Liquidity Provision in the Secondary Market for Private Equity Fund Stakes*

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Abstract

We study the role of liquidity provision and asymmetric information theories in explaining the discounts on private equity stakes sold in the secondary market. We estimate the demand for private equity stakes in the secondary market using a broker's proprietary data on bids between 2009 and 2016 and show that the demand responses to aggregate liquidity shocks vary considerably across bidders and funds: when liquidity conditions deteriorate, the demand for large and old funds decreases, while that for young and small funds increases. Liquidity-driven demand flows are negatively correlated with bids for young and small funds but do not predict changes in net asset values, consistent with the demand flows not having information value.

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1 Introduction

Once marginal due to contractual restrictions on transfers (see Lerner and Schoar (2004)), the secondary market for Private Equity Fund (PEF) stakes took off right after the 2008 financial crisis to an annual turnover of over $30 billion per annum. Behind this growth are the liquidity needs experienced by some investors since the crisis and the increased need of investors to rebalance more actively their private equity exposures as these became a large fraction of their total asset holdings (see Bollen and Sensoy (2016)).

At the same time, substantial capital has been earmarked by various entities to purchase PEF stakes on the secondary market but, as Nadauld, Sensoy, Vorkink, and Weisbach (2017) show, transactions occur on average at a discount to the Net Asset Value (NAV) of a fund.[1,2] These discounts vary significantly over time and across funds, leading potentially to a large liquidity risk faced by the LPs of specific PE funds who may have to sell their stake in the secondary market when discounts are also large. [3]

In this paper, we ask what may determine these discounts by attemtping to identify the channel linking time-varying macroeconomic conditions and fund characteristics to secondary market bids. One explanation found in the literature, echoed by practitioners, is that secondary market discounts are a compensation for liquiditiy provision: when funding liquidity is low, LPs may be forced to sell their stakes for cash while potential buyers are also strapped of cash or constrained to borrow.[4] Another plausible explanation is that secondary market discounts are a compensation for asymmetric information: expecting that incumbent LPs will accept bids that are close to NAV values because they privately discover that their fund's reported NAV is too high, bidders may respond with discounted bids. While we do not view these channels as mutually exclusive, this paper focuses on the liquidity compensation channel. Our main challenge is that the asymmetric information and liquidty provision

[1]For instance, secondary funds raised over $160 billion between 2011 and 2016 to purchase such stakes.

[2]Other buyers include funds-of-funds, which raise third party capital to invest in both the primary and secondary market for PEF stakes; and various asset owners (investment banks, hedge funds, endowments, pension funds, sovereign funds), which have their own teams to manage their PEF stakes purchases. Needing also to rebalance their PEF portfolios, these entities may also be sometimes on the selling side.

[3]Nadauld et al. (2017) report average discounts ranging from an average of 46% in 2009 to 7% in 2014, and higher discounts for young or small funds.

[4]This explanation has been proposed in the academic literature by Hege and Nuti (2011), Kleymenova, Talmor, and Vasvari (2012) and Nadauld et al. (2017).

theories have predictions in common (see, for example, Shleifer (1986)).

The liquidity provision hypothesis states that trades are discounted because there is not enough demand at current market prices that responds to the selling pressure following a liquidity shock. In the case of private equity stakes, a tightening of funding liquidity may increase the expected cost of funding future capital calls and force cash constrained LPs to sell. With sufficient liquidity in the market to respond to the shock, the supply from cash constrained investors would be met without a price change. Insufficient liquidity provision would cause downward price pressure, implying a negative correlation between total demand for the fund (number of bids) and the price bidders are willing to pay. Therefore, to test the liquidity provision hypothesis, it is necessary to show that the demand flow to a particular fund is negatively correlated with bid levels for that fund. Accordingly, the first requirement of our identification strategy is to use demand data, instead of transactions.[5]

We study the demand flows to different private equity funds with a unique data set consisting of all the bids submitted to a London-based secondary market intermediary of private equity stakes between September 2009 and December 2016. Before we consider the correlation between bid levels and demand flow, we first decompose demand into the component due to liquidity provision and the components due to other trading motives, such as aggregate income shocks, or changes in expected returns and risk that cause marginal portfolio rebalancing needs across PE funds or asset classes. We estimate a conditional demand system for stakes in different private equity funds. The demand for each type of fund is jointly determined and modelled as a Poisson distribution with a time-varying mean arrival rate of bids per fund-month. The arrival rate is specified to depend on different aggregate variables capturing the state of liquidity in different markets, aggregate measures of stock market performance, volatility and the state of the economy capturing changes in expected returns and risk that cause portfolio rebalancing needs, as well as the funds' past performance. Our main test statistic for the liquidity provision hypothesis is the partial correlation between the bid level and the component of the flow of demand to a given fund that is explained only by liquidity shocks, which we call *liquidity-driven demand*.

[5] The insight of testing the illiquidity using the joint price and demand response using exogenous variation in the supply of the asset dates from Shleifer (1986). For a recent application to the demand for stocks, see Koijen and Yogo (2017).

The asymmetric information hypothesis also predicts a negative correlation between the liquidity-driven demand response and the bids. Indeed, LPs may be more likely to have an information advantage when valuations are more uncertain, e.g., when market volatility is high due to low market liquidity. [6] To separate the two hypotheses, we follow a tradition in the microstructure literature since Llorente, Michaely, Saar, and Wang (2002) and exploit the fact that even if the liquidity and private information motivations for trading may predict similar *contemporaneous* correlations between demand and prices, they have different *dynamic* implications. In particular, if selling were truly the cause of liquidity shocks, then the fund's expected cash flows will not fundamentally change. As a result bid levels will eventually revert from their pre-shock values. If, on the other hand, demand were responding to the possibility of informed selling, then bids would adjust downwards gradually as they increasingly reflect the private information. Moreover, given that reported NAVs cannot incorporate liquidity discounting under U.S. and European fair value rules (SFAS 157 and IFRS 13, respectively), NAVs will also eventually decrease to a permanent lower value once all information is fully revealed. In short, the asymmetric infomation hypothesis predicts that liquidity-driven demand flows have a *persistent effect* on bids and forecast *lower future* NAVs. The liquidity provision hypothesis implies that current liquidity-driven demand flows have no predictability of future bids nor the fund's NAV.[7]

Our data set consists of 4,365 bids on 497 LBO funds by 144 bidders. These bids are made at a discount of NAV on average and the discounts vary over time as well as cross-sectionally.[8] Our data provider is an important sell-side agent for LPs wishing to exit via the secondary market. Its bid book is comprehensive and representative of the global market:

[6]See Brunnermeier and Pedersen (2009) or Gromb and Vayanos (2011) for theories relating market volatility to asset illiquidity. In Pasquariello (2014), high stock market volatility causes the risk of temporary dislocations between asset prices and their fundamentals.

[7]An asymmetric information effect may also occur if *bidders*, not LPs, receive private information about the fund's value. Following Hasbrouck (1991), any private information known to some bidders, and, therefore, unobservable to the econometrician, is captured in the residual of the demand model. The liquidity-driven demand component is a projection of demand on publicly observable factors and does not contain, by construction, any information known only to the bidder.

[8]Our descriptive statistics closely match those by Nadauld et al. (2017) even though they use transaction prices from a US-based financial intermediary. This similarity is not surprising given that i) bidders submit the same bid to several intermediaries to maximize the probability of matching a selling interest; and ii) submitting bids is costly both in due diligence and in terms of reputation. Hence, bids are informative of the bidder's true intended price.

the average bid in our sample each year matches very closely the average annual transaction prices reported by Greenhill-Cogent.

Our specification of the variables capturing the state of aggregate liquidity is guided by theories of liquidity provision and the motives for demanding immediacy in the sales of private equity. We interpret the demand responses for different types of funds based on the implications of liquidity shocks *across* different PEFs. To wit, a PEF stake combines an equity claim and a credit line feature extended to the GP to draw on for future investment. Therefore, the LP's risk of funding future capital calls decreases with the fund's age, especially in first five years, after which the total amount invested by the GP approaches the agreed total funding commitment. Hence, facing uncertain future funding costs, LPs bear more liquidity risk on stakes of young funds. The empirical implication of the liquidity provision hypothesis is therefore that the negative correlation between bids and demand flows driven by shocks to current funding liquidity or future interest rates should be observed for young but not old funds.

Small funds are also expected to carry more liquidity risk than large ones, if for different reasons. Typically less diversified than larger counterparts, the value of small funds is more sensitive to the performance of single industies. As a result, small funds focusing on 'winner' industries appreciate significantly, forcing LPs to sell because they suddenly become institutionally over-exposed to private equity. Accordingly, our demand system allows for heterogeneous responses in demand for each fund type (e.g., age or size) given the same liquidity or macroeconomic shock.

We find a large heterogeneity in the response of demands for different types of funds and by different types of bidders to aggregate liquidity shocks. For example, the overall number of bids decreases in months where the yield curve steepens, yet this total effect comprises a decrease in bidding for the old and middle-aged funds but a small increase for the younger funds. Similarly, an increase in the Fontaine-Garcia (Fontaine and Garcia (2012)) index of bond market illiquidity, which captures a tightening of current aggregate funding liquidity, is also associated with an overall decrease in demand, especially for old funds, but is associated with an increase in the demand for young funds. We observe similarly heterogeneous patterns across fund sizes, where demand flows out of large funds towards small ones in response to liquidity shocks. The fact that demand contracts on aggregate, but increases for funds where selling pressure is expected to be high in times of low liquidity (e.g., young or small) supports our conjecture that secondary market illiquidity is driven by the interaction between the aggregate state of liquidity and fund characteristics related to their LPs' exposure to liquidity shocks.

Equipped with this estimated demand model, we project the aggregate liquidity indices onto the demands for different fund types to construct the estimated liquidity-driven demand flows. In consistency with the liquidity provision hypothesis, we find a significant negative correlation between bid levels and the liquidity-driven demand. Rejecting the asymmetric information hypothesis, we show that the relation between liquidity-driven demand and bids is contemporaneous and not dynamic: past demand shocks are not correlated with current bids and liquidity-driven demand flows do not predict future fund performance. Moreover, the negative correlation is strongest for the youngest and the smallest funds, whose LPs are expected to face the highest liquidity risk. To summarize, our results are strongly indicative that our proposed demand decomposition isolates the liquidity motive for discounts.

Having verified that our estimated liquidity-driven demand captures the liquidity provision channel, we ask (i) how large are the rents expected for liquidity provision in this market; and (ii) which PE investors, if any, act systematically as liquidity providers? To measure the discount required for providing liquidity, we use our estimate of the sensitivity of bid levels to the liquidity-driven demand. Indeed, the slope of the asset's demand curve is the illiquidity measure in Kyle (1985) ('Kyle's lambda'). We find, for example, that a one standard deviation increase in the liquidity-driven demand for young funds is associated with an average drop in bid values by up to 2.7 percentage points. For small funds the same estimate is 1.2 percentage points. While these differences are important, we note that these are measures of the impacts on bids and not necessarily on *prices*. Since the seller can choose to hold and find higher bidders, we interpret them as an upper bound to the expected liquidity discounts.

To identify the liquidity providers we estimate the liquidity-driven demand by type of investor: Secondary Funds, Funds-of-funds, and other asset owners (pension funds, endowments, banks). Secondary Funds are responsible for three quarters of the bids in our sample and their demand respond strongest to most macroeconomic factors. Yet we find that its the asset owners, not Secondary Funds, who increase their bidding in response to some liquidity shocks. Consistent with liquidity provision, asset owners submit bids that are on average 1.5 percentage points lower when their liquidity-driven demand increases by one sample standard deviation. One possible explanation for this effect is that, because they are not constrained to invest mostly or even exclusively in the secondary market, these investors have the flexibility to bid in this market when capital call risk or portfolio rebalancing puts pressure on constrained investors (secondary and other funds-of-funds).

Our study is one of three empirical studies of the secondary market for PEF stakes. Kleymenova et al. (2012) is the first to explore the determinants of bids in PEF stakes auctions and find that prices are lower if fewer bidders participate in an auction. Here we find a negative correlation, for the younger or the smaller funds only, and once we isolate the number of bids that is explained by liquidity shocks.[9] Nadauld et al. (2017) find that by buyers of PEF stakes earn a higher return than sellers, and suggest the compensation for liquidity provision as an explanation. Our analysis, complements theirs by identifying the liquidity provision channel using demand data, while providing an estimate of the liquidity provision discount across fund types based on a measure of asset illiquidity from the market microstructure literature.

In Lerner and Schoar (2004), private equity investments are illiquid by design so as to screen LPs with deep pockets, who are therefore likely to fund randomly timed capital calls or future financing rounds. The costs of exiting private equity investments via the secondary market are modelled and calibrated by Bollen and Sensoy (2016). Our empirical specification of the determinants of aggregate liquidity shocks follows from the motives for selling in their model. We contribute to this literature by showing that shocks to public equities, corporate bonds, and treasuries markets spillover to the private equity secondary market via the liquidity provision channel, quantifying their price impact, and identifying the funds most affected by this risk.

Recent theories of over-the-counter markets describe how certain investors endogenously take up intermediation roles in the absence of market makers. In Lagos and Rocheteau

[9] Another difference is that our sample *excludes* the financial crisis.

(2009), Hugonnier, Lester, and Weill (2014), and Chang and Zhang (2015), liquidity suppliers are not the agents with the highest current valuation. Our evidence suggests that the liquidity providers are not the investors specialized in the secondary market acquisitions but other asset owners (e.g., investment banks, pension funds, endowments, sovereign wealth funds), i.e., those not limited to invest in private equity and possibly with a lower valuation.[10]

The next section relates the theories of liquidity provision in secondary markets to the case of private equity. We develop testable hypotheses relating discounts and demand responses over time and across funds. Section 3 describes our proprietary data, the market for secondary PEF stakes, and compares our data with existing data. Section 4 develops an empirical model of the demand in this market and presents the results of the estimation. The estimated model is used to generate liquidity-driven demand flows for all fund types, which we use in Section 5 to perform the tests that identify the liquidity provision channel from the asymmetric information hypothesis, while discussing quantification of the liquidity discount. Section 6 discusses additional validity tests of the liquidity channel and Section 7 concludes briefly.

2 Liquidity Shocks in Private Equity

Bollen and Sensoy (2016) are the first to explicitly model the illiquidity costs of private equity investments. In their model, LPs demand immediacy to sell after receiving an idiosyncratic or systematic liquidity shock. These exogenous shocks capture, in a reduced form, three different motives for selling. First, the costs of funding uncalled capital commitments, whose timing is random, may increase unexpectedly. Second, the LP organization may suddenly have an increased demand for cash. Third, unexpected poor performance in public equity markets or, conversely, overperformance in private equity investments, may cause LPs portfolios to be overweighted in private equity with respect to their institutional

[10] Our work also adds to the literature on risk and return of illiquid or thinly traded assets; see, for example Acharya and Pedersen (2005), Albuquerque and Schroth (2015), Ang, Papanikolaou, and Westerfield (2014), Bongaerts, De Jong, and Driessen (2011), Brunnermeier and Pedersen (2009), Duffie, Gârleanu, and Pedersen (2005), Franzoni, Nowak, and Phalippou (2012), Gârleanu (2009), Jurek and Stafford (2015), Longstaff (2009), Sagi (2017), and, for a more private equity focused modelling of illiquidity, Sorensen, Wang, and Yang (2014).

targets.

Below we discuss theories that will guide our specification of liquidity shocks via the three selling channels above. We extend the framework in Bollen and Sensoy (2016) by hypothesizing which characteristics of private equity funds make them more sensitive to these types of shocks and, therefore, more likely to be sold. We discuss potential drivers of the demand operating via different channels in Section 4, when we present the empirical specification of our demand model.

