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Private Company Valuations by Mutual Funds

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Abstract

Mutual funds value private security holdings at considerably different prices, update valuations infrequently, and revise valuations dramatically at follow-on funding events. Predictable private valuation changes at follow-on rounds yield predictable fund returns, but effects are muted for large families, families with large investment in the private security, and families with large percentage stakes in funding rounds. Mutual funds with high exposure to private securities have outflows that are more sensitive to poor fund performance when the venture capital market also performs poorly. The results have welfare implications for retail investors interested in accessing private startups via investments in mutual funds.

Keywords: Mutual funds, Venture capital, Private valuation, Stale prices, Financial fragility

Historically, startup companies have funded growth by turning to seed investors, angel investors, or venture capital before turning to public markets with an initial public offering (IPO). At the time of the IPO, mutual funds typically bid on shares in the IPO, receive an allocation of shares from the underwriter at the IPO offer price, and often enjoy a strong return from the offering price to the close of the first day of public trading. However, in recent years large startup companies like Uber, Airbnb, and Pinterest have chosen to remain unlisted while raising large amounts of capital by selling private securities to mutual funds often years in advance of a public IPO in what some observers have referred to as private IPOs (Brown and Wiles 2015).[1] These large private startups have become so common that the financial press has dubbed those with valuations in excess of $1 billion, $10 billion, and $100 billion as "unicorns", "decacorns" and "hectocorns", respectively. CB Insights reports over 500 unicorns with total cumulative valuation of more than $1.6 trillion as of January 2021.[2] Non-traditional investors in private companies include not only mutual funds but also hedge funds, sovereign wealth funds, and family offices. Together, these investors participated in more than 2,700 VC deals in 2019 alone, and these deals provided $97 billion of funding (over half of the total 2019 VC funding).[3]

Mutual funds' participation in this new startup funding model has welfare implications for retail investors interested in accessing private startups via investments in mutual funds. On the positive side, mutual funds' participation in pre-IPO funding rounds expands individual investors' access to startups, closing the gap in investment opportunity sets between the haves and the have nots.[4] Moreover, the Securities and Exchange Commission (SEC) recently published a "Concept Release on Harmonization of Securities Offering Exemptions" where they appear to be considering allowing private equity investments in defined contribution plans such as 401(k) plans.[5]

On the cautionary side, we identify two issues. First, private securities are inherently hard to value due to shortages of transaction prices and limited information disclosures required of these companies. As a result, valuations of private company securities reported by mutual funds may

[1] Pinterest and Uber went public in April and May 2019, respectively, and Airbnb went public in December 2020.
[2] https://www.cbinsights.com/research-unicorn-companies.
[3] National Venture Capital Association (NVCA)-Pitchbook Venture Monitor (Q4 2019) XLS data pack, available on NVCA website.
[4] See Michaels (2018), "SEC Chairman wants to let more main street investors in on private deals", *The Wall Street Journal*.
[5] See https://www.sec.gov/rules/concept/2019/33-10649.pdf for details.

become stale and deviate from fair values at times. Moreover, mutual fund families may vary in the resources they dedicate to private security investments. Fund families may also have differential access to privileged information about the private companies. Ceteris paribus, we conjecture that fund families with greater resources will update their valuations more frequently and that fund families with greater access to privileged information will rely less on public information release by portfolio companies when valuing these securities. We test these predictions by analyzing the valuation practice differences across fund families as a function of family attributes (e.g., family size, weight of investment in private securities) and information environment (e.g., public information about the private company). We further examine if the mutual fund valuation practice leads to fund return predictability around material corporate events and if the fund family's valuation practice quality modulates the predictability.

Second, most mutual funds have an "open-end" structure, i.e., set up to serve the liquidity demands of their investors. This is in sharp contrast to traditional VC funds, which are typically set up as 10-year limited partnerships, investor commitments are contractually tied up in the fund during the fund duration, and fund investors cannot trade on fund interests at the reported Net Asset Value (NAV).[6] The mismatch between the liquid fund structure and the illiquid and hard-to-value nature of private securities poses a potential challenge for mutual funds. Such liquidity transformation can be associated with significant financial fragility (Chen, Goldstein, and Jiang 2010). Unique to our setting, fund investors have a clear indicator of the performance of the illiquid private securities held by mutual funds based on the returns in the VC market. In particular, we conjecture that mutual fund flows with private securities are particularly sensitive to poor fund returns when those fund returns are accompanied by a poor VC market performance.

We analyze a manually compiled dataset of 334 private securities (for 199 different companies) held by 235 unique mutual funds from 43 fund families between 2010 and 2018. We identify the private security prices reported by mutual funds using quarterly filings of mutual fund holdings with the SEC. A key feature of the dataset is that we identify the specific series that a mutual fund holds (e.g., Series D vs. Series E of Airbnb). Each security series represents a distinct funding event/round for the private firm, is a unique part of the firm's capital structure, and has different contractual terms such as liquidation preference, participation, and dividend preference

[6] NAV management by VCs has an indirect effect on the fund managers' ability to raise follow-on funds (see Jenkinson, Sousa, and Stucke 2013; Barber and Yasuda 2017; and Brown, Gredil, and Kaplan 2019).

(Metrick and Yasuda 2010, 2021). Our identification of each unique security (typically a convertible preferred stock) allows us to carefully measure variation in pricing across funds for the same security at the same point in time and rule out contract features as the source of the pricing variation. An important feature of the pricing of private securities by mutual funds is the prevalence of follow-on series offerings by private firms whereby the issuer of private securities held by mutual funds raises capital—while still remaining private—by issuing a new series of private security in a private placement on a subsequent round date. We identify 96 follow-on funding events during our 2010–2018 sample period with an average deal-over-deal price increase of 47%. There are only 6 down rounds, where the deal-over-deal price decreases.

Our analysis of this dataset proceeds in three steps. First, to set the stage, we provide a rich descriptive analysis of the valuation of private securities by mutual funds. In our analysis of valuation practices, three main results emerge. Valuation changes are rare but generally large, positive, and typically occur around follow-on funding events. There is also material variation in the prices of private securities across funds, which can be traced to variation in pricing at the fund family level. Finally, private securities earn no alpha after we appropriately adjust for the stale pricing of the securities.

We find prices change infrequently by analyzing the quarterly changes in prices of private securities reported in the SEC filings. In nearly half of all security-quarters, mutual funds do not change the price of the private securities they hold (i.e., 46% of quarterly returns are zero). The average private security changes prices every 2.3 quarters. Private securities are often valued at a funding round deal price; 38% of all security-quarter observations are valued at a deal price. This is particularly true when there has been a follow-on deal in the most recent quarter. Of the securities issued in the new funding round, 86% are valued at the deal price at the end of the quarter following the event with most of the remaining securities valued at a 10% discount to the funding round price (perhaps a liquidity discount). Of the securities issued in earlier rounds on the same private company, around 60% are marked to the deal price of the *new* series at the quarter end following the deal (indicating mutual funds often ignore the differences in contractual terms when pricing the different series offerings of the same firm). The large infrequent price jumps and long periods of stale valuation leave private securities earning quarterly returns that are not reliably different from public benchmarks when we appropriately adjust for the stale pricing of these securities.

We observe variation in pricing of the same security at the same time across fund families. The average price dispersion across fund families is 9.6%, which is consistent with the notion that different families have different valuation practices. To put this in perspective, two funds reporting prices of \$19 and \$22 for the same security would generate price dispersion of 10.3%.[7] This level of price dispersion masks large variation across security-quarters. In half of security quarters, dispersion is less than 5.3%, but in one out of four security-quarters, dispersion exceeds 13.5% and in one out of ten security-quarters exceeds 24.8%. In other words, individual investors can be accessing the same pre-IPO startups via mutual funds at significantly different valuations at a given point in time. In contrast to this material variation in pricing across fund families, we observe virtually no variation in pricing within a fund family. For securities held by the funds within the same fund family, the mean price dispersion is a mere 0.1%. This lack of dispersion within fund families can likely be traced to the common use of family-wide valuation committees, which set standards and review pricing decisions for illiquid securities.

Across fund families, we show large fund families and fund families with a higher portfolio weight in private securities update valuations more frequently. These results are consistent with the idea that fund families with more resources or more dedicated private security programs have more frequent valuation updates for their private securities. We also find that mutual funds with a large investment in a specific private company is more likely to update valuations outside of periods with high levels of public information. This result is consistent with the notion that mutual funds with a large stake in a particular company are likely to receive more detailed reports from the issuer company[8] and/or more regularly acquire information on the company.

Second, we investigate whether (i) follow-on rounds by startups are associated with dramatic security price updates by mutual funds and fund return predictability, and (ii) valuation practice differences across fund families modulate the degree of return predictability. We find the returns of mutual funds that hold private securities are predictably large following the start of a follow-on deal. We define the date of the funding round as the day when the company files a restated Certificate of Incorporation in the company's home state. For funds holding the private security, average cumulative abnormal returns (*CAR*s) are 40 bps (25 bps) in the 10-day (5-day)

[7] $10.3\% = \frac{\left[(22-20.5)^2+(19-20.5)^2\right]^{1/2}}{20.5}$.

[8] A model VC term sheet available on the NVCA website includes an "Information Rights" clause that provides "Major Investors" with privileged information access to the startup. See Section 3.5 for details.

window following the funding round date. To link the strong fund returns more tightly to the markups of private securities in the wake of the new funding round, we estimate the weight of private security in each fund's overall portfolio (using quarterly holdings data) and the percentage change in the private security valuation based on the fund's valuation after the new deal and the last valuation reported prior to the new deal. For example, a fund that holds 0.5% of its assets in Airbnb, currently values the security at $50, and increases the value to $100 after the announcement of the new funding round will experience a fund return of 50 bps on the day of the Airbnb markup. To test this conjecture, we regress the post-funding *CARs* of funds on the product of the private security weight in the fund's portfolio and the security price change, which as conjectured generates a reliably positive coefficient estimate.

Next, we examine if fund families vary in their fund return predictability around follow-on rounds. If funds with more resources (either with more assets under management or a bigger investment in private equity) update private valuations more frequently, we would expect to observe less return predictability for these funds. We indeed find the return predictability around follow-on funding returns is muted for bigger fund families and families with large stakes in a funding round.

Third, to test our conjecture about financial fragility of mutual funds holding private securities, we regress the fund flow on lagged fund performance interacted with indicators for (i) high level of private security investments and (ii) VC market returns. The idea is as follows: consider investors holding shares in mutual funds with private security holdings vs. funds without private security holdings. The sensitivity of outflows to bad past fund performance should be stronger if the fund has high levels of private securities ***and*** the VC market also performed poorly because investors know that redemptions by others will impose even greater costs on the fund if they choose to stay in the fund under that situation. The logic here closely follows Chen, Goldstein, and Jiang (2010) but with the additional dimensions of private security investments contributing to fund illiquidity, and fund investors being potentially concerned about future performance of private securities based on the poor overall VC market performance. Consistent with the idea that investors in funds that hold private equity investments face higher strategic complementarities than investors in funds that do not hold private equity investments, we find stronger flow-performance sensitivity for mutual funds holding more private securities after poor fund performance and negative VC market returns.

We conclude by noting our analysis occurs during a tech boom that rivals that of the late 1990s. Thus, we tend to observe large follow-on rounds and price jumps on the private securities we analyze. A more concerning state of the world is one where startups held by mutual funds are failing or being marked down, and enhanced disclosure of mutual funds' illiquid investments following a recent SEC mandate.[9] In these negative market conditions, investors will have an incentive to sell fund shares prior to the markdown of a private company. The selling pressure will reduce the fund's total net assets (TNA), increase the percentage stake in the private company, and create further incentives for other investors to sell. This situation has unfolded in limited circumstances to date. Within our sample, we observe one such case where Firsthand Technology Value Fund, which held over 20% of its assets in restricted, non-listed startup stocks when the Financial Accounting Standards Board (FASB) issued a new guideline for increased disclosure of illiquid assets breakdown for mutual funds.[10] The fund's largest holding, nearly 10% of its assets, was in a private solar company called SoloPower that the fund had valued at more than 400% of its original purchase price. When SoloPower had a follow-on round in December 2010 at the same share price as the previous round (i.e., a "flat round"), the Firsthand Fund reduced the valuation of its SoloPower holding by more than 70%, thus resulting in a large negative correction in the fund's NAV and became a closed-end fund in 2011. A similar case unfolded in the U.K., where trading of shares in the £3.7 billion Woodford Equity fund was suspended in June 2019 due to concerns about its ability to meet redemption requests given its large investment in illiquid securities. The fund was subsequently shut down in late 2019 and investors were still waiting for the finalization of the wind-down of the fund as of December 2020, 18 months after the suspension.

In summary, our paper is the first to provide large-scale evidence of significant time-series and cross-sectional variation in pricing of private securities by mutual funds. We document significant stale valuations of private securities and uncover predictability in fund returns when these valuations are updated infrequently at follow-on funding rounds. We find that there are valuation practice differences across fund families and this impacts the degree to which funds experience return predictability and thus potential flow volatility.

Investors in funds with worse valuation practices are more likely to experience volatile outflows when company valuations go down significantly—because those fund families will be slow to

[9] See https://www.sec.gov/divisions/investment/guidance/secg-liquidity.htm for details.
[10] Form N-CSR filed by Firsthand Funds for period ended December 31, 2009.

update the prices. In anticipation of this, our recommendation for retail investors who aim to gain exposure in private startups via mutual funds would be to invest with larger fund families with more resources dedicated to private equity investments, and those that are participating as key primary investors in the rounds, all else equal.

