SUPPLEMENTARY MATERIAL to

Do Private Equity Managers Have Superior Information on Public Markets?

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1.1. Private information cycle

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

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

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

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

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

Private Equity Information Cycle

1.2. Theoretical predictions

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

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

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

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

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

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

where $f_t^{(j)}$ are dollar-measured fees from the fund $j = 1, 2, 3, ...$ run by the GP, and $I\{j=1; t\}$

is an indicator for whether fund j has been raised before period t.

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

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

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

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

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

, in which the following notation is obeyed:

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

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

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

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

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

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

1.3. Which PE exits are informative?

IPO versus non-IPO

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

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

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

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

through an IPO.

Finite life considerations

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

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

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

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

When do PE exits convey less information?

Suppose that our hypothetical fund has performed very well but already divested its best deals (i.e., those yielding the highest performance fees). The remaining holdings in the fund's portfolio would then likely comprise the deals that failed to payout well. Provided

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

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

that the fraction of this residual in the total distributions to-date is small, its option value (which increases in the assets' idiosyncratic risk as well) may still dominate any expected loss of value to the fund's carry amount due to the likely deterioration in the industry-wide factors.

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

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

Potential power drains

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

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

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

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

However, because the key coefficient of interest is on the interaction of the in-the-money carry proxy and the fraction of recent distributions to the total-to-date (i.e. *Rush*), the measurement error gets mitigated markedly—even for the deal-by-deal basis, high values of Rush insure that the proportional amount of carry has been harvested right before the hypothesized dip in the public benchmark is measured. Nonetheless, it is likely what causes the lack of power in the fuzzy RDD tests (reported in Table A.6 of the main text) in which I compare funds with net IRR just above the Hurdle rate to those with net IRR just below.

IA-2. Simulation-based estimator

2.1. Setup

In this section I provide additional details about the simulations-based method used to obtain results reported in section IV.B of the main text, as well as section IA-3.3.4 of this appendix.

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

Table B.I of Appendix B in the main text reports the results of this estimation. For

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

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

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

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

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

Applying the actual fund inception dates, for each fund-threshold-placebo exit I obtain

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

the months corresponding to the actual and simulated *SubResTime* and match the 12-month forward mean *Industry* return as well as the respective month and industry-month covariates that control for *Pseudo-timing* alternative. These variables are CAY-ratio, VIX, U.S. Treasury yields, corporate credit spreads, the industry index price-earnings and book-to-market ratios. See section II and Table I and II in the main text for details and summary statistics. The data end in October 2013, with the last actual fund stopping-month being March 2013. If the stopping-month is later than June 2014, this placebo exit is truncated so that the forward mean return is computed over at least 6 months. Hence, some of the funds post 2004 vintage will tend to have slightly fewer than 100 placebo exits. The results are robust to dropping these funds (available upon request).

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

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

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

2.2. Statistical properties

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

$$E\Big[Z1_j\Big(SubResTime_j - f(\text{GP-fund characteristics}; \theta_t)\Big)\Big] = 0$$

$$E\Big[Z2_j\Big(Rush_j - g(\text{GP-fund characteristics}; \theta_r)\Big)\Big] = 0$$

$$E\Big[Z3_{ji}\Big(IndRet(\theta_{t,r}, \Sigma) - \boldsymbol{\alpha} InformedRush(\theta_{t,r}, \Sigma) + \alpha_0 Informed + \alpha_1 Rush(\theta_{t,r}, \Sigma) + FFE(j)\Big)\Big] = 0$$

$$E\left[\begin{pmatrix} SubResTime(\theta_{t,r}, \Sigma)_{ji} \\ Rush(\theta_{t,r}, \Sigma)_{ji} \end{pmatrix} \perp FFE(j)\right] = 0$$

$$E\left[\begin{pmatrix} SubResTime(\theta_{t,r}, \Sigma)_{ji} \\ Rush(\theta_{t,r}, \Sigma)_{ji} \end{pmatrix}\begin{pmatrix} SubResTime(\theta_{t,r}, \Sigma)_{ji} \\ Rush(\theta_{t,r}, \Sigma)_{ji} \end{pmatrix}' \perp FFE(j) - W_2(\Sigma, 1)\right] = 0$$

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

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

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

Besides α and the asymptotic variance-based confidence interval, Figure B1 in the main text plots the range for α_s across *independent simulations*. This range indicates how sensitive the estimates are to the seed value choice when we draw at most 100 random exits for

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

each fund. In both Panels, A and B, top-left(right) charts report results for the baseline model with stopping-time defined as crossing 15 (20)% threshold of NAV/(total distributions to-date), while bottom-left (right)—for the baseline model augmented with *Pseudo-timing* controls and 15 (20)% threshold. Panel A investigates how robust the estimates are to exclusion of selected vintage years. Panel B—dummies-out selected exit years.