2.1 The Capital Call Risk Motive

Brunnermeier and Pedersen (2009) show that investors that are financially constrained prefer to sell, or at least avoid, capital intensive assets to reduce the likelihood of being constrained in the future. In this case, assets can be sold even below their fundamental value. Private equity investments are capital intesitive because LPs cede control over the timing of investments to the GP and the capital calls are stochastic. Moreover, investors face a risk of *clustering of capital calls* if several of the funds invested in call capital at the same time. For example, capital calls cluster when GPs use them to pass-through the cash needs of financially constrained or distressed portfolio companies in recessions (Hege and Nuti (2011)).

The capital call risk motive predicts that a tightening of current or future funding liquidity, which increases the expected costs of funding future capital calls, may trigger liquidity sales by LPs in order to ease the pressure from capital requirements. And LPs are likely to sell precisely the assets with the largest amount of uncalled capital, i.e., the *younger* funds.

2.2 The Preference for Cash Motive

A preference for cash may arise when cash constrained investors cannot borrow externally to pursue better investment opportunities. Albuquerque and Schroth (2015) proxy such states of liquidity with the combination of high funding costs and high availability of investment opportunities. The preference for cash motive predicts that in case of a liquidity shock during such periods, LPs will choose to sell their more liquid PE funds, as they satisfy the need for immediacy of cash at the smallest discount. On one hand, these may be the *older* funds, which not only face little uncertainty about the timing of future dividends or capital calls (see Kleymenova et al. (2012)) but also about the valuation of their more mature realised investments. On the other hand, as suggested by Brunnermeier and Pedersen (2009), because of the possibility of a loss spiral, investors may prefer to sell the most volatile assets first, i.e., the funds with the most uncertain future values, such as young and small funds.

2.3 The Portfolio Rebalancing Motive

Institutional investors set targets ex ante for the allocation of private equity in their portfolio. Their portfolios may suddenly become overweighted following periods where the relative performance of private (public) equity has been unusually high (low). As PE funds last for a long time, sales through the secondary market may be required to decrease the allocation back to its target. The portfolio rebalancing motive predicts that negative shocks to stock market excess returns trigger sales of PEFs.

The exposure of particular funds to sudden large rebalancing needs will depend on the degree of diversification in their investments. Large funds tend to invest across industries whereas smaller funds typically focus on single industies. As a result, funds that focused on the top performing industries would have appreciated significantly, causing LPs to be overinvested in private equity, forcing them to sell. Therefore, another prediction of the portfolio rebalancing motive is that a larger dispersion in the returns across industry portfolios, whereby some industries would outperform all others by a larger amount, would cause selling pressure of small funds.[11]

2.4 Summary

The three motives for selling private equity in the secondary market and causing a price impact can be proxied by indices of aggregate funding liquidity, relative performance between the public and private equity classes, the dispersion in returns across industries and the state

[11] We note that rebalancing motive for trading refers to large portfolio adjustments. As such, it is different from marginal adjustments to update the optimal allocations within portoflio targets. Marginal rebalancing, which would respond to smaller changes in expected returns and variances of individual funds, may well be a driver of demand and our empirical specification will control for such fund-specific measures of expected returns and risk.

of investment opportunities in the economy. Young funds are exposed to such shocks via the capital call risk and preference for cash motives, whereas small funds are vulnerable to aggregate volatility and industry performance heterogeneity via the preference for cash and the portfolio rebalancing motive. The former channel may also force selling pressure of stakes in old funds.

We investigate these hypotheses via the specification of the demand model in Section 4, where we also discuss other determinants of demand, which we control for, and operate outside the liquidity provision channel.

3 Data

3.1 Institutional setup

Investors in a private equity fund (simply referred to as *fund*) are called Limited Partners (LPs). They can use an Over The Counter (OTC) secondary market to transfer their limited partnership stake (fund stake) to other investors. The fund manager – called General Partner (GP) – needs to approve the transfer. The buying LP pays the selling LP an amount expressed as a fraction of the fund's latest Net Asset Value (NAV). As NAVs are reported at a quarterly frequency, any cash flow occurring from the date of the latest reported NAV to the transaction date are taken into account when determining the actual cash transfer between the two parties: the purchase price is reduced by the net cash flows (capital distributions minus capital investments) that occurred in that lapse of time.

NAVs are an estimate made by the GP of the fair value of all ongoing investments in a fund. According to the related accounting rules (SFAS 157 for the U.S. and IFRS 13 for Europe), an NAV is an "estimate of the price at which an orderly transaction to sell these assets would take place between market participants under current market conditions." Implicit in the assumption of an orderly transaction is that the GP should not factor in the NAV the illiquidity of the fund's underlying assets. Crain and Law (2017) show that since the implementation of these rules (years 2006-2007), NAVs have been, on average, close to the subsequent aggregate fund net cash flows.

At fund inception – the year of which this occurs is referred to as vintage year – LPs commit to provide a certain amount of capital to the fund over a fixed period of time (referred to as investment period).[12] The amount, number, and timing of *capital calls* are left to the discretion of the GP and are unknown at inception. GPs call capital as they need it, up to the total amount committed at inception. LPs buying a PE stake inherit any remaining capital commitments. Sellers on the secondary market, therefore, sell a combination of on-going investments and unfunded commitments.

Although the first organization specializing in buying fund stakes in the secondary market was created in 1984, transaction volumes did not increase markedly until 2007. One reason behind the birth of this market has been the realization that LPs need to rebalance their private equity portfolio as it became a large fraction of their overall portfolio. At the same time, GPs appeared to no longer view secondary market trades as bad signals about their funds. As a result, numerous private equity funds-of-funds and other asset owners (investment banks, hedge funds, endowments, pension funds, sovereign funds) started to actively trade in this market, alongside specialized secondary funds.[13] Greenhill Cogent estimates that yearly transaction volumes doubled in 2007 and, except for 2009, then increased smoothly from $18 billion in 2007 to $37 billion in 2016.

3.2 Dataset

This secondary market is intermediated by specialized organizations. One such financial intermediary, based in London, and operating on that market since September 2009 (its other operations are older), gave us access to its entire database. Most of the requests it receives are from LPs offering to buy fund stakes, i.e. potential liquidity providers bidding for a pre-identified set of funds at an indicative price (the bid). When bids are quoted as a range (e.g. 80%-85%), we use the midpoint.

Importantly, this financial intermediary is viewed as a market leader for *individual* fund

[12] The aggregate commitments to a fund across all of its LPs is referred to as fund size. The difference between fund size and the sum of all capital calls to a given date is referred to as unfunded commitments, or dry powder. Dry powder is maximal at the time of fund inception and minimal past the investment period.

[13] Paris-based Ardian raised the largest secondary fund to date with $10.8 billion of committed capital in 2016. These secondary funds (and all fund-of-funds) are also structured as limited partnerships.

stake transactions (in contrast to transactions on *portfolios* of funds.) This is an attractive feature because the pricing of individual funds within a portfolio can be influenced by considerations other than the intrinsic market value of the fund stake. To illustrate, a report by Cogent (July 2016) states that "supply / demand mismatch for newer funds has begun to incentivize opportunistic sellers to include some recent vintage funds in sale portfolios in order to achieve their pricing objectives on portfolios that also include older and less desirable funds." As a result, some funds may appear to be more demanded than they actually are and some funds may receive a higher price than they would have had if sold on their own.

For each bid received, we observe the name of the fund, but not that of the bidders (only their type is given to us).[14] We then use Preqin datasets to construct the characteristics of each fund.[15] We observe that 75% of bids are for buyout funds, and that 94% of the bids are for funds focusing on Western Europe (including Scandinavia and UK) and North America. In order to work with a homogeneous sample, we include in our sample only buyout funds focusing on these geographies.[16]

We collect all the bids received up until December 2016, and use them to measure the demand for each type of fund in the secondary market. Demand, not execution volume, is necessary for our tests.[17] Specifically, demand is proxied by the total number of bids received in a given month for a given type of fund. Figure 1 plots the demand for all the funds in our sample between September 2009 and December 2016. In total, there are 4,365 bids. We do not observe a time trend in demand, but note some marked cycles.

[14] The funds most represented in our dataset are well-known funds. Those with the highest numbers of bids are: Apax Europe VII, Bain Capital IX, Blackstone V, and Thomas H Lee VI. They received more than 30 bids each.

[15] We match the funds in our dataset to two databases provided by Preqin. The first database contains fund characteristics such as size, vintage year, fund type (e.g., buyout, venture, infrastructure), and geographic focus. The second Preqin database contains data on fund cash flows and NAVs. This data allows us to calculate future fund performance. Note that we compute a fund's performance in the currency the fund is raised in.

[16] Venture capital funds and emerging market funds in our sample have a much larger discount. Discounts for such funds include additional considerations, such as the higher valuation uncertainty.

[17] Demand data is additionally useful because past transaction prices are a biased estimate of the discount expected by the LP a given fund at a given time. On one hand, LPs of funds with very high expected discounts that are patient enough may choose not to sell, excluding these observations from the sample. Demand data will record bids for these funds even if not traded. On the other hand, current transaction prices may overestimate the expected discount for patient LPs. Demand data allows LPs or the econometrician to forecast the future state of demand, which is useful to pin down the timing of the sale, as a function of forecastable state variables.

Bidders are classified into one of three types. Secondary funds (SF) are the most common type of bidders in our dataset. Funds-of-funds (FoFs) engage in both primary and secondary transactions; they are the second most common type in our dataset. We pool together the ten other types under the label Asset Owners (AOs). AOs includes banks, pension funds, endowments, sovereign wealth funds, and family offices. The countries with most bidders are the U.K. (35%), the U.S. (23%), Switzerland (13%), France (12%), Germany (4%), Norway (4%), Spain (3%), Netherlands (2%), and Canada (1%).

Insert Figure 1 Here

We expect the bids received by our financial intermediary to be the best estimate of the market value of a given fund stake at that given point in time. Although we can never rule out strategic behavior completely, it is important to note that submitting bids is costly both in terms of due diligence and in terms of reputation. A bidder attempting to manipulate the perception of demand, submitting unrealistic bids, or reneging on a submitted bid, would be quickly spotted and excluded from this market (financial intermediaries would ignore future demand or supply emanating from that organization).

In addition, empirically, we observe a number of completed transactions and do not find any significant deviation between initial bids and transaction prices. Moreover we compare the time-series of average bids to the time-series of average transaction prices as reported by the US market leader on the secondary market (Greenhill Cogent). The correlation between the two time-series is 94%, with the two averages being almost the same; see Figure 2 for a plot.[18] The average bid in both samples is low in the early part of the period and displays a slight upward trend at the end of the sample. Similarly, we compare the time-series of yearly averages in our sample to the transaction prices in Nadauld et al. (2017). The correlation is 99%, and the averages are the same.

Most importantly, our identification strategy relies on a good estimate of the demand for stakes by liquidity providers. As a result, the unit of analysis is naturally the number of

[18]Greenhill Cogent, in its (*Secondary Market Trends & Outlook*, reports semi-annual statistics from 2010 to 2013 and annual statistics for 2009, 2014, 2015, 2016. The figure averages our bids at the same frequency for ease of comparison.

bids received by our financial intermediary rather than the price at which transactions have closed, or the number of transactions closed. It is also worth noting that once a potential buyer has identified the funds it wishes to bid for (and the offered price), it is costless to submit that demand to all financial intermediaries. This may explain why we observe such a high correlation between statistics from US-based intermediaries and those from our London-based intermediary.

Insert Figure 2 Here

3.3 Descriptive statistics

Table 1 summarizes the bids in our data set. All variables are defined in Appendix A. The average (median) bid is 88.3% (90.0%) of the latest reported NAV (simply referred to as NAV from here on). We observe a surprisingly wide variation in the bids. About one-in-five bids is made at or above NAV, and the same proportion is made below 75% of NAV (see Figure 3 for a histogram).[19]

Insert Figure 3 Here

Table 1 also shows that there are 144 unique bidders, evenly spread out between our three bidder types. However, SFs place more bids (61 bids per bidder), and therefore account for the majority of the bids in our sample (about 75%). This is consistent with SF being specialized and solely acting on the secondary market. We also note that FoFs place the lowest average bids (82.5%, median = 85%), whereas AOs place the highest bids (93.9%, median = 97.5%).

Insert Table 1 Here

Certain fund characteristics are available only for a sub-set of our data. When we use these characteristics the sample is reduced to 3,093 bids. However, a comparison of the summary statistics between Panels A and B of Table 1 does not reveal any systematic differences

[19] In our subsequent analysis, we winsorize the bid distribution at the 1st and 99th percentiles, which correspond to bids of 30% and 120% of NAV, respectively. These bids seem extreme and may reflect an unusual situation for a given fund. As the bids are all correctly entered by the financial intermediary, we do not drop them out of our sample, but winsorize them to limit their influence in our results.

between the full sample and that sub-sample.

3.4 Fund classification

Some funds in our data concentrate a majority of bids whereas others of very similar size and age receive very few or none for given spells of time. By aggregating the number of bids per month over all funds of similar characteristics we guarantee that the demand for each group , i.e., type, of funds has a Poisson distribution. If done correctly, this grouping of funds into types not only has the advantage of a Poisson distribution's tractability in the estimation of a large demand system but also of including all funds that are homogeneous from the perspective of a bidder providing liquidity to LPs of *any* fund that is equally affected by aggregate liqudity shocks.

We use a statistical approach to determine the classification procedure. We estimate a piece-wise Logit model for the likelihood of a fund with a certain set of characteristics to receive at least one bid in a given quarter. This analysis reveals that i) three characteristics stand out: fund age, fund size and region of investment focus; and that ii) the effects of fund size and fund age are non-linear. The classification procedure is detailed in Appendix B.

We identify four breaking points in fund size and three breaking points in fund age. Funds are then assigned to one of four size categories (bottom tercile [Small], inter-tercile [Mid-size], 66th to 90th percentile [Large], larger than 90th percentile [Very large]), of three age categories (under four years old [Young], between four and seven years old [Mid-life], and over eight years old [Old]), and of two regions of investment focus (Europe, US). Panel A of Table 2 summarizes the total number of bids per month for each of these 24 (= $4 \times 3 \times 2$) fund groups.

Insert Table 2 Here

4 An empirical model of bid arrivals

4.1 Demand model

Let $X_{i,t}$ be the total number of bids for funds of type $i = 1, ..., 24$ during month $t = 1, ..., 88$. We assume that $X_{i,t}$ has a Poisson distribution in which the average number of bids per month, $\lambda_{i,t}$, is conditional on a set of time-varying observable variables, $\mathbf{Z}_t$, that are common to all the funds, e.g., measures of the state f aggregate liquidity, and a vector of time-varying type-specific control variables, $\mathbf{W}_{i,t}$, e.g., the average past performance of funds of type i. The Poisson assumption is natural given that the number of bids can only be positive and that the distribution of bids per month is positively skewed for each fund type. Moreover, even if the Poisson assumption about the arrival of bids were more natural for an individual fund than for a group of funds, the sum of individual arrivals, i.e., the total bids for all funds in a group, will also have a Poisson distribution if the arrivals of bids across funds within the group were independent conditional on the mean arrival rate.

