 and 4 use hypothetical fund exits as the control group (the pooled estimates across 1,000 simulations are reported; the methodology is described in Section IV.A.2 and the Supplementary Material). Standard errors in parentheses are robust to heteroscedasticity and autocorrelation. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Excluded Instrument:	IND_EPS_SUR		IND_FRW_MULTΔ	
	(1)	(2)	(3)	(4)
INFORMED × IND_RET	−3.825**	−2.465**	−1.194	0.846
	(1.733)	(1.042)	(2.968)	(2.569)
IND_RET	0.315	0.097	−1.517	0.300
	(1.249)	(0.228)	(1.842)	(0.343)
INFORMED	0.012	0.017	−0.032	−0.025
	(0.023)	(0.038)	(0.026)	(0.015)
Included instrument	IND_FRW_MULTΔ		IND_EPS_SUR	
Included instrument × 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 statistic	17.9	332.4	6.8	15.3
Observations	848	32,832	848	32,832
R^2 (# of simulations)	0.158	(1,000)	0.15	(1,000)

unnoticed by other investors. As a result, PE activities may increase the informational efficiency of the capital market, providing a channel for how private information becomes impounded into public market prices, as studied by Asriyan et al. (2017).

Appendix A. Simulation-Related Supplement

Appendix A provides the intuition about the simulation-based estimates reported in Section IV.A.2. Additional details and risk-shifting tests are reported in the Supplementary Material.

TABLE A1

Model of Fund Fixed Effects for SR_TIME and RUSH

Table A1 reports a model of funds' SR_TIME and RUSH amounts estimated as seemingly unrelated regressions (SURs) for all funds in my sample. The dependent variables are i) the natural logarithm of the number of quarters since the fund's inception when a threshold of the net asset value (NAV) to total distributions has been crossed from above (must be a quarter with nonzero distributions to limited partners (LPs)) and ii) 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 the same in both linear equations: $\ln(SIZE)_i$, the log of the fund capital committed; TD_PME, the Kaplan–Schoar public market equivalent (PME) computed with respect to the fund's focal industry returns; T3_TD_IRR, an indicator for whether the fund's internal rate of return (IRR) is in the top tercile among the fund type×vintage peers; FN_RAISED, an indicator for whether at least one more fund by the same general partners (GPs) has started investments 2 years after the current fund inception date; FN_IN6Q, an indicator for whether another fund by the same GPs starts investments within 6 quarters from the current fund SR_TIME; FN_CC, the fraction of capital called by the last-most follow-on fund by GPs as a fraction of committed (0 if no follow-on exists); and industry-year fixed effects, the fund industry-by-vintage fixed effects. I include 2 observations per fund where the 15% and 20% thresholds were not crossed simultaneously and the resulting SR_TIME is different. This is the auxiliary model to obtain the fitted values of fund fixed effects (with respect to SR_TIME and RUSH) and parametrize random exit simulations (via the covariance matrix of SUR residuals). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	$\ln(SR\_TIME)$		$\Phi^{-1}(RUSH)$	
	Coefficient	Standard Error	Coefficient	Standard Error
$\ln(SIZE)$	0.017***	(0.006)	−0.092***	(0.023)
TD_PME	−0.036***	(0.004)	0.128***	(0.016)
T3_TD_IRR	−0.165***	(0.014)	−0.151***	(0.052)
FN_RAISED	−0.056**	(0.024)	0.122	(0.086)
FN_IN6Q	−0.110***	(0.021)	0.143*	(0.075)
FN_CC	0.063***	(0.016)	−0.054	(0.057)
Industry-vintage-year fixed effects	Yes		Yes	
R^2	0.442		0.132	
No. of obs.	1,242			