1. Related literature and our contributions

A small but growing strand of literature studies the private investments of mutual funds. Kwon, Lowry, and Qian (2020) analyze the general rise in mutual fund participation in private markets over the last 20 years and conclude that mutual fund investments enable companies to stay private one or two years longer on average. Chernenko, Lerner, and Zeng (forthcoming) analyze contract-level data to examine the consequences of mutual fund investments in these early-stage companies for corporate governance provisions. Huang et al. (forthcoming) study the performance of private startup firms backed by institutional investors and find that they are more mature, have higher likelihoods of successful exits, and in case of IPO exits, receive lower IPO underpricing and higher net proceeds. None of these papers examine the valuation of private securities by individual mutual funds, nor do they study the effects of private security valuation practice on fund-level returns and flows. Cederburg and Stoughton (2018) document variation in pricing across funds and argue that private equity pricing by mutual funds is procyclical with respect to fund performance, which is consistent with the prediction of a theoretical model that they develop. Imbierowicz and Rauch (2020) study pricing of unicorns by mutual funds and emphasize the importance of external factors, such as the valuation of peer companies, as determinants of unicorn pricing. Gornall and Strebulaev (2020b) study the dilutive impact of future financing rounds on the VC security values and compare their model predictions with values reported by mutual funds and issuers. In contrast, our paper documents that private security holdings expose mutual funds to potential return and flow volatility and that better valuation practices associated with both larger fund family resources dedicated to private equity investments and greater information rights vis-à-vis the issuer firms mitigate this risk.

Our work is related to the literature that analyzes the daily pricing of mutual funds. U.S. mutual funds typically offer an exchange of shares once per day at a price referred to as NAV. Stale equity share prices (e.g., foreign equities or thinly traded stocks), which are reflected in a fund's NAV, lead to predictable fund returns (Bhargava, Bose, and Dubofsky 1998; Chalmers, Edelen, and Kadlec 2001; Boudoukh et al. 2002; Zitzewitz 2006). Recent work by Choi, Kronlund, and Oh (2019) shows that these problems associated with stale pricing are exacerbated in case of fixed income funds. Moreover, fund flows indicate investors capitalize on these predictable returns (Goetzmann, Ivković, and Rouwenhorst 2001; Greene and Hodges 2002). We document that private equity valuations are much less frequently updated than public equity and lead to predictable fund returns. Furthermore, we show that valuation practice differences across fund families affect the degree of return predictability. Our study is also related to the literature on the valuation of relatively illiquid assets. Cici, Gibson, and Merrick (2011) study dispersion in corporate bond valuation across mutual funds and find that such dispersion is related to bond-specific characteristics associated with liquidity and market volatility. We examine how the (time-series and cross-sectional) variation in the valuation of private securities by mutual funds is explained by the fund family information-processing resources, information access, and release of public information (e.g., new funding rounds).

Our work also fits into the literature on the valuation and staged funding of venture-backed firms. Limited disclosure requirements prevent researchers from observing VC valuations at the portfolio company level. Thus, Jenkinson, Sousa, and Stucke (2013), Barber and Yasuda (2017), and Brown, Gredil, and Kaplan (2019) all examine valuation practices of VC and private equity funds at the fund level. These papers find that some fund managers (e.g., those with low reputation) engage in fund NAV management during the fundraising campaigns.[11] We contribute to this literature by exploiting disclosure requirements of mutual funds that enable researchers to observe quarterly valuations of individual company holdings. Our findings about valuation practice differences across mutual fund families might extend to VC funds' valuation practices as well. Note, however, that illiquidity of VC fund structure safeguards VC fund investors against correlated investor redemptions, whereas the liquidity of open-end mutual fund structure exposes investors in mutual funds with PE investments to such redemptions and therefore fragility**.**

We find the follow-on round purchase price is often a reference point for the valuation of the previous round private security and, as a result, leads to predictable fund returns. Post-money valuation, the industry short hand for company valuation implied by a new VC round of financing, is defined as the purchase price per share in the new round multiplied by the fully-diluted share count. This measure abstracts away from the fact that VCs and their co-investors invest in startups

[11] Also see Hüther (2016) and Chakraborty and Ewens (2018).

using complex securities, typically a type of convertible preferred stock, and that securities issued in different rounds are not identical in their investment terms. Some academic studies use post-money valuations as proxies for the company valuation. For example, Cochrane (2005) and Korteweg and Sorensen (2010) develop econometric methods that measure risk and return of VC investments at the deal level using portfolio company post-money valuations observed at the time of financing events. Gompers and Lerner (2000) find that competition for a limited number of attractive investments leads to a positive relation between capital inflows and valuations of new investments.

Metrick and Yasuda (2010) and Gornall and Strebulaev (2020a) develop option-pricing based valuation models, which correct for the use of convertible preferred securities in VC financing contracts, to estimate the implied value of VC-backed private companies. These techniques are useful when evaluating the value of the company at the time of financing, but not applicable to how valuations of companies evolve in the absence of new rounds. Our study provides insights into the evolution of the prices of private companies over time.

2. Data

Our raw data on mutual fund holdings of private equity securities come from both CRSP Mutual Fund Database and mutual funds' SEC filings of N-CSR and N-Q forms. Because mutual funds' holdings of private equity securities are rare before 2010, we restrict our analysis to holdings reported between 2010 and 2018.

There are two distinct data challenges we face in constructing a clean data set of private equity security holding by mutual funds. First, neither CRSP nor SEC raw data indicate definitively whether a security held by a mutual fund is a private equity security, so we have to manually identify and verify private equity securities among mutual fund holdings. We do this by matching these fund holdings data with a list of VC-backed companies and recently listed companies. To identify VC-backed companies, we use Thomson Reuters' One Banker database. To identify firms that recently went public, we use both Bloomberg and CRSP databases.

Second, VC-backed private companies typically issue convertible preferred securities to their investors rather than common stock. As discussed above, these securities issued at different financing rounds (called Series A, Series B, etc.) differ in their terms (Metrick and Yasuda 2010; Gornall and Strebulaev 2020a). Thus, for example, if mutual fund X holds and values a Series D preferred stock issued by Airbnb at $23/share and another mutual fund Y holds and values a Series E preferred stock issued by Airbnb at $25/share, it is not necessarily because the two funds differ in their valuation of the company as a whole, but could be because the two securities differ in their contingent claims on the company assets and therefore *should* have different valuations. Thus, to compare valuations of private securities we must identify the issuer (e.g., Airbnb) and exact Series (A, B, C, etc.) of the security. Assigning the Series to a security turns out to be a non-trivial task because security names are not standardized in mutual fund reports of their holdings. For example, mutual funds frequently only report the security by its issuer name.

Using the matching method described in the Internet Appendix A, we carefully identify 334 securities issued by 199 companies (each security is a unique company-round pair). To measure price dispersion across mutual funds, we require that the same security be held by at least 2 mutual funds. This further reduces our sample to 256 unique securities issued by 158 companies. When measuring price dispersion, we do not compare valuations across different Series of the same company and exclude private security holdings that we cannot clearly assign to a specific round.

3. Stale Pricing of Private Companies by Mutual Funds

3.1 Descriptive Statistics

We begin the analyses by presenting evidence on the differences in the valuation of private securities across mutual funds. To illustrate the dispersion in valuation, Figure 1 provides an example of three funds that hold the same private security. Fidelity Contrafund, Morgan Stanley Multicap Growth, and Thrivent Growth Stock apparently purchased Airbnb Series D securities, which were sold in April 2014 at a per share price of $40.71. In June 2014, these three funds all report holding Airbnb at $40.71. In December 2014, Morgan Stanley increases its valuation to $50.41, while the other two funds continue to report $40.71. In June 2015, shortly after Airbnb announced its Series E offering, all three funds substantially increase the reported prices. During the next year, prices reported by the three funds diverge more dramatically but converge again in September 2016 at $105 in the wake of a Series F funding round in September 2016. While we plot three funds that hold Airbnb as an example, 32 mutual funds in our sample hold Airbnb Series D.

We measure the variation in valuation across mutual funds by first calculating the standard deviation of prices across funds holding security s in quarter q ($\sigma_{s,q}$), and then scaling by average price of security s across funds in quarter q ($\overline{P_{s,q}}$):

$$DispPrc\_Avg_{s,q} = \frac{\sigma_{s,q}}{\overline{P_{s,q}}} \qquad (1)$$

Since average price might be skewed by a fund that has marked the security up or down dramatically, we also scale by median price ($DispPrc\_Med_{s,q}$). As an example, a security that is held by two funds in the same quarter at prices of \$19 and \$22 would generate a *DispPrc_Avg* = 2.12/20.5 = 10.3%.

In Table 1, we present summary statistics on our sample of private companies held by at least two mutual funds in each quarter. Panel A shows that the number of funds holding the same security in a given quarter (*NumFd*) averages to 8.1, and the median number of funds is 6. While majority of mutual funds set their reporting cycles in Mar/Jun/Sep/Dec, others report their quarterly holdings and valuations in Jan/Apr/July/Oct or Feb/May/Aug/Nov cycles. To address these reporting cycle mismatches, we group funds by the ending month of their reporting cycles when calculating cross-fund dispersion (i.e., treat quarter ending on March 31, 2015 and the quarter ending on April 30, 2015 as two different quarters). As reported in Panel B, the full sample consists of 158 different firms (e.g., Uber). For these firms, there are 256 unique securities (e.g., Uber Series D, Uber Series E, etc.), which yield 3,962 security-quarter observations of price dispersion, $DispPrc\_Avg_{s,q}$. All securities in Panel B are held by at least two funds in the same quarter ending in the same month.

On average, price dispersion is 3.6% across funds in the same quarter (two funds holding the same security at prices of \$38 and \$40 generating a dispersion measure of 3.6%). The mean standard deviation of prices across funds is \$0.77 and the average (median) security price is \$22.08 (\$22.14). The observed price dispersion is often zero and at times large. We observe less than 1% price dispersion in 68% of security-quarters (2,709 of 3,962 security-quarters), while in 10% of security-quarters we observe price dispersion of 12.3% or more (as shown in the 90th percentile of *DispPrc_Avg*).

Some fund families (e.g., Fidelity and T. Rowe Price) are known to use a centralized committee to determine values for each private company for all its funds and some families employ third-party valuation specialists.[12] If these practices are widespread, we expect to observe greater variation in prices across fund families but much less variation within fund families. To investigate whether this price dispersion results from variation in pricing within a particular fund family (e.g., Fidelity) or across fund families (e.g., Fidelity and T. Rowe Price), in Panel C we calculate price dispersion within a fund family. In this analysis, we require that a security be held by two funds *within the same fund family* in the same reporting month in quarter q. The analysis yields a price dispersion measure for security *s* for fund family *F* in quarter *q*, $DispPrc\_Avg_{F,s,q}$. Fund families in which a single fund holds a security are dropped from this analysis. However, since we have observations for multiple fund families for the same security-quarter, the number of observations (family-security-quarters) increases to 4,363. The price dispersion within fund families is negligibly small at 0.1% on average and is precisely zero for over 95% of family-security-quarters in this sample. For the remaining 5%, the price dispersion could be due to rounding (especially when holdings are reported in thousands) or data errors. The finding indicates that fund families impose one price per security as a general rule and that the documented price dispersion in Panel B occurs virtually entirely across (rather than within) fund families.

In Panel D, we present a complement to the within-fund-family analysis and analyze dispersion across fund families. To do so, we first calculate the average price of security *s* in quarter *q* across funds in family *F*. We then calculate price dispersion across fund families based on the standard deviation and mean of the average price for each fund family. As anticipated, price dispersion across fund families is much larger than within-family price dispersion at 9.6% on average. Building on the results reported in panels C and D, we shift the unit of observation to fund family-security-quarter (as opposed to fund-security-quarter) in subsequent analysis wherever appropriate.

3.2 Return on Private Securities

An important feature of the pricing of private securities is the infrequent updating of the prices as suggested by the Airbnb example of Figure 1. To get a sense for how often funds update prices, we calculate a quarterly return for fund family *F* and security *s* based on the fund family's reported prices for the security in the current and prior quarters:

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[12] See "Here's why mutual fund valuations of private companies can vary" by Francine McKenna on marketwatch.com, published November 20, 2015, and "Wall Street cop asks money managers to reveal Silicon Valley valuations" by Sarah Krouse and Kirsten Grind on the Wall Street Journal, published December 9, 2016.

$$Return\_PVT_{F,s,q} = \frac{P_{F,s,q}}{P_{F,s,q-1}} - 1 \qquad (2)$$

In Table 2, Panel A, we present descriptive statistics on this quarterly return variable (*Return_PVT)* across 8,992 fund family-security-quarter observations. The average quarterly return is 3.7%, but the median return is zero and 42% of all returns are zero. To demonstrate the severity of the staleness in the prices of private securities, we compare these descriptive statistics with those for public securities (*Return_PUB*). Using 248,823 fund family-security-quarter observations for public securities held by fund families in our sample, we observe that unlike the case of private securities, the median quarterly return is 2.6%.

We further highlight the staleness issue in Panel B where we report the percentage of quarters in which the fund family does not change the reported prices of the private and public securities held by it (i.e., quarterly return is zero). To do so, for each fund family-security pair, we calculate the percentage of quarters in which the private security return is precisely zero *(%Zero Return_PVT*). On average across fund-family security pairs, mutual fund families report zero returns for private securities in 46% of all quarters. In contrast, the incidence of zero returns for public securities *(%Zero Return_PUB*) is much lower at 0.4%. Moreover, Panel B also reports the number of quarters until the prices of private securities are updated from the acquisition price (*Qtr to Update_PVT*). It takes on average 2.3 quarters for the fund to update its acquisition price of private securities.

These results are not driven by fund family-security pairs with few quarterly observations. We repeat our analysis by imposing a condition of a minimum of three- or four-quarter holding period for each family-security pair. In untabulated results, we find that the median quarterly return for private securities continues to be zero while the mean return is largely unchanged. In addition, mutual funds still show zero returns in 45% (44%) of all quarters using a three-quarter (four-quarter) filter. In contrast, public securities still exhibit minimal incidence of zero returns (0.4% using either a three- or four-quarter filter). Finally, the number of quarters to update the prices of private securities is about the same, i.e., 2.4 (2.5) quarters since acquisition with a three-quarter (four-quarter) filter. Taken together, stale pricing is much more prevalent and pronounced for private securities as compared to public securities.