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

2.3. Alternative approaches

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

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

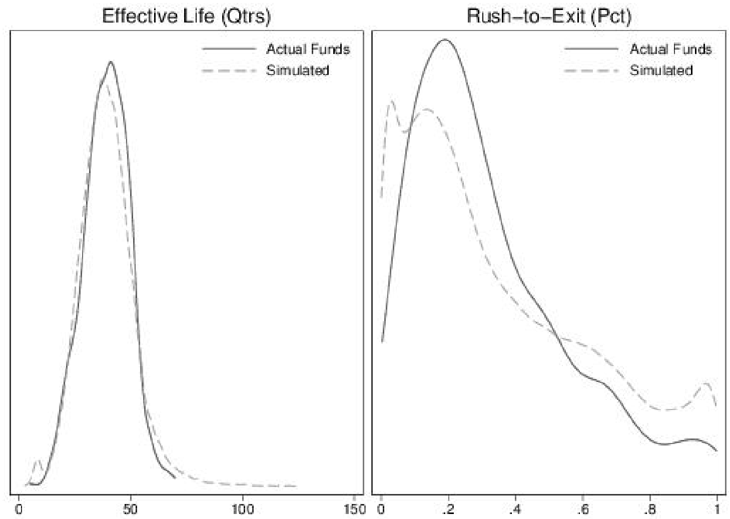
[ia14] The dummy *Informed* and mean *Industry Return* would have to switch sides since the dependent variable needs to be binary.

that particular quarter.

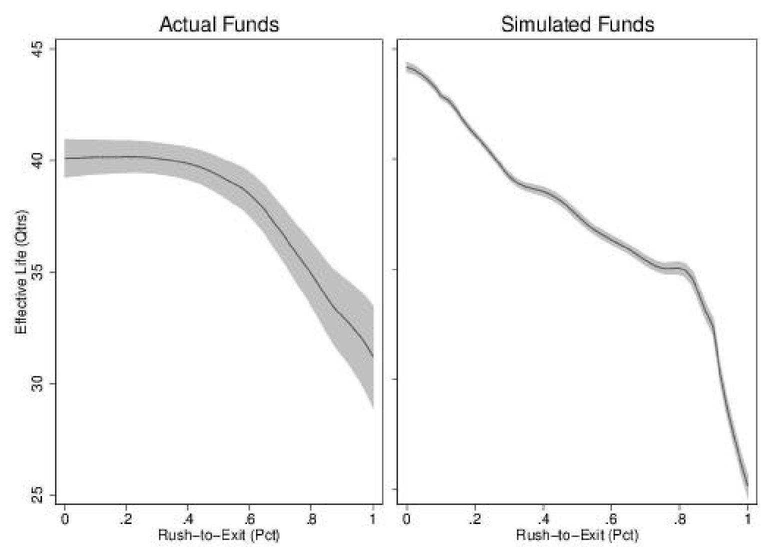
Figure IA-1
Actual fund exits versus simulated

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

Panel A: Univariate Distributions



Panel B: Bivariate Relations



IA-3. Additional results and robustness

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

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

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

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

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

Table IA-1 reports the results of the calendar time portfolio regressions for a long-short strategy that trades on a signal derived from PE fund distributions and is rebalanced quarterly.

Table IA-2 reports results of a placebo analysis, in which I examine if clustering of fund distributions at least a year away from SubResTime also results in predictability of industry returns. The alternative explanation—that the inherent heterogeneity across funds makes their distribution patterns potentially incomparable—predicts α to be different from zero away from SubResTime as well.

3.1. Alternative derivation of TTR

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

$$\overline{PME} = \frac{\sum_{t=0}^{T} D_t e^{-t\bar{r}}}{\sum_{t=0}^{T} C_t e^{-t\bar{r}}} \quad \text{, where} \quad \bar{r} = r_{1:T}/T \ . \tag{IA-6}$$

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

$$\begin{aligned}\Delta &= ln\big(\textstyle\sum_{t=0}^{T} D_t\big) - ln\big(\sum_{t=0}^{T} C_t\big) - \Big[ln\big(\sum_{t=0}^{T} D_t e^{-t\bar{r}}\big) - ln\big(\sum_{t=0}^{T} C_t e^{-t\bar{r}}\big)\Big] \\ &= ln\big(\textstyle\sum_{t=0}^{T} D_t / \sum_{t=0}^{T} D_t e^{-t\bar{r}}\big) - ln\big(\sum_{t=0}^{T} C_t / \sum_{t=0}^{T} C_t e^{-t\bar{r}}\big) \ .\end{aligned} \tag{IA-7}$$