The conditional density of X_{it} is therefore given by

$$
\begin{aligned}
f(x_{it}|t, \mathbf{Z}_t, \mathbf{W}_{it}, \mathbf{1}_i) &\equiv \Pr(X_{it} = x_{it}|\mathbf{Z}_t, \mathbf{W}_{it}, \mathbf{1}_i) \\
&= \frac{\lambda_{it}^{x_{it}} \exp(-\lambda_{it})}{x_{it}!},
\end{aligned}
$$

where $\mathbf{1}_i$ is a vector of binary variables for each of the $j = 1, ..., 9$ characteristics of each fund type i, e.g., Small (yes/no), or Old (yes/no), or US (yes/no), etc. The bid arrival rates are written parametrically as

$$
\lambda_{it} = \exp(\tau t + \mathbf{Z}_t' \boldsymbol{\beta}_i^Z + \mathbf{W}_{it}' \boldsymbol{\beta}_i^W + \sum_{c=1}^{9} 1\{c = i\}\gamma_c) \;\; \forall i, t, \tag{1}
$$

The exponential function guarantees that the number of arrivals is positive. Note that $\boldsymbol{\beta}_i^Z$ is type-specific, allowing for demand for different type of funds to respond differently to macroeconomic shocks. The parameter τ is a common time trend and the parameters $\boldsymbol{\gamma}$ are fixed effects.

Assuming that bids across fund types are independently distributed conditional on $\mathbf{Z}_t$

and $\mathbf{W}_{it}$, then the log-likelihood function for the number of bids $x_{i,t}$ for each fund type in each month is as follows:

$$\ln L(\boldsymbol{\beta}^Z, \boldsymbol{\beta}^W, \tau, \boldsymbol{\gamma} | \{x_{i,t}\}_{i,t}, \{\mathbf{Z}_t\}_t, \{\mathbf{W}_{i,t}\}_{i,t}) = \sum_{t=1}^{88} \left(\sum_{i=1}^{24} x_{i,t} \ln \lambda_{i,t} - \sum_{i=1}^{24} \lambda_{i,t} - \sum_{i=1}^{24} \ln x_{it}! \right).$$

We estimate $\boldsymbol{\beta}^Z, \boldsymbol{\beta}^W, \tau$, and $\boldsymbol{\gamma}$ by maximizing this expression. Note that even if x_{it} is drawn independently from $x_{i't}$ for any $i \neq i'$ conditional on $\mathbf{Z}_t, \mathbf{W}_{it}$, and $\mathbf{1}_i$, the two demands x_{it} and $x_{i't}$ are unconditionally correlated. For this reason, the demands are jointly estimated as a system using the full panel rather than as independent time-series.

The assumption that the Poisson arrival rate of bids, λ, is an exponential function of its determinants $\mathbf{Z}_t$ and their parameters $\boldsymbol{\beta}$ (equation 1), guarantees that the maximum likelihood estimator of $\boldsymbol{\beta}$ is unique.[20]

4.2 Specification

This sub-section describes the set of explanatory variables used to model the average bid arrival rate for each type of fund. The economy-wide variables used as explanatory variables ($\mathbf{Z}_t$) are described in Table 2 - Panel B.[21] All the variables are defined in Appendix A.

4.2.1 Aggregate liquidity conditions and capital call risk

We include in $\mathbf{Z}_t$ the monthly changes in the logarithm of the Federal Reserve System's balance sheet (Δ ln(FED's Total Assets)) as the benchmark borrowing costs.[22] To proxy for time-varying aggregate borrowing constraints, we include the change in the logarithm of the outstanding volume of commercial paper (Δ ln(Commercial paper)). Following Fontaine and Garcia (2012), we also include the monthly changes in the bond premium attributed to funding liquidity risk (Δ(Fontaine-Garcia)).

[20] It is straightforward to show that the system of first-order conditions to maximize the likelihood function is monotonically decreasing on each $\beta_{i,k}$.

[21] Statistics on the portfolio specific variables – which all relate to the fund portfolio relative past performance – are not tabulated.

[22] We choose this variable over the Federal Funds overnight rate because it varies more over time and probably describes the liquidity state better than the interest rate at its nominal lower bound.

The specification includes the monthly changes in the slope of the yield curve (term spread), measured as the difference between the 10-year and 3-month yields on US Treasury bills (Δ(Yield curve slope)), to capture changing expectations of future borrowing costs. Higher future interest rates may force limited partners to sell in anticipation of increasingly more expensive funding of future capital calls.

Temporary bond market illiquidity may also entice limited partners to sell PEF stakes by expecting a strong downward price impact from selling bonds when cash is needed or by suddenly being underweighted in bonds relative to private equity when bond prices are low. Therefore, we complement the Δ(Fontaine-Garcia) index, which incorporates bond market illiquidity shocks, with the monthly differences in the spread between BAA- and AAA-rated corporate bond yields (ΔCorporate spread). As Driessen (2005) shows, the corporate bond spread not only contains default risk information, but is also a priced macroeconomic liquidity risk factor.

4.2.2 Aggregate investment opportunities and the preference for cash

To account for economy-wide investment opportunities, we include four variables in $\mathbf{Z}_t$. The first three describe the current phase of the macroeconomic cyle (booming versus contracting) and are the contemporaneous real OECD GDP growth rate, the contemporaneous monthly return of the value-weighted S&P 500 index ($R_{\text{S\&P500}}$)monthly, and the monthly change in the cyclically-adjusted price-to-earnings ratio of Shiller (2000) ($\Delta\ln$(Shiller PE Ratio)).[23] Second is the . The fourth variable describes current perceptions of future uncertainty, which, as in standard in the literature, we use as a proxy the CBOE's implied volatility index, VIX.[24]

4.2.3 Portfolio rebalancing motives

Exceptional performance by some industries in the economy would impact more the values of funds heavily invested in those industries. Since small private equity funds tend to focus

[23] The OECD GDP figures are reported at a quarterly frequency. We impute the same growth rate to each month belonging to the same quarter.

[24] Both the VIX and the Shiller index could be seen as proxies for times of market over-valuation (see Pasquariello (2014)).

on particular sectors of the economy, a higher volatility of past returns across industries would skew the performance of funds focused on the winning overperforming industries, making investors in these funds over-weighted in private equity and, therefore, pressured to sell. We include the cross-sectional standard deviation of the Fama and French 49 industry portfolio returns (Cross-Industry Volatility) as a proxy for the rebalancing motive channel of the liquidity-driven demand.

4.2.4 Other controls

The vector $\mathbf{W}_{i,t}$ includes fund type-month specific determinants of demand. We expect demand for PEF stakes to contain also a component related to the the need to marginally adjust optimal allocations, as a function of the past performance of the fund itself. To control for a fund's cross-sectional relative performance, we include the average performance of all funds of the same type in excess of the performance by all other funds over the last six months. To control for its relative recent past performance, we include a binary variable indicating whether the average fund type performance over the last months is above the third quartile over the last 3 years.

4.3 Demand model: results

4.3.1 Goodness-of-fit

Table 3 – Panel A shows that our Poisson model together with the retained set of explanatory variables fit well the observed demand for most fund types. The average correlation between the actual and predicted demand is 38% (across the 24 fund types). The average and median p-values of the Wald statistic – null hypothesis of which is that all parameters of the demand for a given fund type are zero – are both below 1% (across the 24 fund types). The average p-value of the binomial deviance statistic – null hypothesis of which is that all the observed and predicted demand are equal – is 27%.[25]

[25] The binomial deviance statistic for the Poisson responses follows a χ^2 distribution and is given by

$$D_i = 2\sum_t \{x_{i,t} \ln \frac{x_{i,t}}{\hat{\lambda}_{i,t}} - (x_{i,t} - \hat{\lambda}_{i,t})\}.$$

In addition to these standard statistics, we compare the correlation structure of the observed demand with that of the predicted demand. We thereby assess the extent to which our model can explain the correlation between the demand of, say, US large young funds and that of US small old funds. Panel A of Figure 4 plots each pair of predicted versus actual correlations. There are $\frac{24\times(24-1)}{2}$ pairwise correlations, and thus as many pairs plotted. We observe that the data points cluster around the 45 degrees line, which indicates that the correlation structure between observed demand time-series is well-captured by the set of explanatory variables together with the Poisson modelling structure we have used.[26] We note that the maximum likelihood estimator does not target to match these correlations directly, yet the fitted model predicts them very well.

Insert Table 3 Here

4.3.2 Demand responses by fund type

For each fund type we have a loading of demand on a state variable ($\boldsymbol{\beta}_i^Z$). Panel B of Table 3 summarizes the demand response to each state variable implied by the estimated 24 loadings, i.e., for all fund types. The estimated loadings of any variable are statistically significant for at least 19 out of 24 demands, showing that specified each state variable plays a role in explaining demand fluctuations. GDP growth, for example, is statistically significantly positively related to the demand of 17 of the 24 types (and negatively so to the demand of 4 types of funds). A comparison of mean and median average effects reveals that the responses are skewed, i.e., disproportionately large for a few fund types.

For most state variables, there are as many funds with a significantly positive demand response as there are with a negative response to the same shocks, e.g., the estimated responses to shocks to the return on the S&P 500 , the VIX, or the (logarithm of) total asset purchases by the FED. This heterogeneity is the demand response is less pronounced for GDP growth – mostly positives – and the corporate credit spread and the slope of the yield curve – mostly negatives.

[26] We repeat the same exercise with de-trended time-series. Figure 4 – Panel B shows that results are similar, indicating that the accuracy in these predicted correlations is not due to a common trend in the time-series.

The magnitude in the responses are also quite heterogeneous for most variables. For example, a one standard deviation increase in the Fontaine-Garcia index of funding illiquidity is associated with an increase in the demands for 12 types of funds by a 0.42 bids on average but also with decreases in the demand for 8 fund types by more than one bid.

The heat map in Figure 5 looks closer into which fund types see a decrease or an increase in bidding for shocks to each state variable. Each box corresponds to the expected change in the demand for all funds in the same size or age category given a positive (denoted by Δ) or a negative (∇) one sample standard deviation shock to the relevant state variable in each row. Rows are sorted in descending order according to the overall demand response (in the 'Total' column). Starting from the left, the figure shows the breakdown of this response by fund size, then by fund age.

Insert Figure 5 Here

As shown in Table 3, shocks to the asset purchases by the Federal Reserve are associated with opposing demand responses across different fund types. Figure 5 shows that the increased bidding during monetary expansions is concentrated on Large and Very Large, Middle-aged, US funds. Note too that an increase in the Fontaine-Garcia bond liquidity premium is associated with a decrease in the total number of bids for Very Large and Old funds, while Small funds and Young funds experience an increased demand. A steepening of the yield curve predicts a much sharper contraction in the demand for Medium, Large, and Very Large funds, as well as a moderate drop of demand for Old and Middle-aged funds. However, yield curve slope increases are also associated with an increase in demand for Small and Young funds.

To summarize, the distribution of estimated demand responses to a tightening of aggregate liquidity and increases in funding costs is consistent twith the capital call risk channel for selling PEF stakes under pressure: the *positive* liquidity-driven demand responses are concentrated in the young funds, i.e., those where a lrger proportion of committed capital remains to be called in the future.

4.3.3 Demand responses by investor and fund types

We reestimate the Poisson demand system using bids by only one type of investors (Funds-of-funds [FoFs], Secondary funds [SFs], and Asset Owners [AOs]) at a time. We ask whether the signs of the demand response to each shock are similar across all investor types, or whether different signs are explained by different investors' bidding intensities. We summarize the demand responses implied by the demand model estimates by investor type using the heat map in Figure 6.

Insert Figure 6 Here

The first observation is that, in absolute terms, the demand by SFs is most sensitive to shocks to any state variable. This result might be expected as SFs are the most frequent bidders as a group. However, it is surprising that the demand by AOs is at least as responsive to shocks to some state variables given that bids by AOs represent just over 20% of bids by SFs. That is, investors that are on average not active in this market may become the most active in some liquidity states.

Second, shocks to some aggregate variables are associated with different and opposite bidding flows by different investors. For example, the aggregate positive response to negative shocks to funding liquidity (and increase in the Fontaine-Garcia bond liquidity premium) is mainly explained by the response of AOs (more than 4 additional bids per month), who are not very active on average (8 bids per month). These results suggest that AOs – who are least constrained by the amount they can invest in the secondary market for PEF stakes – enter the market aggressively in bad times but refrain to do so otherwise. Their bidding behaviour is therefore consistent with that of a liquidity provider.

Finally, there are shocks for which all investors' bidding react in the same direction, if with different magnitudes. The total number of bids by every type investor increases during monetary expansions, and when the stock market is increasing.

Figure 7 shows the disaggregation of bid responses to one sample standard deviation changes in each state variable, by investor *and* fund type. This figure shows richer patterns in the flows of bids. Consistent with our interpretation of AOs as liquidity providers to LPs pressured to sell funds with high capital call risk in times of low liquidity, the figure shows that the increased bidding in times of low funding liquidity, as measured by a high Fontaine-Garcia index, is explained by AOs targeting Young, Middle-Aged, US funds. Similarly, the bidding volume driven by asset purchases by the FED is mostly explained by SFs concentrating on Large, Middle-aged funds. Also quite clearly, AOs and SFs, but not the FOFs, bid more for Small funds in times of high implied volatility.

Insert Figure 7 Here

To sum up, we have shown in this section that the most salient feature of the impact of aggregate measures of liquidity on the total number of bids for PEF stakes is that the demand responses by fund type, and by investor type, are hugely heterogeneous. The result that some investors bid more frequently, whereas others bid less so given the same shock is consistent with the view that certain investors react to macro shocks by providing liquidity (submitting more bids) for sellers of exposed funds and when other investors are constrained.

5 Demand, bids and fund performance

We now explore whether liquidity-driven demand flows towards certain types of fund are associated with lower bid levels. This analysis is conducted at the individual bid level.

5.1 Model and identification

Each observed bid $b_{j,h,d}$ comes from a fund j that we grouped in one of the type i=1,..,24, by a bidder h of type f=1,...,3, on a day d, which pertains to a month t=1,...,88. The reduced form equation we estimate is as follows:

$$b_{j,h,d} = \alpha_i + \alpha_f + \alpha_t + \alpha_Y \mathbf{Y}_{j,h,t} + \alpha_D D_{i,t} + \epsilon_{j,h,d}, \tag{2}$$

where α_i, α_f, and α_t are fixed effects. $\mathbf{Y}_{j,h,t}$ is a vector of control variables containing fund size, fund age as of month t, and the number of bids submitted by bidder h in month t. $D_{i,t}$ is the demand for fund type i during month t (by all bidder types). The demand can be either the observed demand ($D = X$), or the predicted demand ($D = \hat{\lambda}$), or the liquidity-driven demand ($D = \hat{\lambda}_Z$), i.e. the part of the demand predicted by the state variables, $\mathbf{Z}_t$, only.

The coefficient of interest is $\alpha_{\hat{\lambda}Z}$, which describes whether bids are on average higher or lower in times of high liquidity-driven demand. If bidders provide liquidity, then $\alpha_{\hat{\lambda}_Z}$ should be negative because bidders are meeting the increase in supply, but at lower prices. Note that $\alpha_{\hat{\lambda}_Z}$ does not reflect private information since the predicted demand $\hat{\lambda}_{i,t}$ is a function only of variables that are publicly observable, and that it is correctly identified by OLS if the predicted demand variable, $\hat{\lambda}_Z$ is orthogonal to the bid equation error, $\epsilon_{j,h,t}$.

Omitted variables that influence individual bids may also influence demand. However, we use only the component of the demand that is a function of publicly observable time-varying state variables, and we control for time fixed effects. As a (weaker) alternative to time fixed effects, we can also control for all the state variables in $\mathbf{Z}_t$, allowing for these to also have a direct effect on bids. It is possible to estimate such a model because of the non-linearity of the relationship between predicted demand and the state variables.