3.3 Temporal Evolution of Pricing Deviation from Deal Prices

Next, we examine the time series variation in the dispersion of private security prices reported by funds. As suggested by the Airbnb example in Figure 1, price dispersion tends to decrease after a follow-on funding round when some funds update their prices, presumably to match the new deal price. To better understand how fund families mark their private securities, we compare the prices reported by funds to deal price of the security, which serves as a natural price benchmark. We consider three primary benchmark prices for security *s* in quarter q, denoted as $B_{s,q}$: the deal price in the most recent and any of the previous funding rounds, the deal price in the most recent funding round, and the price at which the security was acquired by the family. We define the price deviation as follows:

$$Dev_{F,s,q} = \frac{P_{F,s,q}}{B_{s,q}} - 1 \tag{3}$$

where $Dev_{F,s,q}$, $P_{F,s,q}$, and $B_{s,q}$ are the price deviation, price reported, and benchmark price for security *s* held by fund family *F* in quarter *q*, respectively. For a given benchmark price *B, Dev* measures the percentage deviation of the reported private security prices from *B*. Additionally, we create an indicator variable, *DumDev*, that takes a value of one if the absolute value of *Dev* is above 1%. The average value of *DumDev* over all family-security-quarter observations is denoted as *%Dev*, and represents the proportion of families' reported prices that deviate from the benchmark price in the quarter. In untabulated results, we consider defining absolute deviations only if they are above 5% (rather than 1%) and obtain qualitatively similar results.

Table 3, Panel A, reports *%Dev* results. The sample contains 186 firms (e.g., Uber), 326 securities (e.g., Uber Series C and Series D) with the corresponding benchmark deal prices during the 2010 to 2018 sample period. There are 5,660 (5,894) family-security-quarter observations of reported prices with corresponding deal prices different from the most recent and previous funding rounds (most recent funding round). As shown in Panel A, the column of *%Dev*, 62% of valuations differ by more than 1% in absolute value from the latest and any prior deal price and 65% differ by the same magnitude from the latest deal price. When we compare the reported security prices with the price paid by the fund for the same security at acquisition, *%Dev* is larger at 80%. In other words, more than three-quarter of the private security prices are different from the price at which they were purchased while the remaining families maintain the valuations at cost. The higher deviation from cost price relative to recent deal price suggests that part of the variation in reported security prices is related to marking to deal prices, although the new deal price does not fully eliminate the differences in reported prices.

The final benchmark price is the average of all reported security prices for the same firm held by the fund family, where we require that the family holds at least 2 securities (e.g., Uber Series C and D) of the same firm (e.g., Uber). Recall that these securities may have different contingencies and cash flow rights, so it would be reasonable to observe different prices for these securities even though they are both held on the same firm (Metrick and Yasuda 2010; Gornall and Strebulaev 2020a). The requirement that the family holds multiple securities of the firm reduces the sample significantly to 63 firms and 204 securities. Panel A of Table 3 shows an average *%Dev* of 27%; fund families tend to price different securities at the same price, but we do observe some variation across securities.

To gain a deeper understanding into how follow-on deals affect valuations, we analyze the deviation in reported private security prices from the new deal price in nine quarters around a new funding round (quarter 0). In addition to the measure of percentage of fund families with reported prices deviating from the most recent deal price (*%Dev*), we split the deviation in reported prices into two groups depending on whether the reported price is above (*%Dev*$^+$) or below (*%Dev*$^-$) the benchmark deal price by more than 1%. For each of the two groups (above and below deal price), we also compute the median value of *Dev* conditional on whether the deviation is above or below the latest deal price (*Median Dev*$^+$ and *Median Dev*$^-$, respectively).

For securities held prior to a new funding round, we calculate statistics from quarter −4 to +4 and report results in Table 3, Panel B. In four quarters before the new funding round, about 89% of the reported prices are below future deal price (the median negative price deviation is 34% lower), consistent with higher deal prices in subsequent funding rounds. The price deviations fall dramatically during the new round of financing. Specifically, *%Dev* decreases from 90% in quarter −1 to 40% in quarter 0 as a majority of funds update their security value close to the new deal price. Consequently, only 31% (8%) of the family-security prices are below (above) the new deal price. This corresponds to a median deviation of 16% (23%) below (above) the new deal price. There is also a steady increase in the percentage of fund families that update their security prices to their model values, which in turn contributes to dispersion in prices over time. For example, *%Dev* increases gradually to 79% in quarter +4, with 42% (37%) reporting prices lower (higher) than the latest deal price.

Finally, we examine the variation in reported prices of private firms that first appear following a new round of financing. As shown in Panel C of Table 3, the sample contains 156 firms issuing 207 securities with new round of funding. During the quarter of new funding round (quarter 0), the deviation between reported and deal price is small, i.e., 12% report prices below the deal price and 3% report higher prices. Among the families reporting lower prices, the median "discount" (*Median Dev*$^{-}$) is −10%, which persists for up to three quarters. We conjecture that the lower valuation is consistent with some funds applying a 10% discount in their fair value pricing for illiquid securities.[13] In contrast, among family-quarters with markup in security prices above the deal price, the median markup (*Median Dev*$^{+}$) is large at 16%, and gradually increases over time. As we move forward to four quarters after the new funding round, the reported prices diverge: *%Dev* increases to 76% in one year. In terms of the magnitude of price deviations, this converts to an economically meaningful *Median Dev*$^{+}$ of 37%, and *Median Dev*$^{-}$ of −13%.

Overall, the analyses indicate economically large differences in the prices reported by the cross section of mutual fund families. Moreover, these price deviations evolve over time, with some convergence towards the deal price during new rounds of financing, followed by price divergence over subsequent quarters.

3.4 Do Public Market Factors affect Private Security Valuations?

In this subsection, we use standard asset pricing technology to show mutual fund valuations of private securities respond to public market factors (even after controlling for the large and predictable valuation update during follow-on funding rounds). We do not include exit values at the time of IPOs or M&A exits as our endeavor is to examine how public market factors affect the private security valuations rather than studying the improvement in fund returns due to investments in private companies. Consistent with staleness in reported security prices, we find strong evidence that the changes in valuations respond to market, size and growth-related factors with a lag, and the exposure to these factors explains the average private security returns after we account for the slow updating of prices.

To reach these conclusions, we estimate three pooled time-series regressions using fund family-security-quarter observations:

$$\left(R_{F,s,q} - RF_q\right) = \alpha + \beta\left(R_{m,q} - RF_q\right) + \varepsilon_{F,s,q} \quad (4)$$

[13] Untabulated results suggest that among the families reporting lower prices in quarter 0, 73% could be attributed to a 10% discount (measured within a close range between 9.9% and 10.1%).

$$\left(R_{F,s,q} - RF_q\right) = \alpha + \sum_{l=-2,0} \beta_l \left(R_{m,q-l} - RF_{q-l}\right) + \varepsilon_{F,s,q} \tag{5}$$

$$\begin{aligned}\left(R_{F,s,q} - RF_q\right) = \alpha + \sum_{l=-2,0} \beta_l \left(R_{m,q-l} - RF_{q-l}\right) + \sum_{l=-2,0} h_l\, HML_{q-l} \\ + \sum_{l=-2,0} s_l\, SMB_{q-l} + \varepsilon_{F,s,q}\end{aligned} \tag{6}$$

where $R_{F,s,q}$ is the quarterly valuation change of a private security s in quarter q held by fund family F. For those who own shares in the fund, this valuation change represents the return on the private security as the posted valuations would feed into the daily NAV of the fund. RF_q is the quarterly risk-free rate, proxied by the one-month Treasury bill rate. To address issues of cross-sectional dependence in this regression, we estimate standard errors clustering observations by quarter. In the first regression as indicated in Equation (4), we estimate a one-factor CAPM model with only the contemporaneous market risk premium, $\left(R_{m,q} - RF_q\right)$. In the second regression as indicated in Equation (5), we add lags of the market risk premium to account for the stale pricing along the lines suggested by Scholes and Williams (1977) and Dimson (1979).[14] In the third regression as indicated in Equation (6), we add size (SMB) and value (HML) factors (Fama and French 1993).[15]

The results of this analysis are presented in Panel A of Table 4. Model (1) presents regression results with only a contemporaneous market factor, which illustrates a severe downwardly biased beta estimate of 0.28. Note that the alpha in this simple regression is also economically large and statistically significant at 3% per quarter. However, this low risk and strong performance is misleading and results from stale pricing. Model (2) includes lags of market returns and shows reliably positive loadings at lags of one and two quarters (consistent with sluggish valuation changes) and an alpha that is no longer statistically different from zero. In Panel B, we present the sum of the coefficients on the market risk premium, which shows a much higher and

[14] See Anson (2007), Woodward (2009), and Metrick and Yasuda (2021) for methods similar to ours in assessing risk and return in private equity using index returns and lagged factors. See Kaplan and Sensoy (2015) and Korteweg (2019) for a review of other empirical methods to assess risk and returns in private equity. Also see Cochrane (2005), Kaplan and Schoar (2005), Korteweg and Sorensen (2010), Driessen, Lin, and Phalippou (2012), Franzoni, Nowak, and Phalippou (2012), Jegadeesh, Kräussl, and Pollet (2015), Korteweg and Nagel (2016), and Ang et al. (2018), among others.

[15] Including additional lags of market, size, and value factors does not consistently generate reliable loadings. We also consider the liquidity factor of Pástor and Stambaugh (2003); it does not generate reliably positive loadings, nor does it qualitatively affect the conclusions of this section.

statistically significant beta of approximately 1.25. Model (3) includes size and value factors. The alpha of the private securities does not change materially, but the summed exposures in Panel B suggest the private securities are exposed to size- and growth-related factors. The results in Model (3) indicate private securities respond to market-, size-, and growth-related factors, they do so with a lag, and their performance is unremarkable after appropriately accounting for stale pricing by including lagged factors. These results are in line with venture capital risk and return estimates reported in the literature that explicitly address staleness issues: Ang et al. (2018) report a market beta of 1.85 and negative alpha, and Metrick and Yasuda (2021) report a market beta of 1.47 to 1.85 and an insignificant alpha in multi-factor models.

In prior analyses, we show that follow-on funding rounds generate significant changes in valuations. To determine whether the performance and exposure to common factors are sensitive to these follow-on round quarters, we introduce an indicator variable *Follow-on Dummy*, that takes a value of one if the current quarter is a quarter with a follow-on funding round and is zero otherwise. Models (4) to (6) in Table 4 show the results of the three regressions with the *Follow-on Dummy* added. The coefficients on the *Follow-on Dummy* are large (nearly 23% per quarter) and statistically significant, consistent with substantial deal-to-deal valuation changes. However, the coefficient estimates on the factor exposures and alphas are qualitatively similar to those estimated absent the *Follow-on Dummy*.

3.5 Valuation Practice and Family Characteristics

We next investigate how mutual fund families update their valuations of private securities. We expect that variation in both family and security characteristics influences the ability and incentives of fund families to update their valuations. In this subsection, we explore three possible channels that might affect the frequency of valuation updates: fund family size, the importance of a security in the fund family's portfolio, and whether a fund family is a major investor in a private security. First, large fund families perhaps have more internal resources to closely monitor and update their valuations. Second, families that invest a larger fraction of their portfolios in a private security may devote more resources to the acquisition and interpretation of information about private securities. Third, a family that is a major investor in a particular funding round may update valuations at a different timing than others, because such investors typically negotiate rights to acquire information and/or receive financial statements from portfolio companies on an ongoing basis as part of their investor's rights agreement.[16] Mutual funds participating as lead or key investors in a VC round thus are likely to receive privileged information from portfolio companies that other, more minor investors (or those who purchased the shares in secondary transactions) do not receive.[17] If this channel creates a wedge in information flows between major investors and others, we expect that major investors' valuation update timing differs from those of non-major investors.

Finally, the extent to which family and security characteristics influence families' valuation practices can vary with the availability of more information through public news in general, and news around follow-on funding events. To explore these issues, we estimate the following panel regression:

$$DumUpd_{F,s,q} = \alpha + \beta_1 Char_{F,s,q} + \beta_2 Char_{F,s,q} \times News_{s,q} + \varepsilon_{F,s,q} \qquad (7)$$

where $DumUpd_{F,s,q}$ refers to an indicator variable that equals one if a fund family F revises its valuation of security s in quarter q, and zero otherwise. $Char_{F,s,q}$ is a vector of family or family-security characteristics, including *Ln(Family TNA)*, defined as the logarithm of the family's TNA; *WTPE*, defined as the percentage weight of each private security in a family's total equity portfolio; and *%Round Size*, defined as the total dollar amount of each private security in a family's portfolio, scaled by the deal size of the corresponding funding round. This variable proxies for a key investor status of a fund family in a round. $News_{s,q}$ refers to two proxies for news event, including (1) *Ln(AEV)*, defined as the logarithm of the aggregate event volume from RavenPack database, which measures the count of public news releases over a rolling 91-day window; and (2) *Follow-on Dummy*, defined as an indicator variable that equals one in quarters when the private firm initiates

[16] For example, a sample VC term sheet available on the NVCA website includes the following "Information Rights" boilerplate language:

> ***Information Rights:*** *Any Major Investor ... will be granted access to Company facilities and personnel during normal business hours and with reasonable advance notification. The Company will deliver to such Major Investor (i) annual, quarterly, [and monthly] financial statements, and other information as determined by the Board of Directors; [and] (ii) thirty days prior to the end of each fiscal year, a comprehensive operating budget forecasting the Company's revenues, expenses, and cash position on a month-to-month basis for the upcoming fiscal year; and (iii) promptly following the end of each quarter an up-to-date capitalization table. A "Major Investor" means any Investor who purchases at least $[______] of Series A Preferred.*

See https://nvca.org/model-legal-documents/ for a full sample term sheet.

[17] Fund families with large private equity holdings, such as Fidelity and T. Rowe Price, are known to often lead a late funding round for late-stage startups with unicorn status. See, for example, Foldy (2021) for a VC round in Rivian led by T. Rowe Price and participated by Fidelity. In our sample, Fidelity and T. Rowe Price on average hold 29% and 19% of a funding round, respectively, suggesting their high likelihood of being major investors. In contrast, John Hancock Group has an average 2%, and MassMutual has 0.15% of a funding round.

follow-on funding through a new round, and zero otherwise. Crucially, we include security-quarter fixed effects to focus on the differences in valuation updates across fund families for the same security at the same time. The standard errors are clustered by quarter to account for cross-correlation in family-security characteristics.