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

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

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

$$\Longleftrightarrow$$

$$\sum_{t=0}^{T} D_t - \sum_{t=0}^{T} D_t e^{-t\bar{r}} \simeq \sum_{t=0}^{T} t\bar{r} \cdot D_t e^{-t\bar{r}} \ . \tag{IA-8}$$

It therefore has to be that:

$$\begin{aligned}&\sum_{t=0}^{T} D_t(1 - e^{-t\bar{r}}) - \sum_{t=0}^{T} t\bar{r} \cdot D_t e^{-t\bar{r}} \simeq 0 \\ \rightarrow &\sum_{t=0}^{T} D_t[1 - (e^{-t\bar{r}} + t\bar{r} \cdot e^{-t\bar{r}})] \simeq 0 \ .\end{aligned} \tag{IA-9}$$

Condition (IA-9) is true whenever $1 + t\bar{r} \simeq e^{t\bar{r}}$ and, since $\overline{PME} = PME \cdot TTR$ by definition, equation (1) of main text is equivalent to equation (2) of the main text. □

3.2. Robustness tests

Table IA-4 reports results of a multivariate analysis of the sample funds' TTR properties. Panel A repeats the Table 2, whereas Panel B runs same tests but using TTRs and sequencing against the overal market return (as opposed to the fund *Industry* in the main text). It follows that the persistence and correlation with PME is weaker for the case with broad market index.

Table IA-3 expands the cross-sectional analysis of TTRs' properties from Table 2 of the main text with additional controls in Panel A, and compares the realized TTRs with those under randomly generated exit timing by the actual funds in Panel B.

Table IA-5 reports results of a multivariate analysis of the sample funds' excess TTR properties, defined as a difference in each fund's TTR against the matched industry benchmark and the respective fund's TTR against the broad market. Panel A reports results for Entry TTR, panel B reports results for Exit TTRs.

Table IA-7 reports predictive regressions of return by Informed Rush just as those in Table 4 of the main text but using a dummy variable to denote *Rush* which is a fraction of distributions (to LPs) over the last 6 quarters in the funds' total-to-date. Specifically, $Rush20 = 1$ if $Rush >= 0.2$. *Industry returns* are of S&P500 subindex corresponding to the GICS industry sector of the fund specialty. From this analysis, it follows that results are very similar to those reported in the main text using continuous *Rush* and are not driven by a non-representative minority of funds—(toDateTTR>1 × toDateIRR>Hurdle × Rush20) =1 for 205 funds which is 22% of the sample.

Table IA-6 examines the robustness of the analysis in Table 4 to different inferences methods. I follow Conley (1999) to model the spatial correlation between the return intervals arising from the proximity of SubResTime; I also cluster by vintage year as Kaplan and Schoar (2005) and in two dimensions simultaneously.

Table IA-8 examines the robustnes of the analysis in Table 4 in Fuzzy RDD settings, in which the distance of the fund IRR-to-date from the hurdle rates is used as a forcing variable.

Table IA-9 additionally scrutinizes the potential for simultaneity between Rush and *Informed* indicator to drive the predictability of returns in the main tests. In this analysis, I instrument both, IndustryReturn the Informed indicator. I continue using IndEPSsurprise as the source of variation for IndustryReturn and use a propensity score to instrument Informed indicator. The propensity score is determined by the performance of the current fund's peers and the timing track record of the previous fund managed by the that GP. Therefore, the remaining variation in Informed indicator (and that of Informed×IndustryReturn) is less susceptible to the Grandstanding and Footprint-on-Firms concerns. More specifically, the exclusion restrictions for the validity of this test are: (i) industry future earning surprises do not affect the fund exits today except through GP's industry return outlook, and (ii) strategy-by-vintage median "luck" does not affect the fund exits today except through the odds that the fund carry is in-the-money. This analysis is reported in Table IA-9. It reveals the negative and significant interaction on Informed×IndustryReturn and, thus, supports the hypothesis that future industry returns cause Informed Rush.

3.3. Does Rush hurt holding period returns?

If holding period returns were sacrificed, we would expect that the gains from company selection and nurturing (as measured by holding period returns) to be negatively correlated with those from buying (selling) near the industry troughs (peaks). Although the results in Table IA-4 suggest that this correlation seems to be positive, they are prone to spurious correlation due to fund risk misspecification (see section II.A of the main text) and the overlap in lives across several funds (Korteweg and Sorensen, 2017). Moreover, it is interesting to examine holding period returns of funds in which GPs might have refrained from divesting ahead of the market downturns. If their decisions "to not rush" were driven by the objective to maximize the total return for LPs, we should expect that the average holding period abnormal returns of their funds to be higher (so that those decisions could have been optimal still).