FIGURE A1

Robustness

Figure A1 reports robustness tests for the simulation-based estimates of predictive regressions of the industry returns by informed rush, as reported in Table 5. The top left (right) and bottom left (right) correspond to specifications 1 (2) and 3 (4), respectively. In both panels of the figure, case 1 corresponds to the coefficient estimates on TD_TTR>1 × TD_IRR>HR × RUSH reported in Panel B of Table 5. The solid black line is the mean coefficient value across 1,000 independent simulations, and the area denotes the range of the values. The 95% confidence interval is based on a mean of asymptotic variance (aVar) estimates across the simulations. For cases 2–10, Graph A reports estimates for the same model but with the following fund vintage years being excluded from the estimation, respectively: 1993; 1992; 1990; 2001; 1992–1993; 1990 and 2001; 1990, 1993, and 2001; 1990, 1992, and 2001; and 1990, 1992–1993, and 2001. In Graph B, cases 2–10 include all vintages but augment the model with a dummy denoting the actual fund SR_TIME falling in the following years: 2007; 2009; 2000; 2008; 2007 and 2009; 2000 and 2008; 2000 and 2007; 2000, 2007, and 2009; 2000, 2007, and 2008; and 2000 and 2007–2009.

Graph A. Exclude Selected Vintage Years
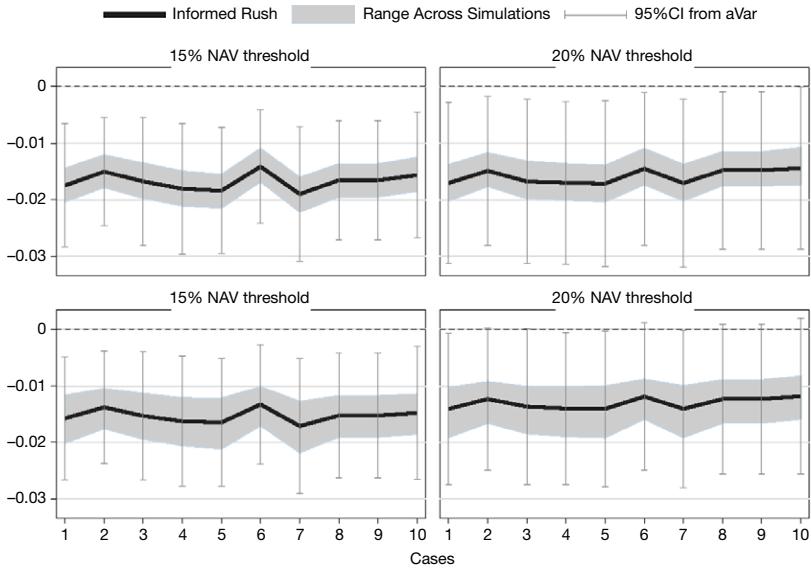
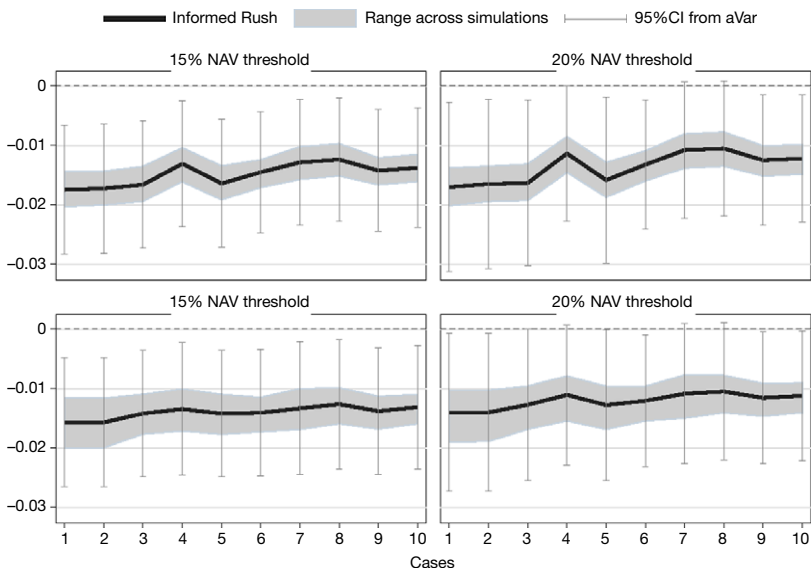Graph B. Dummy-Out Selected Exit Years