We report the results in Table 5. We observe that larger families and families with greater portfolio weight on a private security tend to update more (Models (1) and (2)), and this updating behavior is not affected by either public news releases or follow-on funding round (Models (4) and (5)). These results are consistent with the idea that fund families with greater resources (as measured by TNA) or greater investment in private securities (as measured by portfolio weights in private companies) update valuations more frequently.

Families that are key investors in a round do not update more frequently (Model (3)), but rely less on public release of information about the company than non-key investors in their update decisions (Model (6)). The latter result is consistent with the idea that key investors in a round are partly conditioning their valuation updates on privileged information they receive from the issuer companies. For example, key investor fund families may update their security valuations in advance of follow-on rounds because they become aware of upcoming funding events sooner (via direct updates from the portfolio company or more vigilant monitoring of the company) than non-key investor fund families who learn of the news when it becomes public. Key investor fund families would also learn about negative performance of the company sooner than non-key investor fund families and thus act faster to devalue the securities they hold.

4. Valuation Practice and Return Predictability around Financing Rounds

In this section, we first examine predictability in fund returns around new rounds of financing and whether this predictability is greater among funds with more exposure to the private securities as well as funds that display more staleness in updating prices at normal times. We also investigate if this predictability is associated with abnormal mutual fund flows around follow-on funding rounds.

4.1 Predictability in Fund Returns around Financing Rounds

While mutual funds are required to report to the SEC only quarterly, the funds need to mark the NAVs of their individual stock holdings on a daily basis in order to compute their per share market value (the fund's NAV). The NAV of publicly traded stocks are based on the daily closing market prices of the securities in the fund's portfolio. However, for private security holdings, funds determine the fair value of the security based on a valuation method, which is often determined by a valuation committee for the fund family. With each new round of financing, the valuation of a private security changes, and often dramatically. For example, the purchase price per share of Airbnb Series D is $40.71 in April 2014, while the purchase price in July 2015 for a follow-on round of Airbnb Series E more than doubled to $90.09. Funds holding Airbnb Series D are expected to significantly revise the valuation of their Airbnb holdings around the Series E funding date. Since funds do not update the valuations frequently, when there are new funding rounds—typically at significantly higher prices—we expect predictable changes in funds' valuations, which in turn generates predictability in fund returns.

We examine the daily fund abnormal returns around the follow-on round of financing of the private company held by the mutual fund. For funds that hold private security *s*, the abnormal return on fund *f* on day *t* is defined as follows:

$$AR\_BMK_{f,s,t} = R_{f,t} - R_{BMK,t} \tag{8}$$

where $R_{f,t}$ ($R_{BMK,t}$) is the return on fund *f* (the fund's benchmark portfolio return) on day *t*. These fund benchmarks are based on the Lipper fund objectives obtained from the CRSP Mutual Fund Database. Denoting the follow-on round date for the issuer of private security *s* as day 0, the day 0 abnormal return for a fund *f* that holds the private security *s* is $AR\_BMK_{f,s,0}$. We compute the corresponding cumulative abnormal returns (*CAR*s) over a *k*-day window from day 0 to day *k*:

$$CAR\_BMK[0,k]_{f,s} = \left[\prod_{t=0}^{k}(1 + AR\_BMK_{f,s,t})\right] - 1 \tag{9}$$

Our empirical analysis is based on the cumulative abnormal returns averaged across fund-security pairs over the event window from day *a* to *b*, $CAR\_BMK[a,b]$, and the standard errors are clustered by calendar days to account for cross-correlation in fund returns.

As reported in Panel A of Table 6, our sample consists of 715 fund-security observations, made up of 96 security-rounds with an average of 7 mutual funds holding the security. Accounting for private companies with multiple rounds of follow-on financing, the sample comprises 57 unique private companies held by 156 funds.[18] To be included in the sample, we require that each mutual fund holds a private security prior to a follow-on round of financing by its issuer and that the fund reports holding the same private security in the first quarterly report after the new round of financing. We do not require the fund to participate in the new round of financing.

Panel A of Table 6 reports the cumulative abnormal fund returns over several windows around the follow-on funding date event. For the windows prior to the event, between day −10 and day −1, we do not observe any significant benchmark-adjusted *CAR*s. We obtain significant positive abnormal fund returns during the 3-day to 10-day window after the event date. For example, for the 3-day (5-day, 10-day) event window, the average *CAR* is economically significant at 12 bps (22 bps, 37 bps) with a *t*-stat of 2.45 (2.72, 3.65).[19] Additionally, the impact of new funding round of private securities on overall fund returns does not persist as the *CAR*s are not different from zero beyond the 10-day post-event window. Results (not tabulated for brevity) are similar if we use market-adjusted rather than benchmark-adjusted abnormal returns. Panel B of Table 6 reports similar statistics when we first average fund-security level *CAR*s to family-security level, resulting in 251 family-security observations with an average of 3 mutual fund families holding each security. The average *CAR* remains significant at 13 bps (25 bps, 40 bps) for the 3-day (5-day, 10-day) event window.

Our finding is related to studies that document profitable trading opportunities in mutual funds due to stale pricing of public securities. For example, Chalmers, Edelen, and Kadlec (2001) document that non-synchronous trading of public securities held by domestic U.S. equity funds provides exploitable pricing errors in fund NAV. Bhargava, Bose, and Dubofsky (1998) show that the stale prices generate large abnormal returns in foreign equity funds. Additional evidence of stale stock prices predicting mutual fund returns is provided in Boudoukh et al. (2002) and Zitzewitz (2006). We provide new evidence of return predictability when mutual funds invest in private securities: the valuation changes of these securities are infrequent, but lumpy and highly predictable.

4.2 Cross-Sectional Regressions of *CAR*s

[18] The sample includes 26 companies with multiple follow-on rounds of financing, including Palantir (5 rounds), Moderna and Vroom (4 rounds each), AppNexus, Honest, Nanosys, Pinterest, Uber and WeWork (3 rounds each), and the remaining 17 companies have 2 rounds each.

[19] In untabulated results, when we skip the event day to estimate the abnormal fund performance over [1, 10] window, the average benchmark-adjusted *CAR* drops to 29 bps, indicating significant updating of private security valuations on the event day.

We next test the hypothesis that the predictability in a fund's return is stronger when it holds a large stake in a private company that has a big increase in a fund's valuation after the new funding round. Since the exact weight of the private security in the fund's portfolio on the day of the new round is not available, we rely on the latest holdings of the security reported prior to the financing round. We denote the percentage weight of each private security in a fund's portfolio as *WTPE*. Mutual funds, on average, hold 0.3% of their assets in the private securities we study, although this weight varies significantly from 0.05% (10^{th} percentile) to 0.74% (90^{th} percentile) indicating substantial investment in private securities by some funds (figures not tabulated for brevity). We consider two measures of changes in the valuations. The first measure is the percentage change in valuation in the quarter after the new financing round relative to the fund's prior valuation, labeled as Δ*Value.* The second measure is the percentage change in the deal price of the new round of financing relative to the last valuation reported by the fund, labeled as *Update*. The average values of *Update* are higher compared to Δ*Value* (42% vs. 30%), which is consistent with slow updating of reported mutual fund valuations of private securities, at least by some funds, around new rounds of financing.

Since our earlier results suggest that the valuation of private securities is done at the family level with little within-family variation in valuation, we conduct the analysis at family-security level to examine the link between change in valuations and abnormal returns of family F holding security s over k days following the new funding date, i.e., $CAR\_BMK[0,k]_{F,s}$. We estimate the following cross-sectional regression:

$$CAR\_BMK[0,k]_{F,s} = \alpha + \beta \Delta Value_{F,s} \times WTPE_{F,s} + \varepsilon_{F,s} \tag{10}$$

Under the hypothesis that the abnormal performance is significantly related to the changes in family's valuation of private securities, we expect a positive β coefficient. Moreover, if we have accurate estimates of the private security weight and the change in valuation of the private security, the β coefficient should equal one. For example, a fund that holds 1% of Airbnb Series D and increases the valuation of the holding by 50% should experience an abnormal return of 0.5%.

The estimate of the above regression model is presented in Panel C of Table 6. The results are similar when change in valuation is measured by Δ*Value*×*WTPE* (Models (1), (3), and (5)) or *Update*×*WTPE* (Models (2), (4), and (6)). Consistent with our expectations, we find a strong positive relation between fund family performance and the changes in the valuation. For example, using the 5-day event window, the cross-sectional variation in the abnormal fund returns corresponds to 58% to 76% of the change in private security valuations, indicated by the β estimates in Models (3) and (4).

As shown in Table 5, the valuation practice is also related to family characteristics, such as family TNA and private security holdings measured by portfolio weight (*WTPE*) or percentage of a funding round (*%Round Size*). Since the abnormal performance is mechanically related to private security weight, we control for *WTPE* in all specifications and rely on family TNA and *%Round Size* to capture the cross-sectional variation in valuation practice. Specifically, we estimate the following cross-sectional regression:

$$CAR\_BMK[0,k]_{F,s} = \alpha + \beta_1 Char_{F,s} + \beta_2 WTPE_{F,s} + \varepsilon_{F,s} \tag{11}$$

where $Char_{F,s,q}$ refers to *Ln(Family TNA)* and *%Round Size*, defined as in Equation (7). All other variables are defined as in Equation (10).

The results are tabulated in Panel D of Table 6. Intuitively, if mutual fund families have adjusted their valuations prior to the new funding round, there is less room to update at the follow-on round and we expect to observe lower *CAR*s. We find that larger families and families holding a larger percentage of a funding round display lower abnormal returns after the new funding round, consistent with their less stale updating behavior at normal times. The results are stronger in the 10-day window. These results suggest that fund families with more information-processing capacity and with privileged information access update prices more frequently, resulting in less return predictability around follow-on rounds. Additionally, *WTPE* is positively, but not significantly, related to *CAR*s. On one hand, families with greater portfolio weight tend to update more at normal times, resulting in lower *CAR*s. On the other hand, a large stake in private security predicts higher *CAR*s by construction. Therefore, it appears that these two effects offset each other, resulting in an insignificant relation between *WTPE* and *CAR*s.

In summary, our findings indicate that mutual fund valuation of private securities is frequently stale and this leads to large price changes and fund return predictability around key corporate events such as follow-on rounds. Valuation practice is not uniform across fund families, and fund family characteristics that are positively associated with frequent updating also reduce the fund return predictability.

4.3 Fund Flows around Financing Rounds

If stale pricing and sizable markups lead to predictably large abnormal fund returns around follow-on round events, do investors in mutual funds exploit this by purchasing (selling) funds before (after) the follow-on rounds? We address this question by examining the net fund flows around follow-on round events.

If investors have sufficient information about upcoming follow-on round events and the holdings of private securities by mutual funds, they might capitalize on this information by buying the mutual funds with large stakes in private companies ahead of the follow-on round dates and selling them after the events. If this behavior is common, we would expect abnormally high inflows in days leading up to the follow-on round dates and high outflows in the days after the follow-on rounds. Conversely, if investors are aware of any upcoming public release of negative information by the company, they might sell the mutual funds with stakes in the private company ahead of such events and buy them after the events. While this latter scenario is worth investigating, during the sample period most of the private companies in the sample experienced markups and positive exit outcomes. So we only test for evidence of inflows around follow-on rounds (i.e., positive information events) in this subsection. In contrast, in the next section we examine the impact of poor performance in the overall VC market on flow-performance sensitivity of funds holding private securities.

We use a subset of funds covered by Trimtabs that provides the daily flow data (i.e., 60 funds with 203 fund-security observations or 28% of observations in Table 6),[20] and measure abnormal fund flows around follow-on round dates using two distinct measures. Our first measure, the benchmark-adjusted abnormal flow of fund f holding security s on day t is defined as:

$$AF\_BMK_{f,s,t} = Flow_{f,t} - Flow_{BMK,t} \tag{12}$$

where $Flow_{f,t}$ is the percentage flow of fund f on day t, computed as the ratio of dollar flow to prior day's TNA, and $Flow_{BMK,t}$ is the lagged TNA-weighted average flow across funds in the fund's benchmark category on day t. Our second measure is the z-score for fund f on day t, defined as:

$$Z_{f,t} = \frac{Flow_{f,t} - \overline{Flow}_f}{\sigma_f} \tag{13}$$

[20] Other papers that use the Trimtabs data include Chalmers, Edelen, and Kadlec (2001), Edelen and Warner (2001), Greene and Hodges (2002), Rakowski (2010), Kaniel and Parham (2017), and Agarwal, Jiang, and Wen (forthcoming). For robustness, we repeat our analysis using monthly flows and do not find evidence of significant abnormal flows in the months surrounding a follow-on offering, though monthly flows may not be sufficiently granular to detect unusual activities. Daily flows more precisely identify abnormal investor response in the days around follow-on round dates, which is not feasible with monthly flows.

where $Flow_{f,t}$ is the percentage flow of fund f on day t, $\overline{Flow_f}$ and σ_f refer to the average daily flow and standard deviation of daily flow of fund f during the [*t*−180, *t*−31] window, respectively. Thus, the first measure captures contemporaneous deviation of fund *f*'s flows from that of its cohorts, whereas the second measure captures deviation of fund *f*'s flows from its own historical average flows.

In Table 7, we report the benchmark-adjusted flows in Panel A and the *z*-score in Panel B for the whole sample. We do not find statistically significant fund flows around the follow-on round dates, perhaps because investors are not yet aware of such trading opportunities and/or do not possess necessary information to time their mutual fund investments (e.g., timely information on funds' positions in private securities and valuations of those securities, and the timing and expected outcome of new funding rounds). It is also possible that gains from trading on stale pricing may not be large enough due to the relatively small holdings of private securities in mutual funds' portfolios.

While the positive abnormal returns after the funding rounds provide opportunities for fund investors to time their trades, perhaps mutual funds impose redemption fees to discourage opportunistic short-term trading (Greene, Hodges, and Rakowski 2007). This does not seem to be the case. Redemption fees in mutual funds that hold private securities are rare; only 18 of the 60 funds in the sample have redemption fees (based on data collected from funds' N-SAR filings and prospectuses). Funds can also discourage timing by investors either by explicitly forbidding or imposing sanctions against such practices.