Utilizing funds' holding period abnormal performance as dependant variable in a model used to predict industry returns in the main text (Table IV) and Table IA-7 of this appendix yields the required tests. Table IA-10 reports the results. As before, *Informed* group is represented by its constituents, to-date $TTR > 1$ and $IRR > Hurdle$ and the interaction thereof, whereas *Rush* is a ratio of the fund distributions over 6 quarters to the fund's total to-date. To zoom at GPs' portfolio company selection and nurturing effects, I add industry fixed effects to vintage year fixed effects while there is no purpose to condition on the risk-premia covariates as of the stopping time in this case (dropping industry fixed effects leaves the estimates largely unchanged).

The differences across specifications in Table IA-10 derive from the dependent variable only. In specifications (1) and (2), it is Kaplan-Schoar PME at the latest available date (henceforth, *Last PME*) against the fund industry and the broad market, respectively. While the funds that had neither performance in excess of the hurdle rate nor a good timing track record ($TTR > 1$), indeed appear to attain lower lifetime PMEs when their exits cluster significantly towards the last few quarters of active operations (i.e., $Rush \approx 1$), all the interaction terms with Rush are positive. The cumulative effect on PME for *Informed Rush* (reported in the bottom of the table) is actually positive, although not significant statistically. Thus, I conclude that there is no evidence of holding period returns' sacrifice by GPs exhibiting *Informed Rush*.

The significantly negative coefficient on $TTR > 1$ indicates that the "non-Rushing" *Informed* GPs who were not making any performance fees, have had significantly lower holding period returns for their investors than the control funds. This would be expected if those

GPs were primarily concerned with keeping their option to earn performance fees alive (at the cost of LPs' value maximization objective).[ia15]

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

3.4. Evidence on risk shifting

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

I estimate volatility as annualized standard deviation of monthly returns -6 to 0 and -12 to -8 quarters relative to the respective fund's *stopping-time.* The first window corresponds to the period over which *Rush* is measured. Hence, it shall speak about how the fund distributions' clustering associates with abnormal industry volatility. The second window is even more interesting since high values of *Rush* imply that there were very few distributions made *before* the Rush measurement window while the fund fixed effect projections ensure that the volatility is abnormal relative to the fund inception date×industry and other fund-

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

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

and firm-level covariates (as per the *auxiliary model* in Table B.1 in the main text). The results for the first window can be considered a placebo experiment that informs about the differences in abnormal volatility within *Informed Rush* period, which (if present) may confound our interpretation of the results for the {-12 to -8}-window .

The informed group now comprises funds that (a) have a positive track record of market timing (*TTR>1*), and/or (b) where GPs face a survival risk beyond the term of the current fund. I assume the survival risk to be determined by a combination of the following two conditions: (i) whether net-of-fees IRR was in the bottom or top tercile among type×vintage peers (*Btm/Top*), and (ii) whether a successor fund has been raised (*NoNext/YesNext*).[ia17] To not engage more than three-level interaction terms, I define three non-overlapping groups: *Btm|NoNext*, *Btm|YesNext*, and *Top|NoNext*. In addition, to preclude a look-ahead bias and unrealistic assumptions, I measure *TTR* and *IRR* as of the *fifth* anniversary of the respective fund and constrain the sample to funds with actual stopping-times at least *eight* years from inception. This ensures that the funds are not too young to make any distributions during the {-12 to -8}-window, while the to-date performance signals are meaningful and yet not overlapping with the volatility observation windows.

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

Table IA-11 reports the results for the stopping time defined based on 15% NAV/"total distributions to-date" threshold. All specifications include the projections of fund fixed effect (see Appendix B in the main text) and the main terms of *Rush* and *Informed*. Specifications (3) and (4) also include the levels of VIX index as the fund stopping-quarter and the -12 to -8 quarters or -6 to 0 quarters, respectively, to better absorb heterogeneity across informed

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

funds and zoom at the industry-specific innovations to the volatility. Specifications (1) and (3) show that the volatility during the *Rush* periods is neither abnormal (relative to the hypothetical exits) nor meaningfully different within *Informed* funds across the incentive and skill dimensions. Therefore, the results for {-12 to -8} window shall provide us with a clean test of risk shifting hypothesis.