In addition, as shown in Section 4.3, the estimates of $\beta_{i,k}$ vary *significantly* across fund types, and the sign of the slope coefficients is different across fund types for most explanatory variables. As a result, the predicted demand is unlikely to be correlated with time-varying omitted variables with similar effects (sign and magnitude) across fund types. Moreover, even if time-varying omitted variables were correlated with some variable in $\mathbf{Z}_t$, they would need to have a relationship with bid of the same magnitude and sign as the estimates of $\beta_{i,k}$.

To sum up, as the mapping from $\mathbf{Z}_t$ onto $\hat{\lambda}$ is non-linear and varies for each i, it is unlikely that any time-varying omitted variables will be correlated with $\hat{\lambda}$.[27]

5.2 Bids and Demand: Results

Table 4 presents the estimates of the parameters in the regression model 2. Our test for liquidity provision is that the coefficient of demand, $\alpha_{\hat{\lambda}_Z}$ is negative. We begin by showing the results when $D = X$, i.e. the relationship between observed demand and bids, and find a negative coefficient. Next, in column (2), we use instead $D = \hat{\lambda}$, i.e. predicted

[27]Note that our liquidity-driven demand variable, $\hat{\lambda}_{i,t}$ varies across fund type and time. Therefore, we can estimate its coefficient while additionally controlling for unobservable bid differences over time (month fixed effects) across funds (fund type fixed effects) that are unrelated to liquidity.

demand. Again, the coefficient is negative and significant. In column (3) we use the demand component predicted only by state variables, i.e., we set $D = \hat{\lambda}_Z$. Again, the coefficient is negative and statistically significant, but larger in absolute value.

These results support our hypothesis that demand flows to where there is selling pressure. We observe lower bids for those funds that experience higher liquidity-driven demand than normally in a given month. Note that our results do not contradict the usual view that, overall, bids drop because bidders are withdrawing from the market. However, we find that, *cross-sectionally*, the funds that experience the largest discount are those for which demand is flowing to.

Insert Table 4 Here

To interpret the magnitude of these coefficients, we calculate the average implied difference between bids for a given change in the demand induced by shocks to aggregate liquidity as $\Delta E(\text{Bid}) \equiv \hat{\alpha}^{\lambda} \times \Delta\lambda$, reported in Panel B. We set $\Delta\lambda$ to one sample standard deviation in the liquidity-induced demand for each fund type. This statistic has a similar interpretation to 'Kyle's Lambda' (Kyle (1985)) because it measures the impact on the bid from a change in bidding volume. Panel B shows that a one sample standard deviation increase in the demand for any given type of fund is on average associated with a bid that is lower by 0.67% (column 3). This figure represents an average discount on bids and not necessarily on transaction prices, which could be higher if the seller finds a higher bid. The bidder does not know the other bids and may therefore submit a dominated bid. This estimated discount is therefore an upper bound to the discount expected by the seller. This upper bound notwithstanding, we note that we have 35 transactions in our data for which we are able to follow the negotiation process through time leading to an actual transaction. In those cases, we identify the last bid on the fund prior to the transaction. In 26 cases, the transaction price is identical to the bid, in 4 cases the transaction price is higher (on average less than 1 percentage point) and in 5 cases the transaction occurs at a lower value relative to the prior bid.

Next, we decompose the partial correlation between bid levels and liquidity-driven demand by fund age, interacting the predicted demand with binary variables for Young Funds, Middle-aged funds and Old funds (column 4). While we find a negative correlation between bids and demand for all ages, the effect is strongest for Young Funds: bids are lower by 2.67 percentage points given a one standard deviation increase in the demand for Young funds that is predicted by aggregate liquidity variables. This result is consistent with capital call risk being the source of illiquidity discounts in the secondary market for private equity fund stakes. Indeed, young funds have the highest proportion of dry power and, therefore, their LPs have to meet capital calls in the future. LPs would be most pressed to sell stakes in Young Funds in times of low liquidity, and its precisely for these funds that we find the largest negative association between bid levels and liquidity-driven demand.[28]

In column (5) we decompose the correlation between bids and liquidity-driven demand by fund size. The economic significance is highest for Small and Medium sized funds, although only statistically significant for the latter. One possible explanation for this result is that investments by small funds tend to be less diversified across industries, so that more volatility (overall, as measured by the VIX, or across sectors) may cause small funds focused on the winner industries to be worth more and their LPs to be suddenly overweighted in private equity, forcing them to sell under pressure to conform to their own maximum weights.[29]

5.3 Asymmetric Information and Bid discounts

While our results suggest that bidders are compensated for providing liquidity to funds that experience selling pressure, there is still a concern that the low bids we observe reflect bidders responding to an increase in adverse selection. This could happen for example if some shocks to liquidity bring private signals to sellers. For example, increases in the VIX may also enhance the advantage of some LPs to value stakes more precisely. In such context, uninformed investors may still increase their bidding in response to selling orders by the

[28]Another explanation for this negative correlation could be the demand flows to relatively cheap funds when borrowing is expensive. While young funds may indeed by cheaper, there is no a reason *a priori* why they should be more *discounted* with respect to NAV. Moreover, the inclusion of fund type fixed effects and fund age account for age-related value differences across funds, ruling out this alternative interpretation.

[29]High volatility may also increase the demand for the cheaper, small funds focused on the worst performing sectors, explaining the negative correlation. We can rule this interpretation out because our demand model controls for the fund's past performance and excludes this component from the predicted liquidity-driven demand.

potentially informed LPs, albeit at a discount to compensate for the possibility of adverse selection.

To address this concern, we follow Llorente et al. (2002) and note that although the liquidity and private information motivations for trading predict similar *contemporaneous* correlations between demand and bids, they have different *dynamic* patterns. If the initial demand increase and downward adjustment in bids is due to negative private signals, then bids will remain low until NAVs have incorporated the information, suggesting a relation between lagged demand and bids. In addition, this implies that higher demand predict worse future (NAV-to-NAV) fund performance. If the lower bids made following an increase in demand are instead due to liquidity provision, we expect the effect on bids to revert as soon as liquidity is restored and in addition there will be no predictability of fund performance.

We test whether past demand flows induced by liquidity variables have a persistent effect on bids by regressing bids on all lags of predicted demand up to four months. The estimates in column (1) of Table 5 show that bids are only negatively correlated with contemporaneous demand and not correlated at all with any lag up to the fourth. Columns (2) to (8) show the same lagged correlation structure for all size and age categories of funds. The possibility of private information effects captured in the demand predicted by liquidity variables is largely rejected. The only cases where we observe a negative and significant correlation between bids and lagged demand are for middle-aged or Very large funds (4 months lag), and Medium funds (2 months). Moreover, there is no clear indication of persistence in these correlations, i.e., negative correlations for more than one consecutive lag.

Insert Table 5 Here

Table 6 shows the estimates of the regression of the fund's returns, computed over one, two and three years from the date of the reference NAV, on the liquidity-driven demands by fund age or size. Rejecting the private information motive for trading, columns (1) to (3) show that demand predicted by liquidity variables is uncorrelated with NAV-to-NAV fund returns for a horizon of 1, 2, and 3 years. The estimates are not only statistically insignificant but economically very small.

We do not find negative correlations either between liquidity-driven demand and NAV-to-NAV at any horizon for most fund sizes and ages. The exception are small funds, where NAV-to-NAV fund performance after 2 and 3 years are indeed negatively and significantly correlated with liquidity-driven demand (columns 8 and 9). The correlation between liquidity-driven demand and the two-year returns is negative also for Young funds (column 5), although this correlation implies a return difference of less than 4 basis points (untabulated). Moreover, the correlation is absent for returns calculated over 3 years.

Insert Table 6 Here

6 Additional Results

6.1 Who provides liquidity?

Table 7 explores the relation between bids placed or fund performance and liquidity-driven demand by type of bidder. Columns (1) and (2) show that it is precisely the demand by investors that are not specialized in secondary acquisitions, which we refer to as Asset Owners (AOs), that correlates negatively with their bids. On average, AOs bids are lower by 1 to 1.5 percentage points when their liquidity-driven demand is higher by one sample standard deviation (Panel B, columns 1 and 2). The liquidity-driven demand by AOs is not correlated with the funds' future performance (columns 3 to 5), suggesting that the bid reduction is a compensation for providing liquidity and not adverse selection.

We find no evidence that either Secondary Funds or other Funds-of-funds submit lower bids when increasing their number of bids in response to liquidity shocks. In other words, AOs appear to be the liquidity providers in the secondary market for PEF stakes. Unlike SFs, AOs are not constrained to invest exclusively in secondary market acquisitions, but can diversify across asset classes. Therefore, they have the flexibility to bid in this market when capital call funding risk or portfolio rebalancing puts pressure on other constrained investors (SFs and FoFs).

Insert Table 7 Here

6.2 When do liquidity provision discounts occur?

To validate that our estimated discounts are due to illiquidity in the aggregate, we ask whether the negative correlation between liquidity-driven demand and bids is present mostly in times of low rather than high liquidity. To do so, we regress bid levels on liquidity-driven demand interacted with binary variables indicating months of low (below the 1st tercile), high (above the 2nd tercile), or intermediate liquidity (in between terciles). We run a regression for each liquidity variable and report the estimates along each row of Table 8. Confirming our interpretation of the results above, the negative correlation between bids and the demand for young funds is obtained in months of relatively low or intermediate, but not high, asset purchased by the Federal Reserve (Row 1) and only in months when the yield curve slope steepens above but not below its first tercile (Row 2). Moreover, by splitting the Fed's asset purchases, the changes to the yield curve slope, the Fontaine-Garcia index (Row 4), or the VIX (Row 8) into terciles we now identify a significant negative correlation for middle-aged funds and old funds in times when liquidity is low and volatility is high. In short, we find that a liquidity discount is applied precisely in times of low liquidity.

Insert Table 8 Here

We conduct a similar analysis to validate that the correlation between bids and each investor type's demand, which identified above the other Asset Owners (AOs) as liquidity providers, is observed in times of low rather than high liquidity. Table 9 shows that AOs provide liquidity at all months except when the Fed's asset purchases are in the highest tercile (Row 1), or when changes in the yield curve slope or the Fontaine-Garcia index are in the middle tercile (Rows 2 and 4, respectively). Asset Owners appear to provide liquidity also in times of lower and middle tercile VIX. This table also shows that even Secondary funds may provide liquidity in some states. Namely, when funding liquidity is lowest according to the Fontaine-Garcia index or when the FED's purchases or the corporate spread are highest.

Insert Table 9 Here

7 Conclusions

We show that an important determinant of illiquidity in the secondary market for private equity is explained by the interaction between the aggregate state of liquidity and fund characteristics that make its LPs more vulnerable to liquidity shocks. The demand for funds that are most likely to be exposed to selling pressure increases in response to aggregate liquidity shocks, and the increase in the liquidity-driven demand for such funds is associated with lower bids. This negative correlation is largest for young funds, which a priori present the highest risk of funding future capital calls.

Our evidence is consistent with recent theoretical literature (e.g. Lagos and Rocheteau (2009) and Hugonnier et al. (2014)) that predicts investors take the role of liquidity providers in the absence of designated market makers. Future research could aim to precisely quantify the expected liquidity discount of private equity stakes using a theory of the optimal timing of sales by LPs , and data of the demand, supply and execution of deals.

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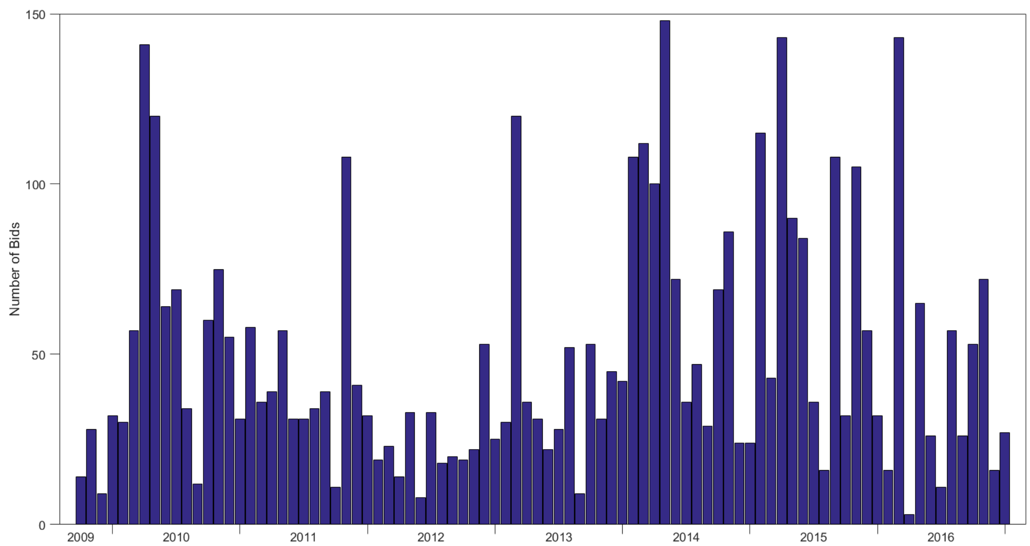

Figure 1: Number of Bids per Month in the Secondary Market. This figure plots the total number of bids submitted each month to a global sell-side broker of Private Equity stakes based in London, between September 2009 and December 2016.

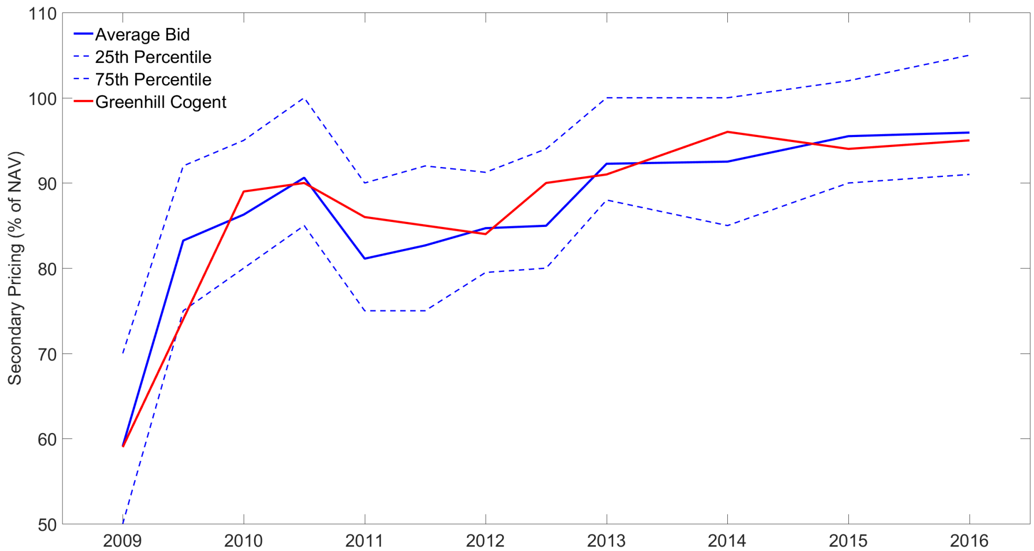

Figure 2: The Average Bid over Time. This figure plots the average High Bid bid over all the funds in our sample compared to the average High Bid reported by Greenhill Cogent 2016. If a bid is submitted as a range, the 'High bid' is the maximum value in the range. Greenhill Cogent reports High Bids at a semi-annual frequency from 2010 to 2013 and annually in 2009, 2014, 2015, and 2016. The corresponding average High Bids for our sample are calculated at the same frequencies as in Greenhill Cogent's. The data includes all bids submitted between September 2009 and December 2016 to a global sell-side broker of Private Equity stakes based in London.