For the funds with redemption fees, the fees charged exceed the abnormal mean *CAR*s that we observe. So, we exclude these funds and repeat our analysis in Panels C and D of Table 6. Untabulated results suggest that the post-funding round 10-day (5-day) *CAR_BMK* for funds with no redemption fee is economically large and statistically significant at 51 bps (34 bps). However, we do not find evidence showing that investors time their investments around the follow-on rounds. Our findings remain unchanged if we conduct similar analysis at family-security level (untabulated for brevity).

In sum, with the small sample we are able to analyze, we do not find compelling evidence of opportunistic trading by investors and perhaps as a consequence, few of the funds holding private equity have redemption fees. As the size of private equity markets is expected to keep growing, it is possible that mutual funds will hold a higher proportion of their portfolios in private securities in the future. Investors' behavior might change as the relative weights of private equity securities in mutual fund portfolios, the potential gains from these trades increase, and the information required to execute these trades become more accessible over time (e.g., via entry of third-party data aggregators).

5. Financial Fragility and Private Equity Investment

As mentioned earlier, there are a couple of examples of fragility in open-end mutual funds that had substantial investments in private securities. The US-based mutual fund, Firsthand Technology Value Fund, that invested in private securities was forced to convert to a closed-end fund in April 2011 after a large reduction in its NAV.[21] More recently, in the summer of 2019, the multi-billion pound U.K. mutual fund LF Woodford Equity Income Fund had to suspend withdrawals as continued poor performance of its public stock holdings and outflows left the fund holding a large proportion of its portfolio in early-stage private securities. Motivated by these examples, we examine if mutual funds holding private securities are more vulnerable than traditional mutual funds to investor runs and financial fragility during periods of downturns in the private equity market because of correlated redemptions by fund investors.

There can be several mechanisms driving the concerted actions of fund investors. First, investors are more likely to withdraw their capital after a fund experiences poor performance because redemptions by others can impose significant costs on funds holding illiquid assets, including extremely illiquid private securities (Chen, Goldstein, and Jiang 2010; Goldstein, Jiang, and Ng 2017). Moreover, in the case of private securities, the VC market performance provides fund investors an explicit signal of the performance of private securities, which can exacerbate the correlated redemptions by fund investors. Second, fund investors may have greater incentives to redeem because they expect persistence in fund's poor performance either due to slow updating of prices of private securities or because past performance is a signal of fund manager's ability. Regardless of the mechanism motivating investor behavior, we examine whether funds invested in private securities are susceptible to investor runs and financial fragility, particularly following poor performance of both the mutual fund and the VC market.

To account for potential heterogeneity between fund families that invest in private securities and those that do not, we focus here on funds *within* mutual fund families that invest in

[21] https://firsthandfunds.com/index.php?fuseaction=funds.tvfqx.

private securities. Specifically, we compare the flow-performance sensitivity between funds affiliated with families that have access to private security investment but differing in their holdings of private securities. Furthermore, we entropy-balance match the PE mutual funds (i.e., mutual funds with private equity investment) with non-PE mutual funds on observable fund and family characteristics each year, including fund flow (*Flow*); benchmark-adjusted fund return (*RETBMK*); the logarithm of fund TNA (*Ln(Fund TNA)*); the logarithm of the number of months since fund inception (*Ln(Fund Age)*); the annualized fund expense ratio (*Expense Ratio*); the annualized fund turnover ratio (*Turnover*); the standard deviation of monthly fund returns in a quarter (*RETVOL*); and the logarithm of family TNA (*Ln(Family TNA)*).[22] The entropy balancing approach allows us to reweight the PE mutual funds and non-PE mutual funds to ensure that differences in these fund and family characteristics do not drive our results. We estimate the following panel regression using a matched sample of PE and non-PE mutual funds:

$$\begin{aligned} Flow_{f,q} = \alpha + \beta_1^{Neg} NegPerf_{f,q-1} \\ + \beta_2^{Neg}\left(NegPerf_{f,q-1} \times High\ PE_{f,q-1} \times NegVC_{q-1}\right) \\ + \beta_3^{Neg}\left(NegPerf_{f,q-1} \times High\ PE_{f,q-1}\right) \\ + \beta_4^{Neg}\left(NegPerf_{f,q-1} \times NegVC_{q-1}\right) + \beta_1^{Pos} PosPerf_{f,q-1} \\ + \beta_2^{Pos}\left(PosPerf_{f,q-1} \times High\ PE_{f,q-1} \times NegVC_{q-1}\right) \\ + \beta_3^{Pos}\left(PosPerf_{f,q-1} \times High\ PE_{f,q-1}\right) \\ + \beta_4^{Pos}\left(PosPerf_{f,q-1} \times NegVC_{q-1}\right) + \gamma M_{f,q-1} + \varepsilon_{f,q} \end{aligned} \tag{14}$$

where $Flow_{f,q}$ refers to the investor flows of fund f in quarter q. $NegPerf_{f,q-1}$ ($PosPerf_{f,q-1}$) equals the benchmark-adjusted return when it is negative (positive) and zero otherwise. $High\ PE_{f,q-1}$ is an indicator variable that equals one if the investment weight in private securities is in the top quintile across all PE mutual funds and zero otherwise. $NegVC_{q-1}$ is an indicator variable that equals one if the VC index return is negative and zero otherwise. The vector *M* stacks all other fund-level and family-level control variables, including the *High PE*, *High PE×NegVC*, *Lag(Flow)*, *Ln(Fund TNA)*, *Ln(Fund Age)*, *Expense Ratio*, *Turnover*, *RETVOL* and *Ln(Family TNA)*. We also include family and quarter fixed effects, and the standard errors are clustered at the family level.

[22] The advantages of entropy balancing approach are discussed in Hainmueller (2012) and Hainmueller and Xu (2013).

The coefficient of interest is β_2^{Neg}, which captures the incremental flow-performance sensitivity for high PE mutual funds during periods of VC market downturns and poor mutual fund performance. We expect β_2^{Neg} to be positive because poor performance of high PE mutual funds should induce investors to withdraw their capital in anticipation of fire-sale externalities associated with other investors' redemptions, particularly following periods of stress in the venture capital market which we proxy by $NegVC_{q-1}$.

We report the results in Panel A of Table 8. We use two different proxies of VC index returns, one from Cambridge Associates VC index in Models (1) to (3) and another one from Thomson Reuters VC Research index in Models (4) to (6). For brevity, we suppress reporting the estimated coefficients for control variables. As shown in Model (1), β_2^{Neg} is positive and significant (0.649). Thus, PE mutual funds experience higher levels of outflows relative to entropy-matched non-PE mutual funds when they experience poor performance (*NegPerf* < *0*) and VC market is also faring badly. In contrast, PE mutual fund flows are not significantly affected by any of the interactions of positive fund performance with high PE holdings and negative VC market performance.

In Panel B, we calculate the total flow effect when PE mutual funds have poor performance and in poor VC markets by summing the coefficients on the *NegPerf* variables (the direct effect and three interactions). The overall flow-performance sensitivity amounts to 0.678 for high PE mutual funds with negative performance during VC market downturns. In contrast, the overall flow-performance sensitivity for high PE mutual funds is not statistically different from zero when either the fund or the VC market exhibits positive performance. This asymmetry in the flow-performance sensitivity suggests that highly illiquid private security holdings amplify the sensitivity of fund flows to poor performance when the VC market declines, consistent with correlated redemptions and fragility following bad states in the private equity market.

Models (2) and (3) report the findings for subsamples of retail investors and institutional investors, respectively. We classify fund share classes into retail and institutional based on the methodology in Chen, Goldstein, and Jiang (2010) and construct matched samples within each subsample, again using the previously described entropy balancing approach.[23] On the one hand,

[23] Since we reweight the PE mutual funds and non-PE mutual funds in each subsample, the full sample result may not lie between the two subsamples.

institutions may be more aware of funds' private equity investments (e.g., stale pricing and the corresponding liquidity risk) and/or have better ability to extract information about fund's future performance from their past performance. This should motivate them to engage more in strategic redemptions. On the other hand, Chen, Goldstein, and Jiang (2010) document that large institutional investors may be less prone to run-like behavior as they may internalize the liquidation costs and externalities associated with investor outflows.

Consistent with institutional investors being informed and redeeming strategically, they are more sensitive to negative performance unconditionally. Moving to high PE mutual funds, institutional investors respond more (less) to bad fund performance when the VC market is bearish (bullish). For instance, the marginal effect indicated by β_2^{Neg} is 0.733 for retail flows and 1.590 for institutional flows, suggesting that both retail and institutional investors of high PE mutual funds display run-like behavior during VC market downturns. Despite the slight differences in the magnitude of response of institutional and retail flows, the joint effect presented in Panel B is similar in both subsamples, and we continue to find statistically significant and economically meaningful flow-performance sensitivity for high PE mutual funds when both the fund and the VC market perform poorly. Our main results also hold when we use the Thomson Reuters VC Research index.

Collectively, these findings highlight one of the disadvantages of the open-end mutual fund structure when it comes to investing in illiquid private securities. During bad times in the private equity investment sector, funds holding more private equity securities are subject to greater outflows when the funds perform poorly. Given the rapid growth of mutual fund participation in private markets and enhanced mandated disclosure of illiquid investments of mutual funds, economically large increases in the holdings of private securities by mutual funds could pose systemic risk arising from investor runs and financial fragility.

6. Conclusion

We provide novel empirical evidence on the valuation of private companies held by mutual funds and examine the financial fragility associated with mutual funds holding private securities. Our analysis highlights emerging issues that should be considered as we allow mutual funds, which are the primary investment vehicle for many individual investors, to hold more difficult-to-value private securities.

We find the valuations of private securities are frequently stale, changing on average once every 2.3 quarters. When new securities on the private company are issued, the deal prices in these offerings serve as a valuation anchor for *both* the newly issued security and securities issued in earlier funding rounds. In 38% of all fund-security-quarter observations, the prices of private securities are posted at a deal price. This number jumps to 86% when the security was part of a deal in the most recent quarter.

We observe large differences in the valuation of the same private security reported by different fund families. The average dispersion (standard deviation) in the prices across multiple fund families holding a private security is 9.6%, which translates to about $3 for a security priced at $19. In 10% of quarters, this price dispersion exceeds 24.8%. In contrast to the dispersion observed at the fund family level, we observe virtually no dispersion in prices across funds within the same family, perhaps because valuation committees assure similar valuations across funds within the same family. Since private security valuations feed directly into the daily NAVs that determine investors' transaction prices, the differences in prices across fund families indicate mutual fund investors are buying into the same private security at different prices.

These pricing dynamics, generally stale prices with infrequent but large markups, lead to fund return predictability. A natural place where this markup is likely to occur is around a follow-on series offering, which are generally accompanied by large deal-over-deal price changes (averaging 47% in our sample). This large deal-over-deal price increase leaves a discernable footprint in fund returns. Defining the new funding round date as the event day, we find the average cumulative abnormal fund return is an economically and statistically significant 40 bps (25 bps) in the 10-day (5-day) window following the funding round. Consistent with these returns being linked to the private securities, we show that the post-funding abnormal returns are positively related to estimates of the economic significance of the impact of the valuation change on fund returns (i.e., quarter-end weight in the private security multiplied by the ratio of the first post-deal valuation to the last pre-deal valuation).

We find that return predictability around follow-on rounds is more muted for fund families with larger information-processing resources and/or fund families that have access to privileged information about issuer companies. To the extent that return predictability leads to flow volatility and other undesirable fund characteristics, our findings suggest that mutual fund investors wishing to gain access to private equity via investments in open-end mutual funds are advised to invest in funds belonging to large fund families and funds in fund families that are major investors in the VC rounds that they participate in.

Finally, we find that flow-performance sensitivity is worse when funds have high private equity exposure ***and*** the VC market performed poorly. This is suggestive of stronger strategic complementarities and financial fragility faced by investors in mutual funds with high exposure to private equity securities. We have recently observed an unprecedented growth in the market for private securities that suggests that mutual funds' participation in this market is likely to grow far beyond the current level. Also, we have witnessed a bullish trend in this market, reminiscent of the dotcom bubble of 2000. A major down move in prices can significantly impact the mutual fund NAVs and potentially lead to investor runs on open-end funds holding private and highly illiquid securities. In a cautionary tale of liquidity mismatch gone awry, the director of the shattered U.K. Woodford Equity Income Fund sold its private securities at a discount as deep as 43% of the pre-closure valuation in order to unwind the fund, resulting in class-action lawsuits by the investors. Such risk is mitigated when the funds are closed-ended. Indeed, in case of the aforementioned U.K. Woodford fund saga, a related closed-end fund, Woodford Patient Capital Trust, was never shut down, rebranded as a Schroders fund, and its trading discount recovered significantly from June 30, 2020 to January 30, 2021.[24] These contrasting cases highlight an important liquidity disadvantage during bad times for open-end mutual fund structure when it comes to investing in untraded, private securities.

[24] Hodgson-Teall and Garvey (2021).

References

Agarwal, Vikas, Naveen D. Daniel, and Narayan Y. Naik, 2011, Do hedge funds manage their reported returns? *Review of Financial Studies* 24(10), 3281–3320.

Agarwal, Vikas, Lei Jiang, and Quan Wen, Why do mutual funds hold lottery stocks? forthcoming in *Journal of Financial and Quantitative Analysis*.

Ang, Andrew, Bingxu Chen, William N. Goetzmann, and Ludovic Phalippou, 2018, Estimating private equity returns from limited partner cash flows, *Journal of Finance* 73(4), 1751–1783.

Anson, Mark J. P., 2007, Performance measurement in private equity: Another look, *Journal of Private Equity* 10, 7–21.

Atanasov, Vladimir, John J. Merrick Jr., and Philipp Schuster, 2019, Mismarking fraud in mutual funds, Unpublished working paper.

Barber, Brad M., and Ayako Yasuda, 2017, Interim fund performance and fundraising in private equity, *Journal of Financial Economics* 124(1), 172–194.