Meanwhile, specifications (2) and (4) of Table IA-11 strongly support the hoarding hypothesis. While the industry volatility associations with the divestment schedules continue to be insignificant for funds that appear to have just timing skill but no incentive to risk-shift (and vice versa), there is a singificant difference when both conditions are satisfied. A positive and significant coefficient of *TTR>1* × *Btm|NoNext* × *Rush* in specification (2) suggests that an inter-quartile (=0.3) increase in *Rush* by such funds associates with approximately 2.5 percentage points higher per annum volatility of the industry returns during the quarters preceding the *Rush*. Since the fraction of distributions prior to the sixth quarter before the stopping equals 1-*Rush*, it follows that these funds had distributed abnormally small fraction of fund assets before the industry volatility became abnormally high. Controlling for the systematic volatility levels within the window and at the fund resolution date (as per specification (4)) does not change the result.

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

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

Figure IA-2
Timing track records: examples

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

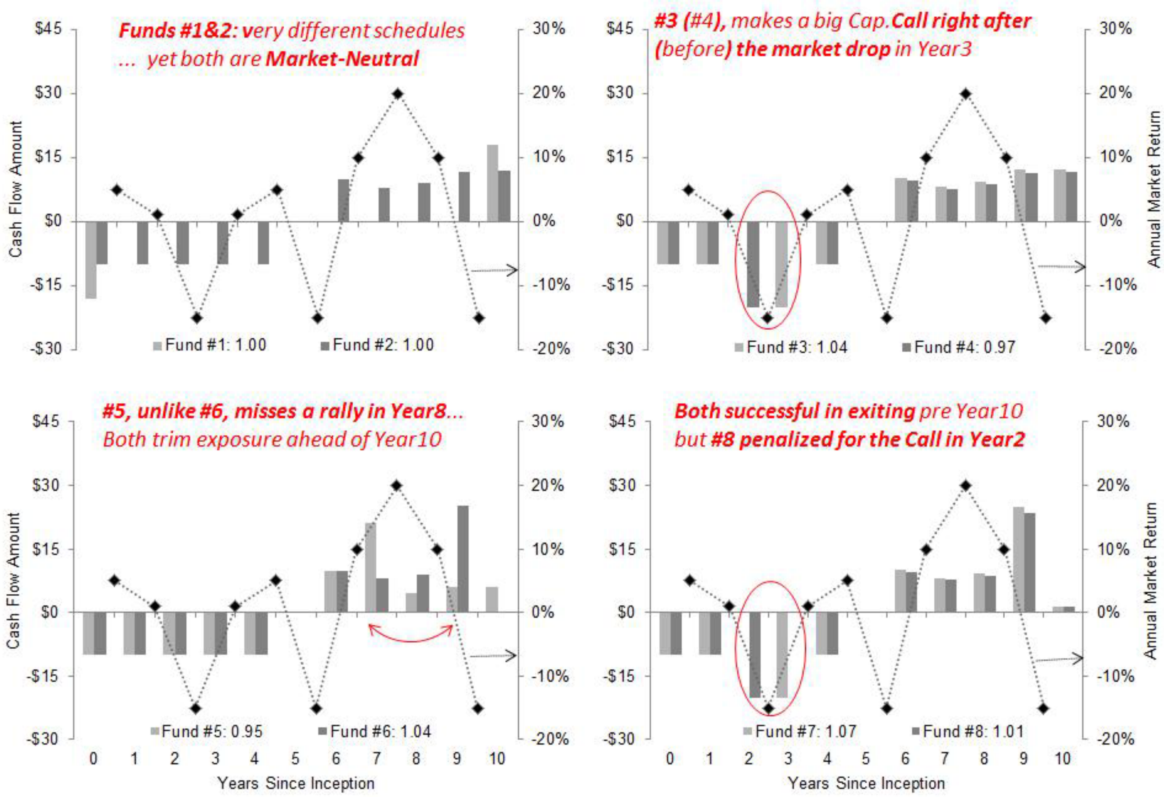
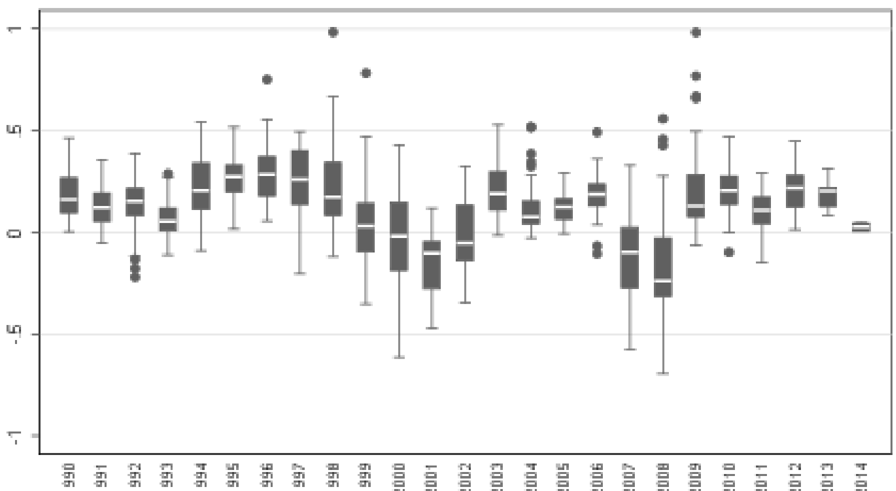