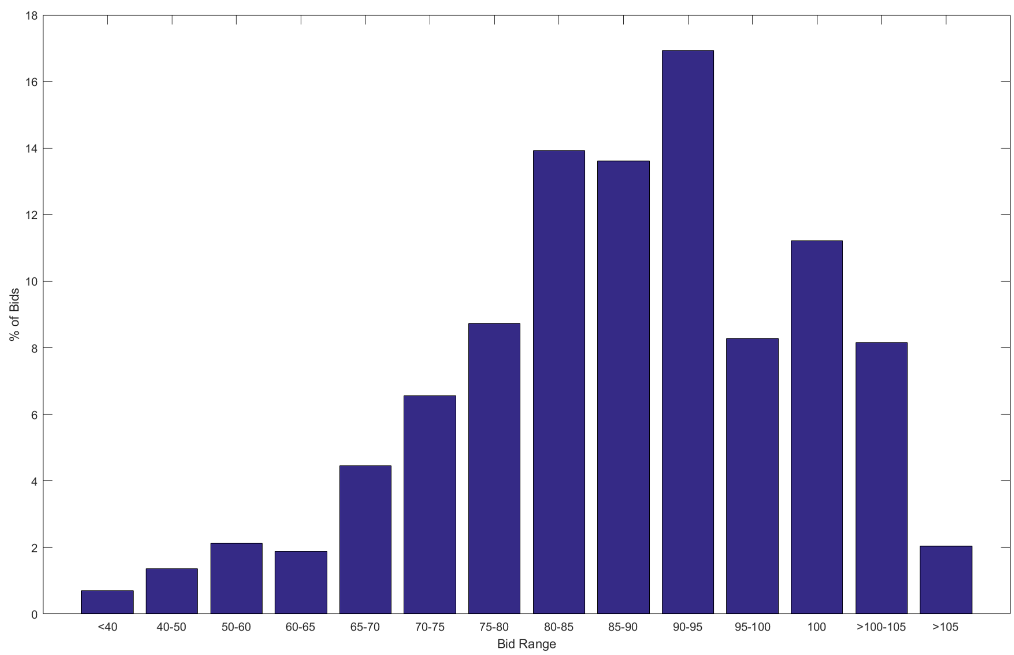

Figure 3: The Distribution of Bids. This Figure shows the distribution of bids submitted each month to a global sell-side broker of Private Equity stakes based in London, between September 2009 and December 2016.

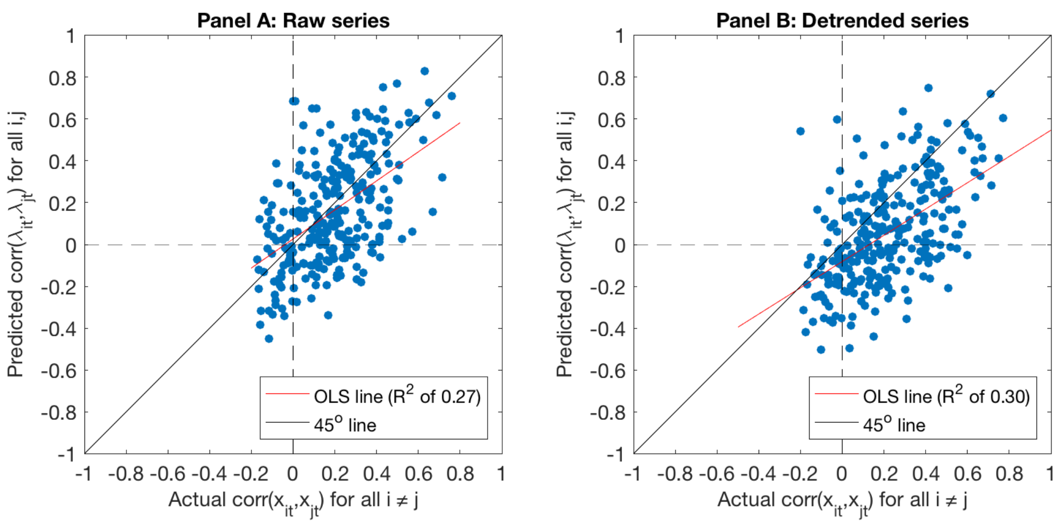

Figure 4: Actual and Predicted Demand Correlations. This figure compares the actual to the predicted time series of total bids (demand) for each fund type in the data. The number of bids per month for each type of fund is predicted using an estimated Poisson distribution, where the mean number of bids per month is a function of time-varying covariates capturing the state of growth, investment opportunities and aggregate liquidity. Panel A shows the scatter plot of the actual correlations between all pairs of fund types against those predicted by the model. Panel B shows the same scatter after detrending the actual and predicted demands. The data includes all bids submitted between September 2009 and December 2016 to a global sell-side broker of Private Equity stakes based in London.

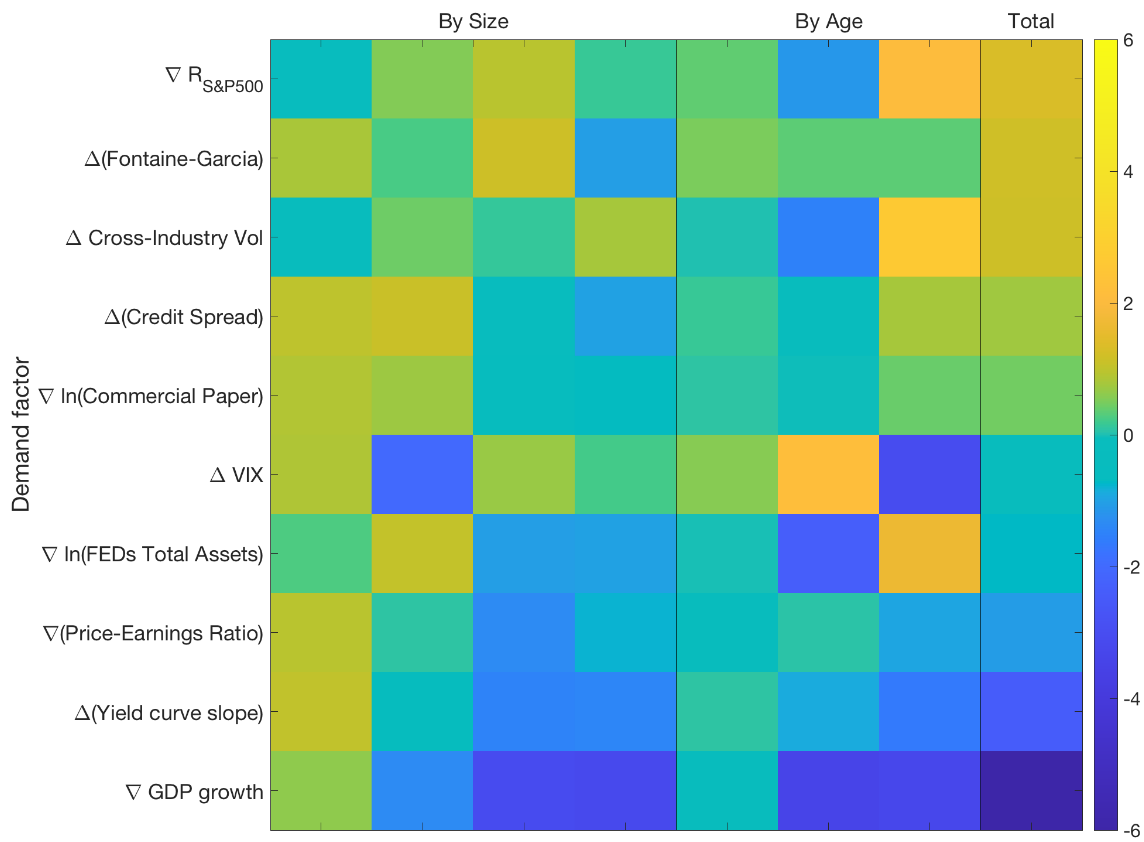

Figure 5: Heat Map of the Demand Response to Aggregate Liquidity Shocks, by Fund Type. This map shows the predicted changes in the number of bids per month for all funds in response to a one sample standard deviation change to each of the explanatory variables of the demand model ('Total' column). Positive (negative) shocks to the explanatory variable are denoted by Δ (∇). Demand responses are broken down by fund size (Small, Medium, Large, Very large) or age (Young, Middle-aged, Old). The demand response is predicted using the estimates of the model of bid arrivals per month per fund type, which is assumed to have a Poisson distribution with a mean number of bids conditional on the demand explanatory variables. The data includes all bids submitted between September 2009 and December 2016 to a global sell-side broker of Private Equity stakes based in London.

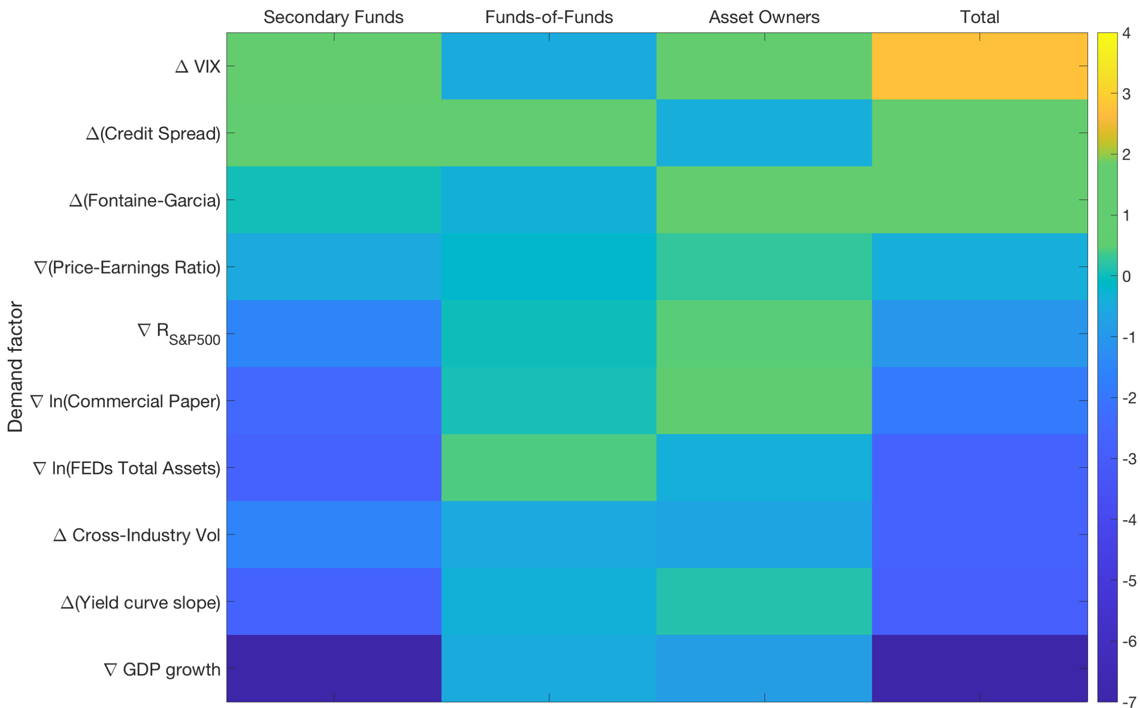

Figure 6: Heat Map of the Demand Response to Aggregate Liquidity Shocks, by Investor Type. his map shows the predicted changes in the number of bids per month for all funds in response to a one sample standard deviation change to each of the explanatory variables of the demand model ('Total' column). Positive (negative) shocks to the explanatory variable are denoted by Δ (∇). Demand responses are broken down by the type of bidder: Secondary funds, Other Funds-of-funds, and Other Asset Owners.The demand response is predicted using the estimates of the model of bid arrivals per month per per investor type per fund type, which is assumed to have a Poisson distribution with a mean number of bids conditional on the demand explanatory variables. The data includes all bids submitted between September 2009 and December 2016 to a global sell-side broker of Private Equity stakes based in London.

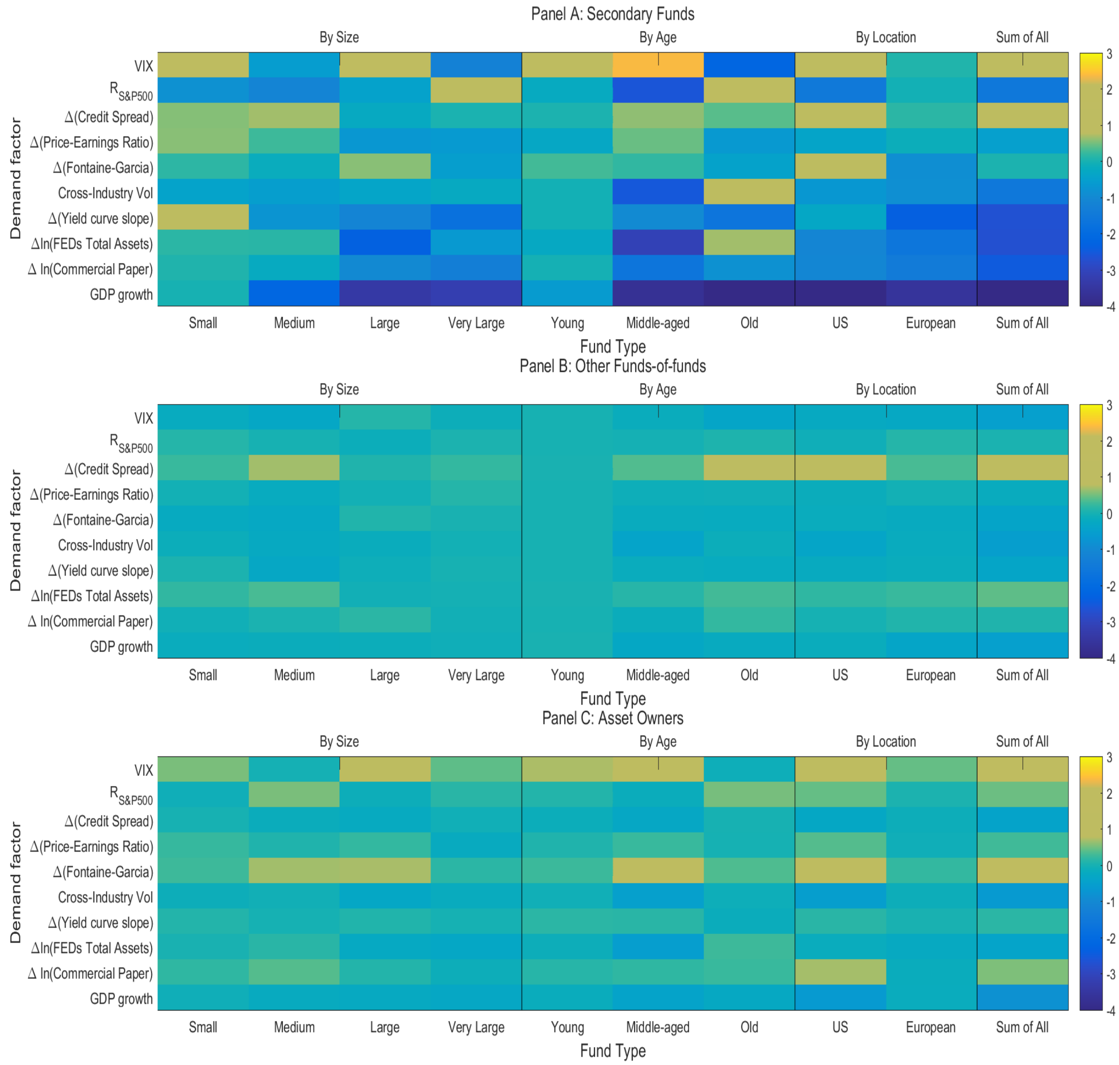

Figure 7: Heat Map of the Demand Response to Aggregate Liquidity Shocks, by Investor and Fund Type. This map shows the predicted average change in the total number of bids per month for each type of fund (according to their size, age, or location) by each type of bidder (Secondary funds, Other Funds-of-funds, and Other Asset Owners) in response to a one sample standard deviation increase for some demand explanatory variable. The average change is predicted using the estimates of the model of bid arrivals per month per investor type per fund type, which is assumed to have a Poisson distribution with a mean number of bids conditional on the demand explanatory variables. The data includes all bids submitted between September 2009 and December 2016 to a global sell-side broker of Private Equity stakes based in London.