Ben-David, Itzhak, Francesco Franzoni, Augustin Landier, and Rabih Moussawi, 2013, Do hedge funds manipulate stock price? *Journal of Finance* 68(6), 2383–2434.

Bhargava, Rahul, Ann Bose, and David A. Dubofsky, 1998, Exploring international stock market correlations with open-end international mutual funds, *Journal of Business Finance & Accounting* 25(5), 765–773.

Boudoukh, Jacob, Matthew Richardson, Marti Subrahmanyam, and Robert F. Whitelaw, 2002, Stale prices and strategies for trading mutual funds, *Financial Analysts Journal* 58(4), 53–71.

Brown, Gregory W., Oleg R. Gredil, and Steven N. Kaplan, 2019, Do private equity funds manipulate reported returns? *Journal of Financial Economics* 132(2), 267–297.

Brown, Keith C., and Kenneth W. Wiles, 2015, In search of unicorns: Private IPOs and the changing markets for private equity investments and corporate control, *Journal of Applied Corporate Finance* 27(3), 34–48.

Carhart, Mark M., Ron Kaniel, David K. Musto, and Adam V. Reed, 2002, Leaning for the tape: Evidence of gaming behavior in equity mutual funds, *Journal of Finance* 57(2), 661–693.

Cederburg, Scott, and Neal Stoughton, 2018, Discretionary NAVs, Unpublished working paper.

Chakraborty, Indraneel, and Michael Ewens, 2018, Managing performance signals through delay: Evidence from venture capital, *Management Science* 64(6), 2875–2900.

Chalmers, John M., Roger M. Edelen, and Greg B. Kadlec, 2001, On the perils of financial intermediaries setting security prices: The mutual fund wild card option, *Journal of Finance* 56(6), 2209–2236.

Chen, Qi, Itay Goldstein, and Wei Jiang, 2010, Payoff complementarities and financial fragility: Evidence from mutual fund outflows, *Journal of Financial Economics* 97, 239–262.

Chernenko, Sergey, Josh Lerner, and Yao Zeng, Mutual funds as venture capitalists? Evidence from unicorns, forthcoming in *Review of Financial Studies*.

Choi, Jaewon, Mathias Kronlund, and Ji Yeol Jimmy Oh, 2019, Sitting bucks: Zero returns in fixed income funds, Unpublished working paper.

Cici, Gjergji, Scott Gibson, and John Merrick, Jr., 2011, Missing the marks? Dispersion in corporate bond valuations across mutual funds, *Journal of Financial Economics* 101(1), 206–226.

Cici, Gjergji, Alexander Kempf, and Alexander Puetz, 2016, The valuation of hedge funds' equity positions, *Journal of Financial and Quantitative Analysis* 51(3), 1013–1037.

Cochrane, John H., 2005, The risk and return of venture capital, *Journal of Financial Economics* 75(1), 3–52.

Dimson, Elroy, 1979, Risk measurement when shares are subject to infrequent trading, *Journal of Financial Economics* 7(2), 197–226.

Driessen, Joost, Tse-Chun Lin, and Ludovic Phalippou, 2012, A new method to estimate risk and return of nontraded assets from cash flows: The case of private equity funds, *Journal of Financial and Quantitative Analysis* 47(3), 511–535.

Edelen, Roger M., and Jerold B. Warner, 2001, Aggregate price effects of institutional trading: A study of mutual fund flow and market returns, *Journal of Financial Economics* 59(2), 195–220.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33(1), 3–56.

Foldy, Ben, 2021, Electric-truck maker Rivian raises $2.65 billion ahead of first vehicle launch, *The Wall Street Journal*.

Franzoni, Francesco, Eric Nowak, and Ludovic Phalippou, 2012, Private equity performance and liquidity risk, *Journal of Finance* 67(6), 2341–2373.

Gaspar, José-Miguel, Massimo Massa, and Pedro Matos, 2006, Favoritism in mutual fund families? Evidence on strategic cross-fund subsidization, *Journal of Finance* 61(1), 73–104.

Goetzmann, William N., Zoran Ivković, and K. G. Rouwenhorst, 2001, Day trading international mutual funds: Evidence and policy solutions, *Journal of Financial and Quantitative Analysis* 36(3), 287–309.

Goldstein, Itay, Hao Jiang, and David Ng, 2017, Investor flows and fragility in corporate bond funds, *Journal of Financial Economics* 126, 592–613.

Gompers, Paul, and Josh Lerner, 2000, Money chasing deals? The impact of fund inflows on private equity valuations, *Journal of Financial Economics* 55(2), 281–325.

Gornall, Will, and Ilya Strebulaev, 2020a, Squaring venture capital valuations with reality, *Journal of Financial Economics* 135(1), 120–143.

Gornall, Will, and Ilya Strebulaev, 2020b, A valuation model of venture capital-backed companies with multiple financing rounds, Unpublished working paper.

Greene, Jason T., and Charles W. Hodges, 2002, The dilution impact of daily fund flows on open-end mutual funds, *Journal of Financial Economics* 65(1), 131–158.

Greene, Jason T., Charles W. Hodges, and David A. Rakowski, 2007, Daily mutual fund flows and redemption policies, *Journal of Banking and Finance* 31(12), 3822–3842.

Hainmueller, Jens, 2012, Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies, *Political Analysis* 20, 25–46.

Hainmueller, Jens, and Yiqing Xu, 2013, ebalance: A Stata package for entropy balancing, *Journal of Statistical Software* 54(7), 1–18.

Hodgson-Teall, Meriel, and Jonathan Garvey, 2021, The importance of liquidity management, Lexology.com (https://www.lexology.com/library/detail.aspx?g=db851fc9-c346-46ee-9126-3815e448a0e3).

Huang, Shiyang, Yifei Mao, Cong Wang, and Dexin Zhou, Public market players in the private world: Implications for the going-public process, forthcoming in *Review of Financial Studies.*

Hüther, Niklas, 2016, Raising funds on performance: Are private equity returns too good to be true? Unpublished working paper.

Imbierowicz, Björn, and Christian Rauch, 2020, The pricing of private assets: Mutual fund investments in 'unicorn' companies, Unpublished working paper.

Jegadeesh, Narasimhan, Roman Kräussl, and Joshua M. Pollet, 2015, Risk and expected returns of private equity investments: Evidence based on market prices, *Review of Financial Studies* 28(12), 3269–3302.

Jenkinson, Tim, Miguel Sousa, and Rüdiger Stucke, 2013, How fair are the valuations of private equity funds, Unpublished working paper.

Kaniel, Ron, and Robert Parham, 2017, WSJ category kings – the impact of media attention on consumer and mutual fund investment decisions, *Journal of Financial Economics* 123(2), 337–356.

Kaplan, Steven N., and Antoinette Schoar, 2005, Private equity performance: Returns, persistence, and capital flows, *Journal of Finance* 60(4), 1791–1823.

Kaplan, Steven N., and Berk A. Sensoy, 2015, Private equity performance: A survey, *Annual Review of Financial Economics* 7, 597–614.

Korteweg, Arthur, 2019, Risk adjustment in private equity returns, Unpublished working paper.

Korteweg, Arthur, and Stefan Nagel, 2016, Risk-adjusting the returns to venture capital, *Journal of Finance* 71(3), 1437–1470.

Korteweg, Arthur, and Morten Sorensen, 2010, Risk and return characteristics of venture capital-backed entrepreneurial companies, *Review of Financial Studies* 23(10), 3738–3772.

Kwon, Sungjoung, Michelle Lowry, and Yiming Qian, 2020, Mutual fund investments in private firms, *Journal of Financial Economics* 136(2), 407–443.

Metrick, Andrew, and Ayako Yasuda, 2010, Venture capital and the finance of innovation, 2nd edition, Hoboken, NJ: John Wiley & Sons.

Metrick, Andrew, and Ayako Yasuda, 2021, Venture capital and the finance of innovation, 3rd edition, Hoboken, NJ: John Wiley & Sons.

Michaels, Dave, 2018, SEC Chairman wants to let more main street investors in on private deals, *The Wall Street Journal*.

Pástor, Luboš, and Robert F. Stambaugh, 2003, Liquidity risk and expected stock returns, *Journal of Political Economy* 111(3), 642–685.

Rakowski, David, 2010, Fund flow volatility and performance, *Journal of Financial and Quantitative Analysis* 45(1), 223–237.

Scholes, Myron, and Joseph Williams, 1977, Estimating betas from nonsynchronous data, *Journal of Financial Economics* 5(3), 309–327.

Sirri, Erik. R., and Peter Tufano, 1998, Costly search and mutual fund flows, *Journal of Finance* 53(5), 1589–1622.

Woodward, Susan E., 2009, Measuring risk for venture capital and private equity portfolios, Unpublished working paper, Sand Hill Econometrics.

Zitzewitz, Eric, 2006, How widespread was late trading in mutual funds? *American Economic Review* 96(2), 284–289.

Table 1. Price dispersion in private company valuations by mutual funds, 2010 to 2018

Panel A presents summary statistics for the number of funds that hold the same security in a given quarter (*NumFd*). Panel B presents summary statistics for the price dispersion measures. Price dispersion (*DispPrc_Avg*) is computed as the standard deviation of prices across funds in the same quarter ending in the same month (*StdPrc*) divided by the average security price across funds (*AvgPrc*). *DispPrc_Med* is computed as the standard deviation divided by median price (*AvgMed*). Panel C calculates price dispersion within fund families, which yields multiple observations for the same security in the same quarter. Panel D calculates price dispersion across fund families (average price is first calculated within the fund family to generate a price dispersion measure). The sample period is from 2010 to 2018.

	No. Firm	No. Security	Security-Quarter Obs.	Mean	Std. Dev.	10%	25%	Median	75%	90%
Panel A: Security-Quarters (Full Sample)										
NumFd	158	256	2,404	8.102	7.199	2	3	6	11	18
Panel B: Security-Quarters (with same ending month) (Full Sample)										
DispPrc_Avg	158	256	3,962	0.036	0.085	0.000	0.000	0.000	0.034	0.123
DispPrc_Med	158	256	3,962	0.038	0.098	0.000	0.000	0.000	0.034	0.122
StdPrc	158	256	3,962	0.770	2.139	0.000	0.000	0.000	0.531	2.244
AvgPrc	158	256	3,962	22.083	31.351	2.591	5.111	11.011	22.539	50.192
MedPrc	158	256	3,962	22.143	31.503	2.565	5.106	11.054	22.120	50.192
Panel C: Within Family, Family-Security-Quarters (with the same ending month)										
NumFd	153	251	4,363	3.052	1.534	2	2	3	3	5
DispPrc_Avg	153	251	4,363	0.001	0.006	0.000	0.000	0.000	0.000	0.000
DispPrc_Med	153	251	4,363	0.001	0.006	0.000	0.000	0.000	0.000	0.000
StdPrc	153	251	4,363	0.018	0.190	0.000	0.000	0.000	0.000	0.003
AvgPrc	153	251	4,363	24.911	32.740	2.824	5.778	13.184	28.650	58.298
MedPrc	153	251	4,363	24.912	32.742	2.822	5.778	13.184	28.651	58.298
Panel D: Across Families, Security-Quarters (with the same ending month)										
NumFam	69	118	1,480	3.752	2.452	2	2	2	6	8
DispPrc_Avg	69	118	1,480	0.096	0.134	0.000	0.002	0.053	0.135	0.248
DispPrc_Med	69	118	1,480	0.099	0.153	0.000	0.002	0.052	0.134	0.252
StdPrc	69	118	1,480	2.138	3.733	0.000	0.076	0.873	2.561	5.279
AvgPrc	69	118	1,480	31.295	35.237	3.997	8.693	16.859	37.677	92.331
MedPrc	69	118	1,480	31.379	35.456	3.970	8.691	16.910	37.650	93.094

Table 2. Stale pricing of private securities

Quarterly return for a family-security-quarter is calculated using the reported prices by family F in quarters q and $q-1$ for security s, $(\frac{P_{F,s,q}}{P_{F,s,q-1}} - 1)$. Panel A reports descriptive statistics across family-security-quarter observations for both private securities (*Return_PVT*) and public securities (*Return_PUB*). In Panel B, for each family-security pair, we calculate the percentage of quarters in which the family does not change the reported price of the security (i.e., quarterly return is zero) for private and public securities. For private securities, we also calculate the number of quarters until prices are updated from the acquisition price.

	No. Security	Obs.	Mean	Std.Dev.	10%	25%	Median	75%	90%
Panel A: Family-Security-Quarter Return Characteristics									
Return_PVT	334	8,992	0.037	0.279	−0.151	−0.005	0.000	0.044	0.219
Return_PUB	6,677	248,823	0.030	0.236	−0.178	−0.070	0.026	0.118	0.222
Panel B: Family-Security Return Characteristics									
%Zero Return_PVT	334	763	0.461	0.304	0.038	0.250	0.455	0.667	1.000
Qtr to Update_PVT	334	763	2.334	1.975	1	1	2	3	5
%Zero Return_PUB	6,677	26,628	0.004	0.057	0.000	0.000	0.000	0.000	0.000

Table 3. Deviation from deal price around follow-on rounds

For each family-security-quarter, price deviation is calculated using the reported price by family F in quarter q for security s and the benchmark price for the same security, ($Dev_{F,s,q} = \frac{P_{F,s,q}}{B_{s,q}} - 1$). *DumDev* is an indicator variable that equals one if the absolute value of *Dev* is above 1% and zero otherwise. $DumDev^{+}$ is an indicator variable that equals one if *Dev* is above 1% and zero otherwise, and $DumDev^{-}$ is an indicator variable that equals one if *Dev* is below −1% and zero otherwise. Panel A employs four sets of benchmark price in private security valuation, including the deal price in the most recent and any of the previous funding rounds (Any Prior Deal Price), the deal price in the most recent funding round (Latest Deal Price), the price at which the security was acquired by the family (Acquisition Price), and the average price reported by all families holding a security in a quarter (Family-Firm Average Price), and reports the number of price deviation, the total number of family-security-quarter observations, as well as the percentage of price deviation. In Panel B, for each family-security pair, we compute the price deviation of early round security valuation from the new round deal price, over nine quarters around the new round. We report the percentage of price deviations, as well as the median price deviation in the subset of positive and negative deviations, respectively. Panel C reports similar statistics for private securities issued in the new round.