Figure IA-3
Sample description

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

Panel A: Industry returns



Panel B: Funds by vintage and TTR group

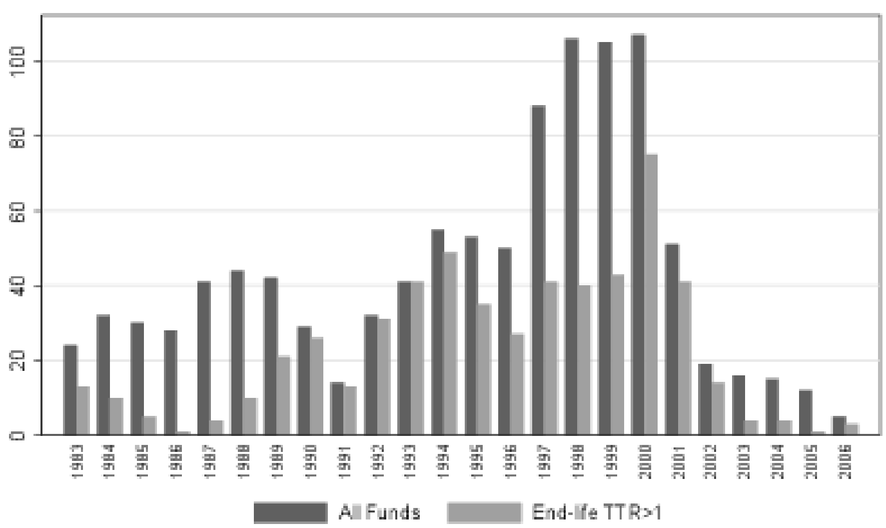
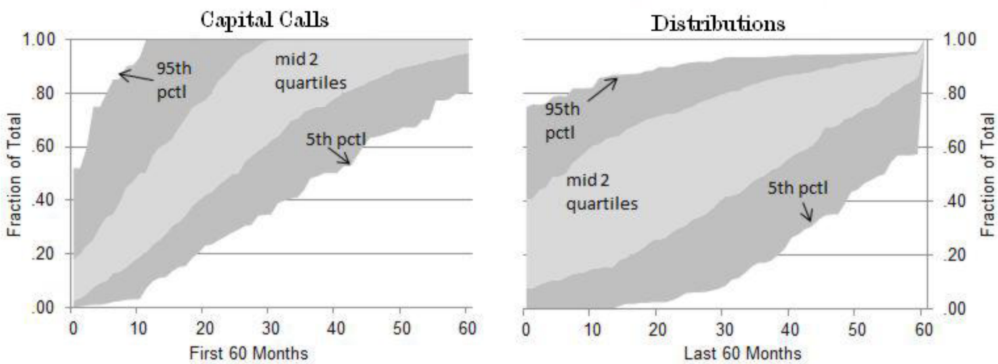


Figure IA-4
Private equity fund cash flows: cross-section

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

Panel A: Buyout



Panel B: Venture

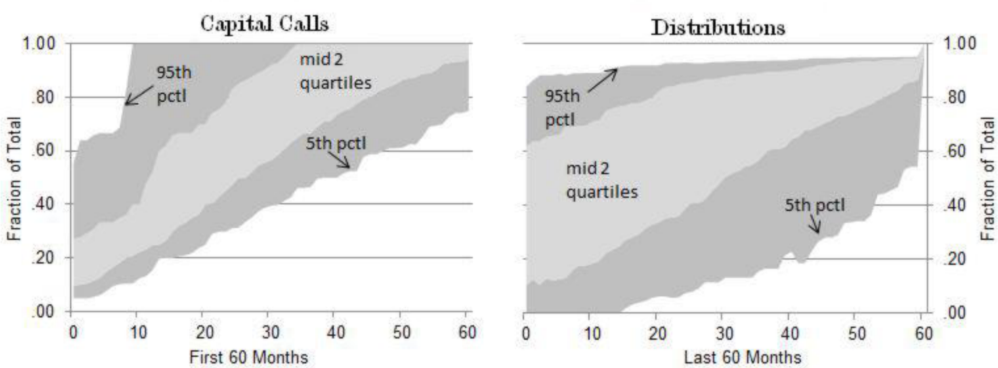
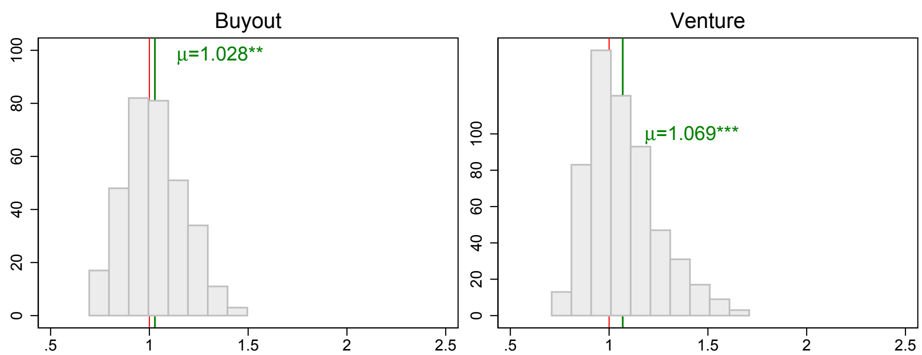