Table 1: Descriptive Statistics

The table reports summary statistics of the characteristics of the targeted funds and the bids submitted to a global sell-side broker of Private Equity stakes based in London, between September of 2009 and December 2016. There are 4,365 bids for 497 funds over 88 months. Bids are expressed as a percentage of the referenced NAV.

Panel A - Full Sample

Bids by	All Bidders			Funds-of-Funds			Secondary Funds			Asset Owners		
	Mean	Median	Std	Mean	Median	Std	Mean	Median	Std	Mean	Median	Std
Bid Placed	88.3	90.0	13.6	82.5	85.0	16.4	87.6	90.0	13.2	93.9	97.5	12.1
Fraction of US Funds	0.31	n/a	n/a	0.31	n/a	n/a	0.33	n/a	n/a	0.20	n/a	n/a
Fund Size	4.7	3.5	4.9	3.5	1.6	4.2	5.1	3.7	4.9	3.8	1.7	4.7
Fund Age	6.6	7.0	2.7	6.5	6.0	2.8	6.8	7.0	2.6	5.9	6.0	2.9
Number of Observations		4,365			348			3,291			726	
Number of Unique Bidders		144			38			54			52	

Panel B - Subsample matched with Preqin cash flow data

Bids by	All Bidders			Funds-of-Funds			Secondary Funds			Asset Owners		
	Mean	Median	Std	Mean	Median	Std	Mean	Median	Std	Mean	Median	Std
Bid Placed	88.6	90.5	13.0	84.0	87.3	15.7	88.2	90.0	12.5	93.0	95.5	12.6
Fraction of US Funds	0.37	n/a	n/a	0.36	n/a	n/a	0.39	n/a	n/a	0.27	n/a	n/a
Fund Size	6.1	5.0	5.0	4.8	3.8	4.5	6.4	5.2	5.0	5.6	4.3	5.1
Fund Age	6.5	7.0	2.6	6.2	6.0	2.9	6.7	7.0	2.5	5.7	6.0	2.7
Fund PME at time of bid	1.18	1.14	0.33	1.20	1.15	0.38	1.18	1.14	0.32	1.16	1.11	0.32
Number of Observations		3,093			230			2,426			437	
Number of Unique Bidders		136			36			53			47	

Table 2: Summary of Data for the Demand Model

This table presents two sets of descriptive statistics. Panel A shows statistics on the number of bids received each month by our data provider between September of 2009 and December of 2016 for the 24 different portfolios of funds that we form. Panel B shows statistics on the economy-wide variables used as explanatory variables in the demand model. They are recorded at a monthly frequency. All variables are defined in Appendix A.

Panel A: Number of bids observed each month for different portfolios of funds

	Mean	Std dev.	Skewness	min	Q1	Median	Q3	Max
All portfolios	2.19	3.65	2.62	0.00	0.00	1.00	3.00	25.00
Portfolios organized by fund size								
Small	1.78	2.81	2.22	0.00	0.00	1.00	2.00	16.00
Medium	1.33	2.44	2.17	0.00	0.00	0.00	2.00	14.00
Large	3.04	4.40	2.31	0.00	0.00	1.00	4.00	25.00
Very large	2.09	3.64	2.60	0.00	0.00	0.00	2.00	25.00
Portfolios organized by fund age								
Young	1.92	3.89	2.74	0.00	0.00	0.00	1.00	19.00
Middle-aged	2.32	3.91	2.78	0.00	0.00	1.00	3.00	25.00
Old	2.06	3.10	1.99	0.00	0.00	1.00	3.00	17.00
Portfolios organized by region of investment focus								
Europe	2.15	3.39	2.38	0.00	0.00	1.00	3.00	20.00
US	2.38	4.24	2.73	0.00	0.00	1.00	2.00	25.00

Panel B: Economy wide variables used as explanatory variables ($\mathbf{Z}_t$)

	Mean	Std dev.	Skewness	min	Q1	Median	Q3	Max
GDP growth	1.85	0.99	−2.34	−3.60	1.70	2.00	2.30	3.50
$R_{\text{S\&P 500}}$	0.01	0.04	−0.11	−0.08	−0.01	0.01	0.03	0.11
Δ(Price-Earnings Ratio)	0.11	0.65	−1.12	−2.56	−0.22	0.20	0.52	1.44
Cross-Industry Vol	0.04	0.01	1.06	0.02	0.03	0.04	0.05	0.08
VIX	0.19	0.06	1.53	0.11	0.14	0.17	0.21	0.43
$\Delta\ln$(Commercial Paper)	0.00	0.05	0.23	−0.13	−0.03	−0.01	0.02	0.13
$\Delta\ln$(FED's Total Assets)	0.01	0.01	0.68	−0.01	0.00	0.00	0.02	0.05
Δ(Fontaine-Garcia)	0.00	0.28	−0.80	−1.05	−0.14	0.03	0.16	0.72
Δ(Yield curve slope)	−0.02	0.19	−0.29	−0.68	−0.14	−0.01	0.10	0.53
Δ(Credit Spread)	−0.01	0.09	0.50	−0.24	−0.06	−0.02	0.05	0.26

Table 3: Estimates of the Demand Model

This table summarizes the goodness-of-fit measures (Panel A) and the Maximum Likelihood estimates (Panel B) of the Poisson models of the demand for each of 24 fund types. The mean number of bids for all funds of type i in month t is given by

$$\lambda_{it} = \exp(\tau t + \mathbf{Z}_t' \boldsymbol{\beta}_i^Z + \mathbf{W}_{it}' \boldsymbol{\beta}_i^W + \sum_{j=1}^{J} 1\{i = j\}\gamma_j) \ \forall i, t,$$

where the variables in $\mathbf{Z}_t$ measure the state of aggregate liquidity or aggregate investment opportunities. The sample includes all bids for all fund types between September 2009 and December 2016. The estimated economic effects of each variable correspond to a change in the average number of bids given a one sample standard deviation change in the explanatory variable. The Wald statistic is for the null hypothesis that all parameters for each fund type demand are zero. The Binomial deviance statistic is for the null hypothesis that the difference between the actual number of bids and the predicted average number of bids each month is zero. All variables are defined in Appendix A.

Panel A: Goodness-of-fit

	Mean	Median		Mean	Median
Wald statistic	2605	484	Binomial deviance	81.62	70.70
p-value	0.00	0.00	p-value	0.27	0.00
Pseudo R^2	0.17	0.15	$corr(X_{i,t}, \hat{\lambda}_{i,t})$	0.38	0.38

Panel B: Economic effects implied by the parameter estimates associated to aggregate variables ($\mathbf{Z}_t$)

	Statistically significant positive effects				Statistically significant negative effects			
Variable	#	Mean	Stdev	Median	#	Mean	Stdev	Median
GDP growth	17	0.44	0.52	0.19	4	−0.12	0.18	−0.02
$R_{\text{S\&P 500}}$	10	7.46	9.84	2.47	12	−4.99	4.49	−3.01
Δ(Price-Earnings Ratio)	13	0.28	0.33	0.11	8	−0.30	0.37	−0.14
Cross-Industry Vol	9	15.93	15.92	10.55	13	−13.73	19.05	−3.07
VIX	10	5.63	6.54	2.96	13	−4.19	4.70	−2.17
Δ ln(Commercial Paper)	11	2.52	2.39	1.99	8	−2.32	3.04	−0.82
Δ ln(FED's Total Assets)	12	21.94	39.07	4.79	10	−7.59	7.83	−3.69
Δ(Fontaine-Garcia)	12	0.42	0.60	0.22	8	−1.09	1.52	−0.39
Δ(Yield curve slope)	7	0.87	0.94	0.40	15	−1.08	1.07	−1.07
Δ(Credit Spread)	13	1.35	1.71	0.41	6	−3.87	8.94	−0.54

Table 4: The Relation between Bid Levels and Demand

This table presents estimates of the regressions of the bid placed on different measures of demand (total number of bids per type fund, i, per month, t) predicted by the demand model of Table 3. Bids are expressed as a percentage of the referenced NAV. Demand by fund type per month is either the observed demand ($X_{i,t}$), the predicted demand using all of the model's explanatory variables ($\hat{\lambda}_{i,t}$) or the predicted demand using only state variables ($\hat{\lambda}^{\mathbf{Z}}_{i,t}$). Control variables for all regressions include the exact (log of) size and age of the bidded fund, and the (log of) the number of bids by the bidder. All regressions include also month, bidder and fund type fixed effects. Standard errors (in parentheses under each estimate) are clustered at the fund type level. Estimates followed by the symbols ***, **, or * are statistically significant at the 1%, 5%, or 10% levels, respectively. Please refer to Appendix A for a definition of all the variables.

Panel A: The dependent variable is the bid placed, as a % of reference NAV:

	(1)	(2)	(3)	(4)	(5)
Observed demand ($X_{i,t}$)	-0.154^{*}				
	(0.086)				
Predicted demand ($\hat{\lambda}_{i,t}$)		-0.138^{**}			
		(0.057)			
Liquidity-driven demand ($\hat{\lambda}^{\mathbf{Z}}_{i,t}$)			-0.207^{**}		
			(0.081)		
$\hat{\lambda}^{\mathbf{Z}}_{i,t} \times \mathbf{1}\{\text{Young Fund}\}$				-4.281^{***}	
				(1.204)	
$\hat{\lambda}^{\mathbf{Z}}_{i,t} \times \mathbf{1}\{\text{Middle-aged Fund}\}$				-0.142^{**}	
				(0.055)	
$\hat{\lambda}^{\mathbf{Z}}_{i,t} \times \mathbf{1}\{\text{Old Fund}\}$				-0.539^{***}	
				(0.137)	
$\hat{\lambda}^{\mathbf{Z}}_{i,t} \times \mathbf{1}\{\text{Small Fund}\}$					-0.490
					(0.386)
$\hat{\lambda}^{\mathbf{Z}}_{i,t} \times \mathbf{1}\{\text{Medium Fund}\}$					-1.208^{***}
					(0.395)
$\hat{\lambda}^{\mathbf{Z}}_{i,t} \times \mathbf{1}\{\text{Large Fund}\}$					-0.190
					(0.164)
$\hat{\lambda}^{\mathbf{Z}}_{i,t} \times \mathbf{1}\{\text{Very large Fund}\}$					-0.146^{**}
					(0.061)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Fund Type Fixed Effects	Yes	Yes	Yes	Yes	Yes
Bidder Type Fixed Effects	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes
Observations	4,365	4,365	4,365	4,365	4,365
Adjusted R^2	0.25	0.28	0.28	0.28	0.28

Table 4

Panel B: Economic significance of slope coefficients ($\hat{\alpha}$) in Panel A

	$\Delta E(\text{Bid }\%) \equiv \hat{\alpha}^{\lambda} \times \Delta\lambda$				
	(1)	(2)	(3)	(4)	(5)
$\Delta\lambda = \text{Std.Dev.}(\hat{\lambda})$ for					
All fund types	-0.563^{*}	-0.631^{**}	-0.672^{**}		
	(0.312)	(0.260)	(0.263)		
Young Funds				-2.666^{***}	
				(0.750)	
Middle-aged Funds				-0.566^{***}	
				(0.219)	
Old Funds				-1.197^{***}	
				(0.303)	
Small Funds					-1.171
					(0.922)
Medium Funds					-1.297^{***}
					(0.424)
Large Funds					-0.477
					(0.413)
Very large Funds					-0.634^{**}
					(0.263)

Table 5: The Relation between Bid Levels and Demand over Time

This table presents estimates of the regressions of the bid placed on different measures of demand (total number of bids per type fund, i, per month, t), and their lags, predicted by the demand model of Table 3. Bids are expressed as a percentage of the referenced NAV. Demand by fund type per month is predicted using only state variables ($\hat{\lambda}^{\mathbf{Z}}_{i,t}$). Control variables for all regressions include the exact (log of) size and age of the bidded fund, and the (log of) the number of bids by the bidder. All regressions include also month, bidder and fund type fixed effects. Standard errors (in parentheses under each estimate) are clustered at the fund type level. Estimates followed by the symbols ***, **, or * are statistically significant at the 1%, 5%, or 10% levels, respectively. Please refer to Appendix A for a definition of all the variables.

	Fund Type							
Lags of liquidty-driven demand ($\hat{\lambda}^{\mathbf{Z}}$)	All (1)	Young (2)	Mid-aged (3)	Old (4)	Small (5)	Medium (6)	Large (7)	Very large (8)
$\hat{\lambda}^{\mathbf{Z}}_{i,t}$	−0.166**	−3.100***	−0.149	−0.754***	−1.738***	−0.772	−0.098	−0.154
	(0.078)	(0.889)	(0.089)	(0.262)	(0.399)	(0.685)	(0.219)	(0.090)
$\hat{\lambda}^{\mathbf{Z}}_{i,t-1}$	−0.006	0.410	0.030	0.549	2.449**	2.246**	0.193	0.064
	(0.159)	(1.529)	(0.129)	(0.460)	(1.071)	(0.943)	(0.356)	(0.065)
$\hat{\lambda}^{\mathbf{Z}}_{i,t-2}$	−0.071	−2.906	−0.160	−0.084	−2.664	−1.628**	−0.448	−0.063
	(0.155)	(2.416)	(0.191)	(0.661)	(1.642)	(0.643)	(0.549)	(0.174)
$\hat{\lambda}^{\mathbf{Z}}_{i,t-3}$	0.005	−0.359	0.144	−0.172	0.927	−1.109	−0.001	0.230**
	(0.135)	(1.391)	(0.146)	(0.403)	(1.289)	(0.796)	(0.669)	(0.109)
$\hat{\lambda}^{\mathbf{Z}}_{i,t-4}$	−0.177	0.390	−0.273**	0.374	0.757	0.040	0.115	−0.467***
	(0.104)	(1.327)	(0.111)	(0.651)	(0.842)	(1.334)	(0.174)	(0.163)
Observations	3,618	3,618	3,618	3,618	3,618	3,618	3,618	3,618
Adjusted R^2	0.32	0.32	0.32	0.23	0.23	0.23	0.23	0.23

Table 6: The Relation between Fund Returns and Demand

This table presents estimates of the regressions of the fund performance following each bid on different measures of demand (total number of bids per type fund, i, per month, t) predicted by the demand model of Table 3. The dependent variable is the fund's NAV-to-NAV public market equivalent performance T years from the NAV at the end of the quarter a bid was placed, referred to as $t = 0$, defined as $\frac{\text{NAV}_T \times \frac{I_0}{I_T} + \sum D_t \times \frac{I_0}{I_t}}{\text{NAV}_0 + \sum C_t \times \frac{I_0}{I_t}}$, where D_t are distributions made and C_t are capital calls issued at time t, and I_t is a market index value, set to the S&P 500 for US funds, the FTSE 250 for UK funds, and the STOXX Europe 600 for all other European funds. Demand by fund type per month is predicted using only state variables ($\hat{\lambda}^{\mathbf{Z}}_{i,t}$). Control variables for all regressions include the exact (log of) size and age of the bidded fund, and the (log of) the number of bids by the bidder. All regressions include also month, bidder and fund type fixed effects. Standard errors (in parentheses under each estimate) are clustered at the fund type level. Estimates followed by the symbols ***, **, or * are statistically significant at the 1%, 5%, or 10% levels, respectively. Please refer to Appendix A for a definition of all the variables.