	No. Firm	No. Security	∑ DumDev	No. Family-Security-Quarters	%Dev
Panel A: Deviation of Security Valuation					
Any Prior Deal Price	186	326	5,660	9,132	0.620
Latest Deal Price	186	326	5,894	9,132	0.645
Acquisition Price	182	314	7,227	9,086	0.795
Family-Firm Average Price	63	204	1,377	5,193	0.265

Event Quarter	No. Firm	No. Security	No. Family	No. Family-Security-Quarters	%Dev	$\%Dev^{+}$	$\%Dev^{-}$	Median Dev^{+}	Median Dev^{-}
Panel B: Deviation of Early Round Security Valuation from the New Round Deal Price									
−4	50	90	35	292	0.990	0.096	0.894	0.589	−0.339
−3	58	105	37	332	0.985	0.084	0.901	0.580	−0.336
−2	62	113	39	369	0.978	0.103	0.875	0.440	−0.310
−1	63	116	40	393	0.903	0.142	0.761	0.190	−0.308
0	70	140	41	484	0.395	0.083	0.312	0.232	−0.159
1	64	124	41	452	0.538	0.133	0.405	0.210	−0.130
2	59	114	40	424	0.528	0.205	0.323	0.190	−0.167
3	52	102	35	388	0.655	0.281	0.374	0.232	−0.207
4	46	89	30	362	0.785	0.365	0.420	0.212	−0.208
Panel C: Deviation of New Round Security Valuation from the New Round Deal Price									
0	156	207	40	440	0.143	0.025	0.118	0.163	−0.100
1	150	198	39	419	0.322	0.136	0.186	0.169	−0.100
2	132	178	38	386	0.461	0.236	0.225	0.292	−0.100
3	119	161	38	353	0.663	0.402	0.261	0.263	−0.138
4	107	146	35	310	0.761	0.426	0.335	0.372	−0.127

Table 4: Quarterly private company alphas

This table presents the results of a pooled regression of fund family-security-quarter percentage valuation changes (less the risk-free rate) of private companies held by mutual funds on factor returns (market risk premium, size, and value factors of Fama and French, 1993) and market condition (follow-on funding quarter for the company). Three models are estimated: (1) a one-factor market model with no lags, (2) a one-factor market model with two lags, and (3) a three-factor model with two lags of market, size, and value factors. Models 1 to 3 present a single alpha estimate. Models 4 to 6 include an indicator variable *Follow-on Dummy*, that equals one in quarters when the company engages in a follow-on funding round and zero otherwise. Standard errors are clustered by quarter.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel A: Coefficient Estimates and Regression Statistics						
Alpha	0.030***	0.005	0.007	0.014*	−0.011	−0.008
	(3.23)	(0.45)	(0.71)	(1.67)	(−1.02)	(−0.86)
Follow-on Dummy				0.227***	0.227***	0.218***
				(6.54)	(6.88)	(6.77)
MKTRET	0.281**	0.372***	0.312**	0.332***	0.423***	0.349***
	(2.39)	(3.30)	(2.17)	(2.89)	(4.35)	(2.65)
$MKTRET_{t-1}$		0.431***	0.420**		0.434***	0.438**
		(2.72)	(2.19)		(2.89)	(2.50)
$MKTRET_{t-2}$		0.445**	0.309**		0.436**	0.334**
		(2.22)	(1.99)		(2.28)	(2.19)
HML			−0.486***			−0.388***
			(−6.16)			(−4.63)
HML_{t-1}			−0.169			−0.136
			(−1.30)			(−1.07)
HML_{t-2}			−0.324**			−0.317**
			(−2.12)			(−2.00)
SMB			0.742***			0.695***
			(4.47)			(4.26)
SMB_{t-1}			0.257			0.192
			(1.41)			(1.14)
SMB_{t-2}			0.539**			0.411*
			(2.25)			(1.95)
R-squared	0.003	0.012	0.026	0.043	0.052	0.062
Observations	8,992	8,992	8,992	8,992	8,992	8,992
Panel B: Summed Factor Exposures						
Market Beta	0.281**	1.247***	1.041**	0.332***	1.294***	1.121***
	(2.39)	(3.64)	(2.61)	(2.89)	(4.10)	(3.07)
HML Tilt			−0.979***			−0.841***
			(−3.71)			(−3.32)
SMB Tilt			1.537***			1.299***
			(3.74)			(3.36)

*, **, *** - significant at the 10, 5, and 1% level (respectively).

Table 5: Regression of private company valuations on family characteristics

This table presents the results of the following panel regressions with security-quarter fixed effects and the corresponding t-statistics with standard errors clustered by quarter:

$$DumUpd_{F,s,q} = \alpha + \beta_1 Char_{F,s,q} + \beta_2 Char_{F,s,q} \times News_{s,q} + \varepsilon_{F,s,q},$$

where $DumUpd_{F,s,q}$ refers to an indicator variable that equals one if a fund family F revises its valuation of security s in quarter q, and zero otherwise. $Char_{F,s,q}$ is a vector of family or family-security characteristics, including *Ln(Family TNA)*, defined as the logarithm of the family's total net assets (TNA); *WTPE*, defined as the percentage weight of each private security in a family's total equity portfolio; and *%Round Size*, defined as the total dollar amount of each private security in a family's portfolio, scaled by the deal size of the corresponding funding round. $News_{s,q}$ refers to two proxies for news event, including (i) *Ln(AEV)*, defined as the logarithm of the aggregate event volume from RavenPack, which measures the count of public news releases over a rolling 91-day window; and (ii) *Follow-on Dummy*, defined as an indicator variable that equals one in quarters when the private firm initiates follow-on funding through a new round, and zero otherwise.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Ln(Family TNA)	0.011**			0.017**		
	(2.07)			(2.49)		
WTPE		0.120***			0.126*	
		(3.07)			(1.89)	
%Round Size			−0.027			0.224**
			(−0.34)			(2.48)
Ln(Family TNA) × Ln(AEV)				−0.005		
				(−1.45)		
WTPE × Ln(AEV)					−0.014	
					(−0.39)	
%Round Size × Ln(AEV)						−0.329***
						(−4.52)
Ln(Family TNA) × Follow-on Dummy				−0.013		
				(−0.98)		
WTPE × Follow-on Dummy					0.127	
					(1.23)	
%Round Size × Follow-on Dummy						−0.175
						(−0.42)
R-squared	0.706	0.741	0.682	0.707	0.741	0.687
Observations	3,493	2,651	2,155	3,493	2,651	2,155

*, **, *** - significant at the 10, 5, and 1% level (respectively).

Table 6. Mutual fund returns around follow-on financing round of private equity holdings

For each round of follow-on financing for a private security s, the abnormal return on fund f on day t is defined as $AR\_BMK_{f,s,t} = R_{f,t} - R_{BMK,t}$, where $R_{f,t}$ ($R_{BMK,t}$) is the return on fund f (the fund's benchmark portfolio) on day t. The cumulative abnormal returns (*CAR*s) from day a to day b is: $CAR\_BMK[a,b]_{f,s} = \left[\prod_{t=a}^{b}(1 + AR\_BMK_{f,s,t})\right] - 1$, and we then average $CAR\_BMK[a,b]_{f,s}$ across fund-security pairs to obtain $CAR\_BMK[a,b]$. Day 0 refers to the follow-on round date for private security s. Panel A reports the number of securities, funds, average number of funds per security and fund-security observations, as well as the average benchmark-adjusted CARs across all fund-security-quarters. Standard errors are clustered by calendar days (filing date of follow-on security-round). Panel B reports similar statistics when we first compute benchmark-adjusted *CAR*s for each family-security-quarters, then average across all family-security-quarters. Panel C presents the results of the following cross-sectional regressions (across families and private securities) and the corresponding *t*-statistics with standard errors clustered by calendar days (filing date of follow-on security-round):

$$CAR\_BMK[0,k]_{F,s} = \alpha + \beta \Delta Value_{F,s} \times WTPE_{F,s} + \varepsilon_{F,s},$$

where $CAR\_BMK[0,k]_{F,s}$ refers to the benchmark-adjusted *CAR*s of family F holding private security s over from day 0 to day k, and k takes the value of 3, 5, or 10. $\Delta Value_{F,s}$ refers to the percentage change in the valuation by family F of the private security s reported in the quarter after the new financing round, relative to the family's valuation in the quarter before the new round, and $WTPE_{F,s}$ refers to the investment weight of family F in security s according to the latest holdings. $\Delta Value_{F,s}$ is further replaced with $Update_{F,s}$, defined as the percentage change in the deal price of the new round of financing of the private security s relative to the last valuation reported by family F. Panel D reports similar statistics of the following cross-sectional regressions:

$$CAR\_BMK[0,k]_{F,s} = \alpha + \beta_1 Char_{F,s} + \beta_2 WTPE_{F,s} + \varepsilon_{F,s},$$

where $Char_{F,s,q}$ is a vector of family or family-security characteristics, including *Ln(Family TNA)*, defined as the logarithm of the family's total net assets (TNA); and *%Round Size*, defined as the total dollar amount of each private security in a family's portfolio, scaled by the deal size of the corresponding funding round. All other variables are defined as above.

*Panel A: Benchmark-adjusted CAR around Follow On Round (Averaged across **Fund**-Security-Quarters)*

No. Security	No. Fund	Funds per Security	Fund-Security Obs.	CAR							
				[−10, −1]	[−5, −1]	[−3, −1]	[0, 3]	[0, 5]	[0, 10]	[11, 15]	[16, 20]
96	156	7	715	0.101	0.001	−0.040	0.122**	0.218***	0.371***	−0.021	0.016
				(1.04)	(0.01)	(−0.58)	(2.45)	(2.72)	(3.65)	(−0.30)	(0.26)

*Panel B: Benchmark-adjusted CAR around Follow On Round (Averaged across **Family**-Security-Quarters)*

No. Security	No. Family	Families per Security	Family-Security Obs.	CAR							
				[−10, −1]	[−5, −1]	[−3, −1]	[0, 3]	[0, 5]	[0, 10]	[11, 15]	[16, 20]
96	37	3	251	0.116	−0.002	−0.031	0.134**	0.254***	0.398***	0.034	0.034
				(1.36)	(−0.02)	(−0.49)	(2.48)	(3.41)	(4.09)	(0.54)	(0.58)

*, **, *** - significant at the 10, 5, and 1% level (respectively).

Table 6—Continued

	[0, 3]		[0, 5]		[0, 10]	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel C: Benchmark-adjusted CAR After Follow On Round Regressed on Change in Valuation and Fund Holding						
ΔValue × WTPE	0.395**		0.755***		1.395***	
	(2.32)		(2.84)		(4.50)	
Update × WTPE		0.288*		0.582**		1.153***
		(1.77)		(2.30)		(3.39)
Constant	0.107*	0.106*	0.203***	0.198**	0.303***	0.287***
	(1.92)	(1.83)	(2.69)	(2.48)	(3.06)	(2.76)
R-squared	0.019	0.012	0.043	0.029	0.090	0.071
Obs	251	251	251	251	251	251
Panel D: Benchmark-adjusted CAR After Follow On Round Regressed on Family Characteristics						
Ln(Family TNA)	−0.027		−0.039		−0.070**	
	(−1.17)		(−1.50)		(−2.02)	
%Round Size		−0.009*		−0.011*		−0.017**
		(−1.74)		(−1.89)		(−2.20)
WTPE	0.190	0.210	0.249	0.280	0.414	0.474
	(0.76)	(0.85)	(0.64)	(0.74)	(1.15)	(1.36)
Constant	0.435	0.141*	0.690**	0.250**	1.147**	0.353***
	(1.41)	(1.77)	(2.00)	(2.32)	(2.54)	(2.89)
R-squared	0.025	0.037	0.028	0.036	0.052	0.060
Observations	251	250	251	250	251	250

*, **, *** - significant at the 10, 5, and 1% level (respectively).

Table 7. Mutual fund flows around follow-on financing round of private equity holdings

In Panel A, for each round of follow-on financing for a private security s, the abnormal flow of fund f on day t is defined as $AF\_BMK_{f,s,t} = Flow_{f,t} - Flow_{BMK,t}$, where $Flow_{f,t}$ is the percentage flow of fund f on day t, computed as the ratio of dollar flow to prior day's total net asset (TNA). $Flow_{BMK,t}$ is the lagged TNA-weighted average flow across funds in the fund's benchmark category on day t. In Panel B, the *z*-score for fund f on day t is defined as $Z_{f,t} = (Flow_{f,t} - \overline{Flow}_f)/\sigma_f$, where $Flow_{f,t}$ is the percentage flow of fund f on day t, $\overline{Flow}_f$ and σ_f refer to the average daily flow and standard deviation of daily flow of fund f during the $[t-180, t-31]$ window, respectively. Denoting the follow-on round date for private security *s* as day 0, we first compute the average abnormal flows (or *z*-score) over a *k*-day window for each fund, then average across fund-security pairs. Standard errors are clustered by calendar days (filing date of follow-on security-round). The number of securities, funds, average number of funds per security and fund-security observations are reported. We exclude funds that do not hold the security *s* after the follow-on round. Panels C and D report similar statistics on benchmark-adjusted flow and *z*-score when we only include funds that do not charge redemption fees at the time of the follow-on round.