Figure IA-5
Timing track records: industry versus overall market

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

Panel A: Broad market TTRs



Panel B: Industry TTRs

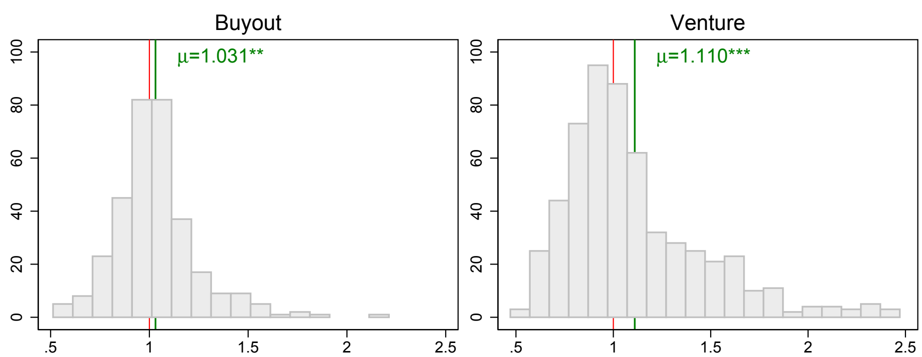
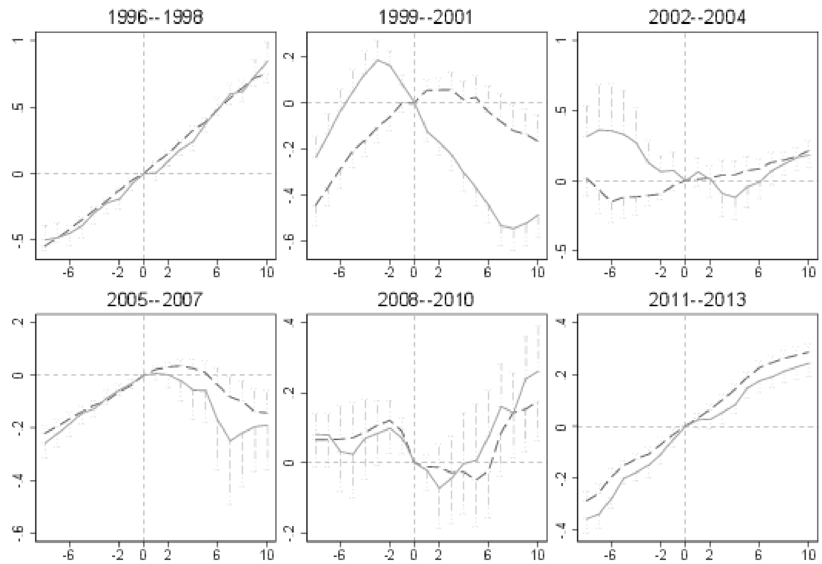


Figure IA-6
Informed Rush: more event studies

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

Panel A: High Rush by exit year



Panel B: Full sample: what if no Rush?