	Returns horizon: $T =$								
	1 year (1)	2 years (2)	3 years (3)	1 year (4)	2 years (5)	3 years (6)	1 year (7)	2 years (8)	3 years (9)
Liquidity-driven demand: $\hat{\lambda}^{\mathbf{Z}}_{i,t}$	0.000	0.004	0.001						
	(0.002)	(0.003)	(0.001)						
$\hat{\lambda}^{\mathbf{Z}}_{i,t} \times \mathbf{1}\{\text{Young Fund}\}$				−0.018	−0.057**	−0.032			
				(0.017)	(0.022)	(0.031)			
$\hat{\lambda}^{\mathbf{Z}}_{i,t} \times \mathbf{1}\{\text{Middle-aged Fund}\}$				0.002	0.006**	0.003***			
				(0.002)	(0.003)	(0.001)			
$\hat{\lambda}^{\mathbf{Z}}_{i,t} \times \mathbf{1}\{\text{Old Fund}\}$				−0.009	−0.008	−0.007			
				(0.006)	(0.007)	(0.007)			
$\hat{\lambda}^{\mathbf{Z}}_{i,t} \times \mathbf{1}\{\text{Small Fund}\}$							−0.024	−0.055***	−0.048***
							(0.020)	(0.017)	(0.012)
$\hat{\lambda}^{\mathbf{Z}}_{i,t} \times \mathbf{1}\{\text{Medium Fund}\}$							0.029	−0.023	0.014
							(0.022)	(0.045)	(0.053)
$\hat{\lambda}^{\mathbf{Z}}_{i,t} \times \mathbf{1}\{\text{Large Fund}\}$							−0.004	−0.002	−0.003
							(0.003)	(0.003)	(0.003)
$\hat{\lambda}^{\mathbf{Z}}_{i,t} \times \mathbf{1}\{\text{Very large Fund}\}$							0.001	0.006**	0.004***
							(0.003)	(0.003)	(0.001)
Observations	2,652	2,121	1,482	2,652	2,121	1,481	2,652	2,121	1,481
Adjusted R^2	0.32	0.41	0.28	0.33	0.41	0.38	0.33	0.41	0.38

Table 7: The Relation between Bid Levels and Demand, by Type of Bidder

This table presents estimates of the regressions of the bid placed or of the fund performance following each bid on different measures of demand (total number of bids per type fund, i, per month, t) predicted by the demand model of Table 3. Bids are expressed as a percentage of the referenced NAV (column 1). In columns 2 to 4, the dependent variable is the fund's NAV-to-NAV public market equivalent performance from the NAV at the end of the quarter a bid was placed, referred to as $t = 0$, defined as $\frac{\text{NAV}_T \times \frac{I_0}{I_T} + \sum D_t \times \frac{I_0}{I_t}}{\text{NAV}_0 + \sum C_t \times \frac{I_0}{I_t}}$, where D_t are distributions made and C_t are capital calls issued at time t, and I_t is a market index value, set to the S&P 500 for US funds, the FTSE 250 for UK funds, and the STOXX Europe 600 for all other European funds. $\hat{\lambda}_{i,t}$ is the predicted emand by each type of bidder per fund type per month. Control variables for all regressions include the exact (log of) size and age of the bidded fund, and the (log of) the number of bids by the bidder. All regressions include also month, bidder and fund type fixed effects. Standard errors (in parentheses under each estimate) are clustered at the fund type level. Estimates followed by the symbols ***, **, or * are statistically significant at the 1%, 5%, or 10% levels, respectively. Please refer to Appendix A for a definition of all the variables.

Panel A: Estimated regression coefficients

Liquidity-driven demand ($\hat{\lambda}^{\mathbf{Z}}$)	Bid as a % of Reference NAV (1)	Returns horizon: $T =$ 1 year (2)	2 years (3)	3 years (4)
$\hat{\lambda}^{\mathbf{Z}}_{i,t}$ by bidder type :				
Secondary funds	−0.231	−0.011***	−0.008**	−0.002
	(0.183)	(0.004)	(0.003)	(0.004)
Other Funds-of-funds	0.422	0.010	−0.050	−0.105
	(1.594)	(0.035)	(0.069)	(0.072)
Other Asset Owners	−1.529**	0.008	0.011	−0.008
	(0.525)	(0.014)	(0.028)	(0.022)
Control Variables	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes

Panel B: Economic significance of slope coefficients ($\hat{\alpha}$) in Panel A: $\Delta E(\text{Bid }\%) \equiv \hat{\alpha}^{\lambda} \times \Delta\lambda$

$\Delta\lambda$ is Std.Dev($\hat{\lambda}^{\mathbf{Z}}_{i,t}$) for	(1)	(2)	(3)	(4)
Secondary funds	−0.493	−0.025***	−0.017**	−0.004
	(0.390)	(0.008)	(0.008)	(0.009)
Other Funds-of-funds	0.114	0.003	−0.014	−0.028
	(0.432)	(0.010)	(0.020)	(0.019)
Other Asset Owners	−1.018***	0.004	0.006	−0.004
	(0.350)	(0.007)	(0.015)	(0.012)

Table 8: The Relation between Bid Levels and Demand, conditional on Aggregate Liquidity

This table presents estimates of the regressions of the bid placed on different measures of demand (total number of bids per type fund, i, per month, t) for Young, Middle-aged and Small funds predicted by the demand model of Table 3. Bids are expressed as a percentage of the referenced NAV. Demand by fund type per month is predicted using all of the aggregate liquidity variables only ($\hat{\lambda}^{\mathbf{Z}}_{i,t}$) and interacted with binary indicators of whether each given liquidity variable z_t is below the first tercile (Lower) above the second tercile (Upper) or in between (Middle). Each row corresponds to the regression where demand is interacted with the tercile indicators of each liquidity variable. Control variables for all regressions include the exact (log of) size and age of the bidded fund, and the (log of) the number of bids by the bidder. All regressions include also month, bidder and fund type fixed effects. Standard errors (in parentheses under each estimate) are clustered at the fund type level. Estimates followed by the symbols ***, **, or * are statistically significant at the 1%, 5%, or 10% levels, respectively. Please refer to Appendix A for a definition of all the variables.

Panel A: Estimated regression coefficients.

		$\hat{\lambda}^{\mathbf{Z}}_{i,t} \times \mathbf{1}\{\text{Young}\} \times \mathbf{1}\{z_k\}$			$\hat{\lambda}^{\mathbf{Z}}_{i,t} \times \mathbf{1}\{\text{Mid-aged}\} \times \mathbf{1}\{z_k\}$			$\hat{\lambda}^{\mathbf{Z}}_{i,t} \times \mathbf{1}\{\text{Old}\} \times \mathbf{1}\{z_k\}$			R^2
	Liquidity variable (z_t) tercile:	Lower	Middle	Upper	Lower	Middle	Upper	Lower	Middle	Upper	
(1)	Δ ln(FED's Total Assets)	−4.563**	−4.477***	−5.049	−0.840*	−0.302**	−0.012	−0.904***	−0.452***	−0.345	0.29
		(1.643)	(1.109)	(3.637)	(0.461)	(0.143)	(0.111)	(0.244)	(0.144)	(0.653)	
(2)	Δ(Yield curve slope)	−2.343	−6.630***	−4.884***	−0.286***	−0.423**	−0.011	−0.649***	−0.570***	−0.306	0.29
		(1.949)	(1.839)	(1.414)	(0.101)	(0.162)	(0.089)	(0.132)	(0.178)	(0.200)	
(3)	Δ(Credit Spread)	−7.427***	−8.744***	−1.478	−0.003	−0.370***	0.001	−0.513*	−0.388**	−0.664**	0.29
		(1.035)	(2.916)	(2.103)	(0.087)	(0.118)	(0.291)	(0.293)	(0.179)	(0.271)	
(4)	Δ(Fontaine-Garcia)	−5.282***	−8.127***	−3.422***	−0.035	−0.480***	−0.219	−0.393	−0.422***	−0.809***	0.29
		(1.365)	(1.502)	(1.151)	(0.088)	(0.102)	(0.183)	(0.299)	(0.123)	(0.219)	
(5)	Δ ln(Commercial Paper)	−4.634**	−4.206***	−4.540***	−0.432**	−0.111	−0.018	−0.335	−0.670**	−0.641***	0.29
		(1.677)	(1.393)	(1.591)	(0.184)	(0.116)	(0.106)	(0.285)	(0.319)	(0.198)	
(6)	Δ(Price-Earnings Ratio)	−2.794	−6.128**	−5.609***	−0.289**	−0.064	−0.012	−1.132***	−0.784***	−0.225*	0.29
		(1.877)	(2.426)	(1.641)	(0.118)	(0.089)	(0.067)	(0.277)	(0.167)	(0.128)	
(7)	Cross-Industry Vol	−1.708	−3.327	−5.829***	−0.100*	−0.074	−0.355**	0.371	−0.503	−0.662***	0.29
		(2.025)	(1.994)	(1.152)	(0.052)	(0.093)	(0.153)	(0.501)	(0.447)	(0.138)	
(8)	VIX	1.268	−3.540	−4.337***	0.223	−0.148***	−0.393***	−0.557***	−0.622	−0.617***	0.29
		(3.221)	(3.712)	(1.399)	(0.157)	(0.036)	(0.124)	(0.184)	(0.485)	(0.124)	

Table 8

Panel B: Economic significance of slope coefficients ($\hat{\alpha}$) in Panel A; $\Delta E(\text{Bid }\%) \equiv \hat{\alpha}^{\lambda} \times \Delta\lambda$

		$\hat{\lambda}^{\mathbf{Z}}_{i,t} \times \mathbf{1}\{\text{Young}\} \times \mathbf{1}\{z_k\}$			$\hat{\lambda}^{\mathbf{Z}}_{i,t} \times \mathbf{1}\{\text{Mid-aged}\} \times \mathbf{1}\{z_k\}$			$\hat{\lambda}^{\mathbf{Z}}_{i,t} \times \mathbf{1}\{\text{Old}\} \times \mathbf{1}\{z_k\}$		
	Liquidity variable (z_t) tercile:	Lower	Middle	Upper	Lower	Middle	Upper	Lower	Middle	Upper
(1)	Δ ln(FED's Total Assets)	−2.570***	−3.123***	−2.358	−1.536*	−1.122**	−0.059	−1.981***	−1.157***	−0.479
		(0.926)	(0.774)	(1.698)	(0.844)	(0.530)	(0.547)	(0.535)	(0.368)	(0.906)
(2)	Δ(Yield curve slope)	−1.524	−4.232***	−2.762***	−1.175***	−1.006***	−0.059	−1.536***	−1.271***	−0.610
		(1.268)	(1.174)	(0.799)	(0.417)	(0.386)	(0.461)	(0.311)	(0.396)	(0.397)
(3)	Δ(Credit Spread)	−4.893***	−4.501***	−1.002	−0.015	−1.541***	0.001	−1.239*	−0.814**	−1.386**
		(0.682)	(1.501)	(1.426)	(0.414)	(0.492)	(0.808)	(0.707)	(0.376)	(0.565)
(4)	Δ(Fontaine-Garcia)	−3.343***	−3.937***	−2.455***	−0.199	−1.385***	−0.641	−0.759	−0.897***	−2.071***
		(0.864)	(0.728)	(0.826)	(0.504)	(0.295)	(0.536)	(0.577)	(0.261)	(0.562)
(5)	Δ ln(Commercial Paper)	−2.967***	−2.815***	−2.161***	−1.435**	−0.399	−0.089	−0.626	−1.508**	−1.571***
		(1.074)	(0.932)	(0.757)	(0.613)	(0.416)	(0.513)	(0.533)	(0.719)	(0.485)
(6)	Δ(Price-Earnings Ratio)	−1.734	−2.032**	−3.798***	−1.238**	−0.198	−0.051	−1.995***	−1.538***	−0.628*
		(1.165)	(0.804)	(1.111)	(0.504)	(0.278)	(0.292)	(0.487)	(0.327)	(0.362)
(7)	Cross-Industry Vol	−0.969	−2.025*	−3.886***	−0.493*	−0.227	−1.076**	0.442	−0.822	−1.831***
		(1.148)	(1.213)	(0.768)	(0.258)	(0.284)	(0.465)	(0.597)	(0.731)	(0.381)
(8)	VIX	0.336	−0.943	−2.985***	0.698	−0.713***	−1.502***	−0.980***	−1.162	−1.777***
		(0.853)	(0.989)	(0.964)	(0.490)	(0.176)	(0.475)	(0.324)	(0.906)	(0.358)

Table 9: The Relation between Bid Levels and Demand by Investor Type, conditional on Aggregate Liquidity

This table presents estimates of the regressions of the bid placed on different measures of demand (total number of bids per type fund, i, per month, t) by Funds-of-funds (FoFs), Secondary funds (SFs) and Other Asset Owners (AOs) predicted by the demand model of Table 3. Bids are expressed as a percentage of the referenced NAV. Demand by fund type per month is predicted using all of the aggregate liquidity variables only ($\hat{\lambda}^{\mathbf{Z}}_{i,t}$) and interacted with binary indicators of whether each given liquidity variable z_t is below the first tercile (Lower) above the second tercile (Upper) or in between (Middle). Each row corresponds to the regression where demand is interacted with the tercile indicators of each liquidity variable. Control variables for all regressions include the exact (log of) size and age of the bidded fund, and the (log of) the number of bids by the bidder. All regressions include also month, bidder and fund type fixed effects. Standard errors (in parentheses under each estimate) are clustered at the fund type level. Estimates followed by the symbols ***, **, or * are statistically significant at the 1%, 5%, or 10% levels, respectively. Please refer to Appendix A for a definition of all the variables.

Panel A: Estimated regression coefficients.