FIGURE A2

Placebo Tests

Figure A2 displays placebo tests for the simulation-based estimates of predictive regressions of industry returns by rush reported in Table 5. The left-hand (right-hand) charts correspond to specification 3 (4). Graph A plots α estimates and 95% confidence intervals over these independent simulations if the actual fund's SR_TIME and distributions were replaced by the corresponding expectations from the fund-fixed-effect model reported in Table A1. Graph B plots the fraction of placebo exits that have a t-statistic lower than that of the actual funds in each independent simulation, as well as the mean value across simulations. Case 1 of Graph C corresponds to the coefficient estimates on TD_TTR>1 × TD_IRR >HR × RUSH from Panel B of Table 5. Cases 2–10 replace the fund's industry with another S&P 500 Global Industry Classification Standard (GICS) subindex so that 10 corresponds to results against the GICS that is the least correlated with the fund's industry (based on the monthly returns over 5-year rolling windows). The solid black line is the mean coefficient value across 1,000 independent simulations, and the area denotes the range of the coefficient across the simulations. The 95% confidence interval is based on a mean of asymptotic variance estimates across the simulations.
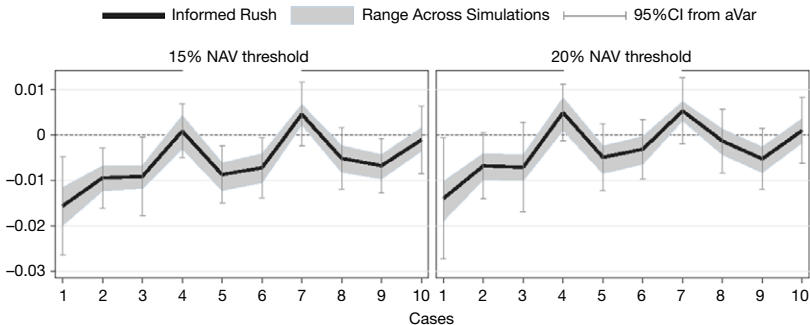
Graph A. Fund-Fixed-Effect Predictions
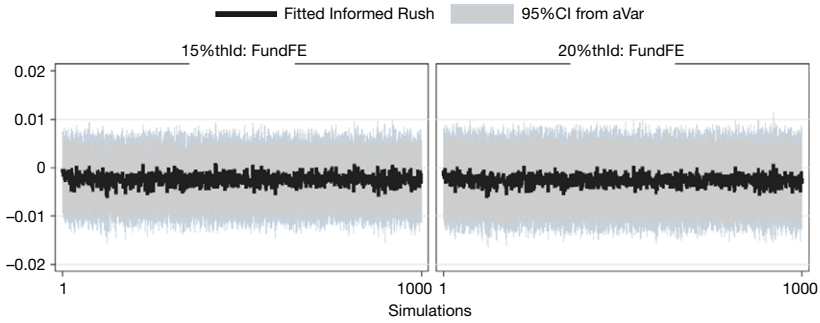
Graph B. Fraction of Random Draws with t-Statistic < Actual Fund
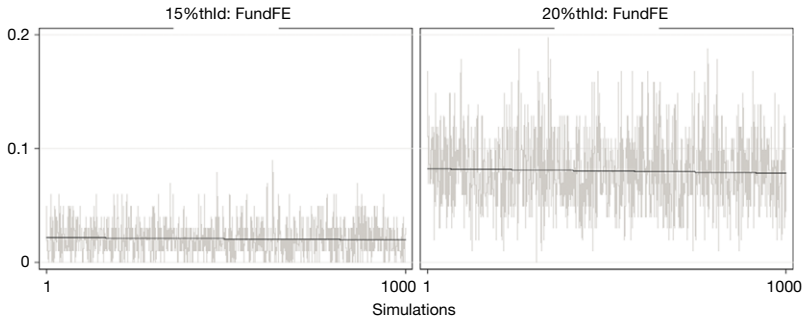
Graph C. Proximity-Ranked Industries

Appendix B. Key Variable Definitions

IND_RET: S&P 500 GCIS subindex that the PE fund primarily specializes in, according to Burgiss. For 61 unclassified funds, I assign "Industrials" as the industry focus. Source: Burgiss, Compustat.