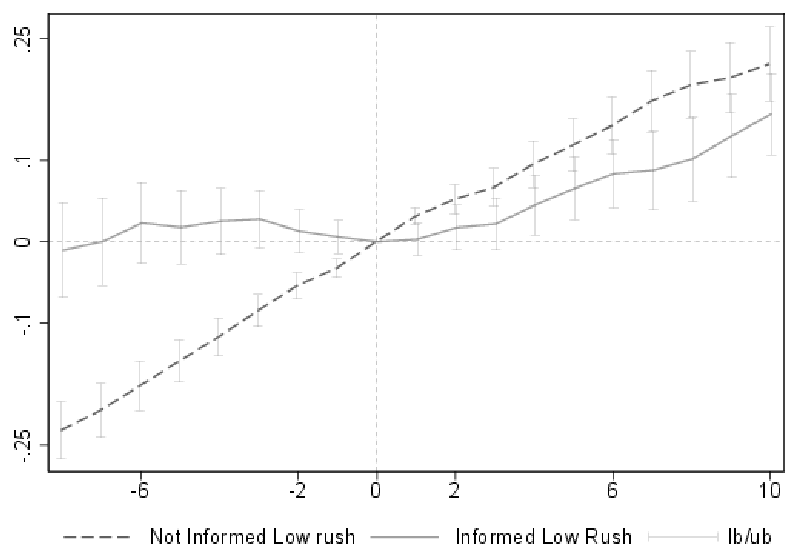


Table IA-1
Calendar Time Portfolios: Quarterly Abnormal Returns

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

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

Table IA-2
Informed Rush versus Uninformed: Placebo

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

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

Table IA-3
TTR Cross-section: Robustness and Placebo

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

Panel A: TTRs based on the actual exit schedules

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Table IA-4
Timing track records: associations and persistence

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

Panel A: TTR versus Industry

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

Panel B: TTR versus Broad Market

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

Table IA-5
Industry minus Broad market TTRs: Entry VS Exits

This table reports OLS regression estimates for the industry timing track records in excess of that of the broad market. The dependent variable in each model is a difference between the fund TTR computed against the industry benchmark and its TTR computed against the broad market. Panel A reports results for ***Entry TTRs***, Panel B—***Exit TTRs***. TTR measures the gross-return due to selling near the market peaks during the fund life-time and buying near the troughs, which can be broken down to the entry [exit] components dues to the pattern of capital calls [distributions] as shown in equation 1 of the main text. The sample is comprised of 349 (592) U.S.-focused buyout (venture) funds.. The explanatory variables are: 'Declared Ind.>50%P' – a dummy taking the value of 1 if a single industry represents more than 50% of the fund investments made during its life-time, 'Venture' – a dummy that takes the values of 1 if the fund type is venture, the interaction thereof, and the fund industry and vintage year fixed effects. Standard errors in parentheses are clustered by GP, */**/*** denote significance at 10/5/1% confidence level.

Panel A: Entry TTRs

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

Panel B: Exit TTRs

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

Table IA-6
Informed Rush: Robustness to Inference Methods

This table reports standard errors (SEs) computed under different assumptions for the coefficient on *TTR>1* × *IRR>Hurdle* × *Rush* from the main text's Table 2, Panel A and B respectively (and the respective specifications (1) through (4)). *Spatial HAC* denotes standard errors obtained by using the overlap in the return measurement window following the respective *SubResTime*, following the method of Conley (1999). Since the returns are 12-month average, the maximal overlap is 4 quarters corresponding to a weight of 1 in the outer product of residuals and, hence an correlation of 1 between those two exits. This auto-correlation is set to decay linearly to zero for return intervals that are more than two quarters away from overlapping, e.g. one ends in December 1999 and the other starts in June 2000. *Two-way* clustered standard errors are obtained as a linear combination of one-way clustered covariance matrices as shown in Thompson (2011).

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

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

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

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

Table IA-7

Informed Rush: robustness to variable definition

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

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

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

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

Table IA-8
Informed Rush versus Uninformed: Fuzzy RDD

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

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

where $IndustryReturn_{ij}$ is the mean monthly *Industry* return over 12 months following the fund i *SubResTime*, the dependent variable is obtained as a residual of full-sample regressions of $IndustryReturn_{ij}$ on c_i, return *Predictive covariates.* $Rush_{ij}$ measures the intensity of fund's distributions to LPs right before *SubResTime*. $Informed_{ij}$ is the indicator variable denoting funds with both *toDateTTR>1* and *toDateIRR>Hurdle* as of *SubResTime* based on 15% residual NAV threshold. The sample is comprised of 349 (592) U.S.-focused buyout (venture) funds. Specification (1) includes all funds from the sample whereas specifications (2), (3), and (4) only include funds for which *ToDateIRR* is, respectively within 7.5%, 5%, and 2.5% distance from Hurdle rate. All specifications also control for the third-order polynomial of *ToDateIRR*-distance from Hurdle rate (i.e. the "forcing variable", X_{ij}) as well as vintage year fixed effects (λ_j). Standard errors in parentheses are clustered at *SubResTime*, */**/*** denote significance at 10/5/1%.

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

Table IA-9
Return predictability and earnings news: full IV

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

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

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

Panel A: Instrumentation of the Informed Status with its Propensity

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

Panel B: Informed Status Probability Model

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

TABLE IA-10
Does Informed Rush sacrifice holding period returns?

This table reports OLS estimates of the following model:

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

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

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

TABLE IA-11
Risk shifting evidence

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

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

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

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

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