		$\hat{\lambda}^{\mathbf{Z}}_{i,t}$ by FoFs $\times \mathbf{1}\{z_k\}$			$\hat{\lambda}^{\mathbf{Z}}_{i,t}$ by SFs $\times \mathbf{1}\{z_k\}$			$\hat{\lambda}^{\mathbf{Z}}_{i,t}$ by AOs $\times \mathbf{1}\{z_k\}$			R^2
	Liquidity variable (z_t) tercile:	Lower	Middle	Upper	Lower	Middle	Upper	Lower	Middle	Upper	
(1)	Δ ln(FED's Total Assets)	−3.771	2.884	−1.520	−0.581*	−0.804***	0.340	−2.792***	−1.855*	−1.128	0.37
		(2.644)	(2.017)	(1.905)	(0.325)	(0.243)	(0.256)	(0.556)	(1.008)	(0.996)	
(2)	Δ(Yield curve slope)	0.897	0.835	−1.526	−0.698**	0.024	−0.027	0.390	−4.174***	−1.053	0.37
		(2.681)	(1.671)	(2.636)	(0.293)	(0.198)	(0.351)	(1.010)	(0.624)	(0.641)	
(3)	Δ(Credit Spread)	−5.102	1.551	1.905	0.070	0.024	−0.689**	−0.550	−3.467***	−0.632	0.37
		(3.365)	(1.89)	(2.289)	(0.275)	(0.234)	(0.266)	(1.714)	(0.629)	(0.644)	
(4)	Δ(Fontaine-Garcia)	−1.881	1.932	2.070	0.227	−0.124	−0.724**	−1.330	−2.592***	−0.434	0.37
		(1.651)	(2.712)	(2.068)	(0.316)	(0.292)	(0.264)	(1.403)	(0.670)	(1.172)	
(5)	Δ ln(Commercial Paper)	2.426	−2.612	1.038	−0.659*	−0.122	−0.055	−1.414*	−0.935	−2.838**	0.37
		(3.053)	(2.000)	(2.810)	(0.317)	(0.228)	(0.257)	(0.664)	(0.910)	(0.998)	
(6)	Δ(Price-Earnings Ratio)	3.508*	−5.585**	0.194	−0.533*	0.001	−0.125	−1.256	0.308	−2.545***	0.37
		(1.904)	(1.975)	(1.714)	(0.302)	(0.283)	(0.284)	(1.431)	(1.497)	(0.587)	
(7)	Cross-Industry Vol	0.167	−6.025**	2.976	0.064	0.405	−0.739**	−1.868	−0.104	−2.351***	0.37
		(1.977)	(2.565)	(2.381)	(0.269)	(0.376)	(0.253)	(1.178)	(0.565)	(0.761)	
(8)	VIX	0.986	−2.199	0.512	0.115	0.140	−0.637**	−2.986***	−2.467***	−1.100	0.37
		(2.369)	(2.133)	(3.286)	(0.319)	(0.232)	(0.248)	(0.953)	(0.789)	(0.714)	

Table 9 – *Continued*

Panel B: Economic significance of slope coefficients ($\hat{\alpha}$) in Panel A; $\Delta E(\text{Bid }\%) \equiv \hat{\alpha}^{\lambda} \times \Delta\lambda$

		$\hat{\lambda}^{\mathbf{Z}}_{i,t}$ by FoFs $\times$ $\mathbf{1}\{z_k\}$			$\hat{\lambda}^{\mathbf{Z}}_{i,t}$ by SFs $\times$ $\mathbf{1}\{z_k\}$			$\hat{\lambda}^{\mathbf{Z}}_{i,t}$ by AOs $\times$ $\mathbf{1}\{z_k\}$		
	Liquidity variable (z_t) tercile:	Lower	Middle	Upper	Lower	Middle	Upper	Lower	Middle	Upper
(1)	Δ ln(FED's Total Assets)	−0.745	0.851	−0.405	−1.031*	−1.597***	0.806	−1.534***	−1.303*	−0.734
		(0.522)	(0.595)	(0.508)	(0.577)	(0.484)	(0.606)	(0.306)	(0.708)	(0.648)
(2)	Δ(Yield curve slope)	0.265	0.215	−0.404	−1.520**	0.053	−0.055	0.241	−2.371***	−0.753
		(0.792)	(0.43)	(0.699)	(0.638)	(0.433)	(0.71)	(0.626)	(0.355)	(0.458)
(3)	Δ(Credit Spread)	−1.482	0.355	0.535	0.164	0.053	−1.328***	−0.285	−1.970***	−0.525
		(0.977)	(0.433)	(0.643)	(0.645)	(0.502)	(0.512)	(0.888)	(0.358)	(0.534)
(4)	Δ(Fontaine-Garcia)	−0.484	0.481	0.638	0.493	−0.247	−1.624***	−0.758	−1.738***	−0.265
		(0.425)	(0.675)	(0.637)	(0.685)	(0.58)	(0.592)	(0.8)	(0.45)	(0.715)
(5)	Δ ln(Commercial Paper)	0.662	−0.663	0.297	−1.220**	−0.245	−0.133	−1.015**	−0.532	−1.602***
		(0.834)	(0.507)	(0.805)	(0.588)	(0.458)	(0.624)	(0.476)	(0.518)	(0.563)
(6)	Δ(Price-Earnings Ratio)	1.017*	−1.388***	0.051	−1.108*	0.003	−0.269	−0.702	0.181	−2.162***
		(0.552)	(0.491)	(0.455)	(0.628)	(0.614)	(0.608)	(0.8)	(0.878)	(0.499)
(7)	Cross-Industry Vol	0.042	−1.566**	0.883	0.148	0.697	−1.532***	−1.091	−0.056	−1.919***
		(0.495)	(0.667)	(0.706)	(0.627)	(0.648)	(0.525)	(0.688)	(0.305)	(0.621)
(8)	VIX	0.277	−0.614	0.126	0.234	0.305	−1.393**	−1.678***	−1.090***	−0.862
		(0.666)	(0.595)	(0.808)	(0.648)	(0.504)	(0.542)	(0.535)	(0.349)	(0.559)

Appendix A Definitions of variables

Variable	Description
Dependent Variables	
Bid (% of NAV)	The bid placed for a particular fund, expressed as a percentage of NAV.
Return of Fund (T years NAV-to-NAV)	The return of the fund is defined as the public market equivalent of the fund between the reported NAV at the end of the quarter the bid was placed, and the reported NAV T years later. The first NAV is accounted for as an initial investment and the final NAV as a distribution. Formally, the calculation is $\frac{\text{NAV}_T \times \frac{I_0}{I_T} + \sum D_t \times \frac{I_0}{I_t}}{\text{NAV}_0 + \sum C_t \times \frac{I_0}{I_t}}$, where D_t are distributions made and C_t are capital calls issued at time t, and I_t is a market index value, set to the S&P 500 for US funds, the FTSE 250 for UK funds, and the STOXX Europe 600 for all other European funds.
Bid and LP Variables	
Bidder is a Fund-of-Funds	Takes the value of 1 if the bid was made by a fund-of-funds, and 0 if it was made by a secondary fund or an asset owner.
Bidder is a Secondary Fund	Takes the value of 1 if the bid was made by a secondary fund, and 0 if it was made by a fund-of-funds or an asset owner.
Bidder is an Asset Owner	Takes the value of 1 if the bid was made by an asset owner, and 0 if it was made by a fund-of-funds or a secondary fund. The types of LPs included in the asset owner category are: insurance companies, banks, asset managers, government agencies, pension funds, foundations, endowments and others.
Number of Bids made by the Bidder (log)	The logarithm of the total number of bids placed by the bidder in the last 10 days (including the date of the bid).
Fund Variables	
Age	Number of years since the fund's inception.
European Fund	Takes the value of 1 if the fund is a European fund, and 0 otherwise.
Fund Size (log)	The logarithm of the fund size as reported in Preqin.

Variable	Description
Large Fund	Takes the value of 1 if the fund size is more than \$1.5 billion but less than \$5 billion, and 0 otherwise.
Medium Fund	Takes the value of 1 if the fund size is more than \$0.5 billion but less than \$1.5 billion, and 0 otherwise.
Middle-aged Fund	Takes the value of 1 if the fund is between 4 and 7 years old, and 0 otherwise.
Old Fund	Takes the value of 1 if the fund Age$\geq$ 8 years, and 0 otherwise.
Public Market Equivalent (PME)	The fund's public market equivalent (PME). It is measured between two dates t_1 and t_2 as the ratio of the discounted value of all distributions during the period to the discounted value of all capital calls during the period. The NAV at t_1 is included as a capital call in the calculation and the NAV at t_2 as a distribution. The discount rate used is the public equity market return, where the index used is S&P500 for US funds, FTSE 250 for UK funds, and the STOXX Europe 600 for all other European funds.
Small Fund	Takes the value of 1 if the fund size is less than \$0.5 billion, and 0 otherwise.
US Fund	Takes the value of 1 if the fund is a US fund, and 0 otherwise.
Very Large Fund	Takes the value of 1 if the fund size is more than \$5 billion, and 0 otherwise, corresponding to the 90th percentile.
Young Fund	Takes the value of 1 if the fund Age$\leq$ 3 years.
Aggregate Variables	
Δln(Commercial Paper)	Logarithm of the total value of outstanding financial commercial paper (in monthly first differences; source: Federal Reserve Board).
Δ(Credit Spread)	Difference between the yields on BAA- and AAA-rated corporate bonds (in monthly first differences; source: Federal Reserve Board).
Δln(FED's Total Assets)	Logarithm of the total value of the Federal Reserve System's Assets (in monthly first differences; source: Federal Reserve Board).

Variable	Description
ΔFontaine-Garcia (Bond Liquidity premium)	The Fontaine and Garcia (2012) measure of the value of funding liquidity, obtained as the bond premium age factor in an arbitrage-free term structure model (in monthly first differences; source: Jean-Sebastien Fontaine's website).
GDP growth	Real growth in GDP for the OECD area, measured over the same quarter in the previous year (source: OECD).
$R_{S\&P500}$	Monthly returns, including all distributions, on a value-weighted S&P 500 market portfolio (excluding American Depository Receipts (ADRs); source: CRSP).
Δ(Price-Earnings Ratio)	The aggregate market price/earnings ratio in a given month (in monthly first differences; source: Robert Shiller, provided at http://www.econ.yale.edu/ shiller/data.htm). The measure used is the cyclically adjusted price/earnings ratio (CAPE).
VIX	The CBOE volatility index.
Cross-Industry Volatility	Calculated each month as the cross-sectional standard deviation of the Fama and French 49 industry portfolio returns.
Δ(Yield Curve Slope)	Difference between the 10-year and 3-month yields on US Treasury bills (in monthly first differences; source: Federal Reserve Board).

Appendix B Fund classification procedure

To inform us of how to classify fund types for our empirical demand model we examine the likelihood of receiving a bid as a function of observable characteristics. We consider fund size, age, and location and run a logit model on the likelihood that a fund receives a bid in a given quarter using the subsample of funds that we can match with Preqin data. We include the 375 funds in our sample that are covered by Preqin, as well as 285 comparable funds in the Preqin database which do not show up in our sample.[30] We define an indicator variable taking the value of 1 if a fund receives a bid in a given quarter, and 0 otherwise. Table B - Panel A presents logit regressions that characterize the likelihood of receiving a bid within a given quarter. The three models we run differ only in the set of fixed effects that are included.

Consistent with Nadauld et al. (2017) we find that larger funds are more likely to receive bids. The effect of fund age is non-linear: it has an inverted U-shape where young and old funds are less likely to receive a bid. We find that US funds are less likely to receive bids. This is likely due to two reasons: our data provider is London based and Preqin has a better coverage of the US market and is thus more likely to have coverage of US funds that did not receive any bids.

We re-run the logit with dummy variables representing different size, age and performance categories to identify potential breakpoints to use for fund classifications. Results are reported in Panel B. For fund age, we define our age dummies for funds above a given age. This allows us to observe the points where there are significant changes in demand. We observe a breakpoint at the age of 3 (consistent with the assumption in Nadauld et al. (2017) that funds below age 3 are special, and less likely to be targeted). There is a jump in demand at age 6, and it turns negative at age 8 with a relatively large jump at age 10 (the typical liquidation age). To keep it simple we define three age categories: young funds (three years old or less), middle aged funds (between 4 and 7 years old), and old funds (eight years old and above). For fund size we observe a significant jump for funds that are above the 30th

[30] A fund is comparable if it is a Buyout fund focusing on Europe or the US and is of a vintage of 2000 or later. A given fund-quarter is included if the fund is no older than 12 years old and the NAV is at least 10 % of committed capital. This ensures that the set of funds that we compare resembles funds that received bids in our data.

percentile, and then it keeps on increasing from the 60th percentile onwards. We therefore decide to create a small fund category corresponding to the bottom tercile, one mid-size category corresponding to mid tercile, a large category that goes to the 90th percentile and a very large category for funds beyond the 90th percentile. This corresponds to cutoffs at \$0.5 bn, \$1.5 bn and \$5 bn, respectively.

This results in us forming 24 groups by assigning each fund to one of four size categories, one of three age categories and whether it is a US or European fund.

Table B: Bid probabilities and fund characteristics

This table presents the estimates of a logit model of the probability that a given private equity fund receives a bid in a given quarter. The dependent takes the value of 1 in any quarter that the given fund received at least one bid, or zero otherwise. The data includes all 375 funds receiving a bid between September 2009 and December 2016 through a global sell-side broker of Private Equity stakes based in London, as well as 285 comparable funds in Preqin that are not included in our proprietary data sets, of a vintage later than 2000, and with a NAV of at least 10 % of committed capital. The 'Fraction in Sample' is the fraction of fund-quarter observations in which we observe a bid. The coefficients show the change in this probability for an infinitesimal (discrete) change in each continuous (binary) variable. The marginal effects are evaluated at the variables sample means. The Z-Statistics are reported in parenthesis below. The model is estimated including a constant and controlling for the number of funds in the fund family, whether the fund is a low reputation fund, and for the fund's past performance, measured as the PME to date. Independent variables are winsorized at the 1% level. Estimates followed by the symbols ***, **, or * are statistically significant at the 1%, 5%, or 10% levels, respectively.

Panel A

	(1)	(2)	(3)
Fund Size (log)	0.052***	0.043***	0.042***
	(0.002)	(0.002)	(0.002)
Fund Age	0.033***	0.029***	0.025***
	(0.003)	(0.002)	(0.005)
Fund Age Squared	−0.002***	−0.002***	−0.002***
	(0.000)	(0.000)	(0.000)
US Fund	−0.084***	−0.072***	−0.07***
	(0.003)	(0.003)	(0.003)
Quarter Fixed Effects	No	Yes	Yes
Vintage Fixed Effects	No	No	Yes
Controls	Yes	Yes	Yes
Fraction in Sample	0.119	0.119	0.119
Number of Observations	11,810	11,810	11,810
Pseudo R^2	0.325	0.378	0.383

Panel B

	(1)	(2)	(3)
Fund Age $\geq$ 1 years	0.025*	0.019*	0.017
	(0.018)	(0.015)	(0.014)
Fund Age $\geq$2 years	0.024***	0.019***	0.016***
	(0.009)	(0.008)	(0.007)
Fund Age $\geq$3 years	0.017***	0.018***	0.017***
	(0.007)	(0.006)	(0.006)
Fund Age $\geq$4 years	0.009	0.012**	0.009*
	(0.006)	(0.005)	(0.005)
Fund Age $\geq$5 years	0.007	0.006	0.002
	(0.006)	(0.005)	(0.005)
Fund Age $\geq$6 years	0.017***	0.012**	0.007
	(0.006)	(0.005)	(0.005)
Fund Age $\geq$7 years	0.006	0.001	0.000
	(0.005)	(0.005)	(0.004)
Fund Age $\geq$8 years	−0.012**	−0.012***	−0.013***
	(0.006)	(0.005)	(0.005)
Fund Age $\geq$9 years	−0.005	−0.004	−0.005
	(0.006)	(0.005)	(0.005)
Fund Age $\geq$ 10 years	−0.022***	−0.015***	−0.016***
	(0.008)	(0.006)	(0.006)
Fund Size $\geq$20th percentile	0.032***	0.026***	0.025***
	(0.014)	(0.011)	(0.011)
Quarter Fixed Effects	No	Yes	Yes
Vintage Fixed Effects	No	No	Yes
Controls	Yes	Yes	Yes

Panel B

	(1)	(2)	(3)
Fund Size ≥30th percentile	0.025**	0.020**	0.020**
	(0.011)	(0.009)	(0.009)
Fund Size ≥40th percentile	0.009	0.009	0.010
	(0.009)	(0.007)	(0.007)
Fund Size ≥50th percentile	0.000	−0.001	−0.001
	(0.008)	(0.007)	(0.007)
Fund Size ≥60th percentile	0.027***	0.023***	0.022***
	(0.007)	(0.006)	(0.006)
Fund Size ≥70th percentile	0.027***	0.024***	0.023***
	(0.006)	(0.005)	(0.005)
Fund Size ≥80th percentile	0.035***	0.031***	0.029***
	(0.005)	(0.004)	(0.004)
Fund Size ≥90th percentile	0.046***	0.042***	0.041***
	(0.004)	(0.004)	(0.004)
US Fund	−0.076***	−0.068***	−0.065***
	(0.004)	(0.004)	(0.003)
Quarter Fixed Effects	No	Yes	Yes
Vintage Fixed Effects	No	No	Yes
Controls	Yes	Yes	Yes
Fraction in Sample	0.119	0.119	0.119
Number of Observations	11,810	11,810	11,810
Pseudo R^2	0.321	0.366	0.373