INFORMED (RUSH): The interaction of TD_TTR>1 and TD_IRR>HR (and RUSH). The triple interaction of these variables is also referred to as "informed rush" in the text and exhibits (Tables 4, 5, 6, A1, and IA-6; Figures A1 and A2). Source: Burgiss.

PME: Public market equivalent of Kaplan and Schoar (2005) with respect to the fund's public equity benchmark, defined as $\text{PME} = \sum_{t=1}^{T} D_t \times e^{r_{t,T}} / \sum_{1}^{T} C_t \times e^{r_{t,T}}$, where $r_{t,T}$ is IND_RET from the capital call (C_t) or distribution (D_t) date until the fund resolution (Tables 2 and IA-3; Figure 1). Source: Burgiss, Compustat.

Predictive covariates: Macroeconomic and financial variables that have been used in the literature (e.g., Welch and Goyal (2008)) to explain variation in risk premia, all measured as of the respective fund's SR_TIME: the industry's price-to-earning and book-to-market ratios, the CAY ratio of Lettau and Ludvigson (2001), Chicago Board Options Exchange (CBOE) Volatility Index (VIX), U.S. Treasury yields (10-year and 3-month yields), corporate credit spreads (BAA to AAA, and AAA to UST), and the industry 5-year cumulative abnormal return (CAR). The variables computed at the industry level contain prefix the "IND_" (Tables 4, 5, 6, A1, and IA-6; Figures A1 and A2). Source: Bloomberg, CRSP, Compustat, Federal Reserve Board (FRB), Sydney Ludvigson.

RUSH: Fraction of distributions over 6 quarters before the SR_TIME in the fund's total distributions up to SR_TIME (Tables 4, 5, 6, IA-1, and IA-6; Figures 3, 4, A1, and A2). Source: Burgiss.

SR_TIME: Time elapsed since the fund inception until the quarter when the fund's NAVs fall below either 15% or 20% of its cumulative distributions; indicates the calendar quarter when residual exposure of the fund assets to the market fluctuations becomes relatively low (and so is the exposure of GPs' personal wealth for the in-the-carry funds) (Tables 4, 5, 6, A1, IA-1, and IA-6; Figures 3 and 4). Source: Burgiss.

TD_TTR: Same as TTR but excludes cash-flow and return data beyond that date. Specifically, both $\overline{\text{PME}}$ and PME are computed using the latest NAV available as of the date as the terminal cash flow, and $r_{t,T}(r_{1,T})$ are measured with T set to the date (e.g., 5 years since the fund inception, as of the time fund NAVs fall below 15% of cumulative distributions, etc.). TD_PME and TD_IRR are similarly defined (Figures 1 and 2). Source: Burgiss, Compustat.

TD_TTR>1: Indicator variable taking a value of 1 if the fund's to-date TTR in the quarter right before SR_TIME exceeds 1, and 0 otherwise (Tables 4, 5, 6, IA-1, and IA-6; Figures 3, 4, A1, and A2). Source: Burgiss.

TD_IRR>HR: Indicator variable taking a value of 1 if the fund's reported IRR in the quarter right before SR_TIME exceeds 8% (0%) for buyout (venture) funds (Tables 4, 5, 6, IA-1, and IA-6; Figures 3, 4, A1, and A2). Source: Burgiss.

TTR: The timing track record; the gross return due to selling near the market peaks during the fund lifetime and buying near the troughs, defined as $\text{TTR} = \overline{\text{PME}}/\text{PME}$, where $\overline{\text{PME}} = \sum_{t=1}^{T} D_t \times e^{r_{1,T} \times (1-t/T)} \sum_{1}^{T} C_t \times e^{r_{1,T} \times (1-t/T)}$,

and $r_{1,T}$ is IND_RET from the fund inception (unlike from the *cash-flow date* in the PME) until the fund resolution. See Section III.A for details. When referred to as the *exit* (or *entry*) TTR, the values for all C_t (or D_t) are set to 0s, and the fund life period is not from inception to end of life but from the first (fourth) to sixth (last) year since inception (Tables 2, 3, IA-3, and IA-5; Figures 1 and 2). Source: Burgiss, Compustat.

Supplementary Material

To view supplementary material for this article, please visit http://dx.doi.org/10.1017/S0022109021000107.

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