No. Security	No. Fund	Funds per Security	Fund-Security Obs.	[−30, −1]	[−20, −1]	[−10, −1]	[−5, −1]	[−3, −1]	[0, 3]	[0, 5]	[0, 10]	[0, 20]	[0, 30]
Panel A: Benchmark-adjusted Flow around Follow On Round													
48	60	4	203	−0.010	−0.010	−0.012	−0.013	−0.016	−0.017	−0.011	0.002	−0.001	−0.010
				(−0.86)	(−0.76)	(−0.88)	(−0.63)	(−0.80)	(−1.17)	(−0.80)	(0.06)	(−0.09)	(−0.89)
Panel B: Z-Score on Flow around Follow On Round													
48	60	4	203	0.024	0.016	0.005	−0.010	−0.012	0.019	0.003	−0.169	−0.091	−0.087
				(0.73)	(0.37)	(0.09)	(−0.14)	(−0.15)	(0.35)	(0.06)	(−1.02)	(−0.96)	(−1.09)
Panel C: Benchmark-adjusted Flow around Follow On Round (Funds without Redemption Fee)													
37	42	4	140	0.001	0.001	0.001	0.017	0.011	0.001	0.006	0.023	0.010	−0.001
				(0.17)	(0.11)	(0.14)	(1.15)	(0.79)	(0.05)	(0.40)	(0.65)	(0.53)	(−0.07)
Panel D: Z-Score on Flow around Follow On Round (Funds without Redemption Fee)													
37	42	4	140	0.040	0.026	0.018	0.080	0.103	0.073	0.023	−0.171	−0.109	−0.111
				(0.98)	(0.56)	(0.31)	(1.19)	(1.37)	(1.15)	(0.41)	(−0.75)	(−0.86)	(−1.03)

*, **, *** - significant at the 10, 5, and 1% level (respectively).

Table 8. Flow-performance sensitivity

Panel A presents the results of the following panel regressions with family and quarter fixed effects and the corresponding *t*-statistics with standard errors clustered by family:

$$\begin{aligned} Flow_{f,q} = \alpha &+ \beta_1^{Neg} NegPerf_{f,q-1} + \beta_2^{Neg}\left(NegPerf_{f,q-1} \times High\ PE_{f,q-1} \times NegVC_{q-1}\right) \\ &+ \beta_3^{Neg}\left(NegPerf_{f,q-1} \times High\ PE_{f,q-1}\right) + \beta_4^{Neg}\left(NegPerf_{f,q-1} \times NegVC_{q-1}\right) \\ &+ \beta_1^{Pos} PosPerf_{f,q-1} + \beta_2^{Pos}\left(PosPerf_{f,q-1} \times High\ PE_{f,q-1} \times NegVC_{q-1}\right) \\ &+ \beta_3^{Pos}\left(PosPerf_{f,q-1} \times High\ PE_{f,q-1}\right) + \beta_4^{Pos}\left(PosPerf_{f,q-1} \times NegVC_{q-1}\right) + \gamma M_{f,q-1} + \varepsilon_{f,q} \end{aligned}$$

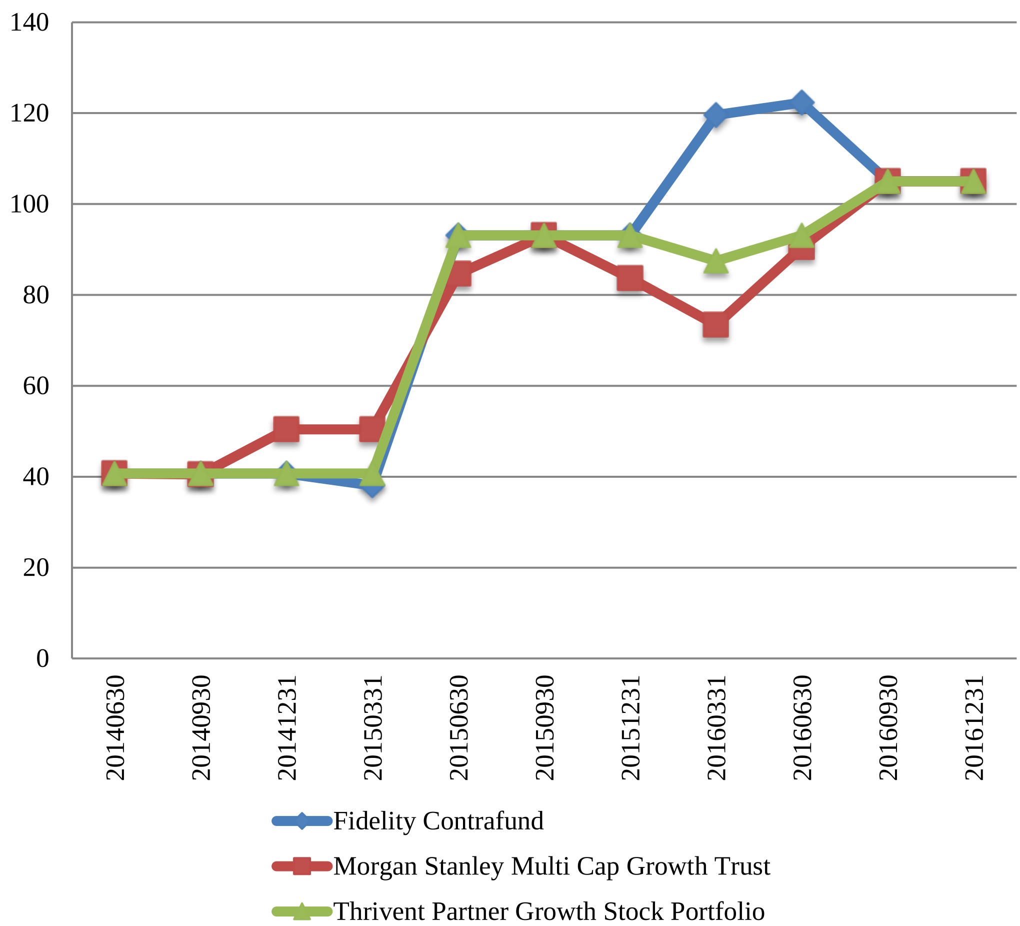
where $Flow_{f,q}$ refers to the investors flows of fund f in quarter q. *NegPerf* (*PosPerf*) equals the benchmark-adjusted return when it is negative (positive) and zero otherwise. $High\ PE_{f,q-1}$ is an indicator variable that equals one if fund investment weight in private equities is in the top quintile and zero otherwise. $NegVC_{q-1}$ is an indicator variable that equals one if the VC index return is negative and zero otherwise. The VC index return is from Cambridge Associates VC index (Models 1 to 3) and Thomson Reuters VC research index (Models 4 to 6). The vector *M* stacks all other fund-level and family-level control variables, including the *High PE*, *High PE* × *NegVC*, *Lag(Flow)*, *Ln(Fund TNA)*, *Ln(Fund Age)*, *Expense Ratio*, *Turnover*, *RETVOL* and *Ln(Family TNA)* (untabulated for brevity). We focus on mutual fund families that invest in private equities, and implement an entropy balancing approach to match the PE funds (i.e., funds with private equity investment) with non-PE funds on observable fund and family characteristics each year. We report results for the full sample (Models 1 and 4), as well as for retail (Models 2 and 5) and institutional (Models 3 and 6) flows. Panel B reports the overall flow-performance sensitivity for high PE funds during periods of negative and positive VC index returns, respectively.

	Cambridge Associates VC Index			Thomson Reuters VC Research Index		
	Flow	Retail Flow	Institutional Flow	Flow	Retail Flow	Institutional Flow
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel A: Coefficient Estimates and Regression Statistics						
NegPerf	0.365***	0.405***	0.734***	0.325***	0.404***	0.654***
	(4.26)	(4.84)	(4.38)	(3.48)	(3.95)	(3.38)
NegPerf × High PE × NegVC	0.649**	0.733**	1.590**	0.457	0.634*	1.383*
	(2.13)	(2.41)	(2.22)	(1.22)	(1.78)	(1.74)
NegPerf × High PE	−0.285*	−0.497**	−0.925***	−0.152	−0.377	−0.841***
	(−1.88)	(−2.67)	(−3.56)	(−0.72)	(−1.33)	(−3.17)
NegPerf × NegVC	−0.052	0.098	−0.661	0.009	0.028	−0.414
	(−0.26)	(0.61)	(−1.40)	(0.05)	(0.19)	(−1.01)
PosPerf	0.549***	0.480***	0.601*	0.516***	0.440***	0.544*
	(5.62)	(4.28)	(1.89)	(5.17)	(4.58)	(1.75)
PosPerf × High PE × NegVC	0.139	0.287	−0.395	−0.783	−0.796	−1.164
	(0.25)	(0.47)	(−0.17)	(−1.15)	(−1.23)	(−1.39)
PosPerf × High PE	−0.267	−0.185	0.200	−0.180	−0.045	0.361
	(−0.85)	(−0.76)	(0.63)	(−0.54)	(−0.22)	(1.17)
PosPerf × NegVC	0.052	−0.301	−0.132	0.284	0.081	0.101
	(0.15)	(−1.31)	(−0.54)	(0.93)	(0.23)	(0.31)
Controls	Y	Y	Y	Y	Y	Y
R-squared	0.206	0.240	0.223	0.209	0.241	0.223
Obs	16,835	12,617	3,844	17,412	13,020	3,993
Panel B: High PE Fund Total Flow Sensitivity in Different Fund Return (NegPerf or PosPerf) and VC Market Conditions (NegVC or PosVC)						
NegPerf × High PE × NegVC	0.678***	0.738***	0.738*	0.639***	0.689***	0.782
($\sum_{i=1}^{4} \beta_i^{Neg}$)	(3.96)	(3.98)	(1.82)	(3.73)	(4.14)	(1.39)
NegPerf × High PE × PosVC	0.081	−0.092	−0.191	0.173	0.027	−0.187
($\beta_1^{Neg} + \beta_3^{Neg}$)	(0.64)	(0.54)	(0.92)	(0.94)	(0.10)	(0.89)
PosPerf × High PE × NegVC	0.473	0.282	0.275	−0.163	−0.320	−0.158
($\sum_{i=1}^{4} \beta_i^{Pos}$)	(0.87)	(0.52)	(0.10)	(0.33)	(0.72)	(0.20)
PosPerf × High PE × PosVC	0.282	0.296	0.801**	0.336	0.395**	0.905***
($\beta_1^{Pos} + \beta_3^{Pos}$)	(0.91)	(1.59)	(2.39)	(0.98)	(2.14)	(2.97)

*, **, *** - significant at the 10, 5, and 1% level (respectively).

Figure 1. Airbnb Series D valuations reported by three mutual funds

The Series D round for Airbnb closed at $40.71 on April 16, 2014. The lines depict the quarterly valuations for Airbnb by three mutual funds in their quarterly reports.



Internet Appendix

Appendix A

To identify private equity securities, we proceed as follows.

1. We start with all unique security names without CUSIP reported in the CRSP Mutual Fund Database. There are initially 308,133 unique security names without CUSIP. We eliminate securities that are unlikely to be U.S. private equity using keywords in security names (e.g., "bond", "coupon", "7%", "Put" "Forex" "Mortgage"). This reduces the number of unique security names to 27,127.
2. We create a union of VC investment data from Thomson Reuters and the IPO data from Bloomberg and CRSP to generate a list of VC-backed companies.
3. We match U.S. active equity mutual funds in the CRSP Mutual Fund investment data with the VC-backed company list on issuer company name by using fuzzy name matching.

The above matching process provides us with a sample of mutual fund investments in VC-backed, pre-IPO companies. We next need to identify the specific security (e.g., Airbnb Series C vs. Airbnb Series D) held by each mutual fund. To do so, we proceed as follows:

1. We start from the list of VC-backed companies held by mutual funds and use the company names as keywords to search through mutual funds' SEC filings (N-CSR and N-Q forms). For those filings with positive hits, we manually collect holdings information on *all* restricted and illiquid securities. In particular, we collect information on fund name, reporting date, security name, security type, number of shares, value of holdings, acquisition date, and acquisition cost. Mutual funds group their portfolio investment into sub-categories (such as common stock, preferred stock, and convertible preferred stock), and report them in the "Statement of Investments" in the SEC filings. The investment category together with any additional Series information included in the security name (e.g., "Series E Preferred Security") are collected to identify security type. In addition, some mutual funds also report acquisition date and acquisition cost for restricted and illiquid securities in the SEC filings; this information is not available in CRSP but is crucial for us to identify Series name as described later. This comprehensive data collection

also expands the sample of private firms, and our final sample is not limited to the original coverage of VC-backed companies.

2. Separately, we create a dataset of VC funding rounds for VC-backed companies that identifies the round investment date, per share purchase price, and Series name. We collect this data mainly from the company's Certificate of Incorporation documents (COIs) accessed via Genesis' Private Company Insight database, and supplement it with other sources such as S-1 filings for companies that subsequently went public, company press releases, and TechCrunch, PitchBook, and SharePost databases. Each observation in this dataset is a distinct security (e.g., Uber Series E), and we assign a unique security ID to each observation of this dataset ("security ID master file"). Typically, the purchase price per share is different across rounds (e.g., Series E's purchase price is different from Series D, which is also different from Series C, etc.). This becomes crucial in our ability to assign a specific round to a security, as described below in point 5.
3. We merge the CRSP holding data with the SEC filing data, by fund name, company name, and reporting date. When a fund holds multiple Series from the same company at the same time, we further match by Series name (if available in both CRSP and SEC), number of shares and its value. We also manually check the quality of the merged sample and reconcile the two databases to the extent possible. One thing to notice is that this match is not always one-to-one. For instance, CRSP reports an aggregate position of "Uber", while SEC filing indicates that the fund actually holds multiple securities of Uber the company including Series D and Series E convertible preferred stock. When the number of shares and value of those individual Series (e.g., "Uber Series D" and "Uber Series E") sum up to the aggregate amount in CRSP (e.g., "Uber"), we replace CRSP data with the Series-specific information from SEC filings.
4. Next, we analyze the security name and extract information about the Series name in the CRSP-SEC merged sample. If the CRSP mutual fund holding data or SEC filing clearly identifies the Series name (e.g., "Uber Series F Preferred" and "Uber P/P Ser F"), then we assign this investment a security ID uniquely associated with that company *and* that round.

5. For remaining security holdings that do not clearly identify the Series name (e.g., it is listed simply as "Uber"), we rely on the acquisition date and acquisition cost from the SEC filings. Specifically, we match the SEC filing data and the security ID master file (described above in point #2). If the acquisition cost per share matches the per share purchase price of a particular funding round, and the acquisition date approximately matches the round investment date (in the same quarter), then we assign this investment a security ID uniquely associated with that company and that round.
6. Finally, we adjust the number of shares and per share purchase price for stock splits. We obtain the dates and split ratios from COIs, S-1 filings, and press.

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