The Composition of Limited Partners in Private Equity Funds

by

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Abstract

This dissertation contributes to our understanding of the role of Limited Partner (LP) composition in private equity and venture capital fund performance. It consists of two essays.

In the first essay, I establish causal evidence for the contribution of LPs within a private equity fund to fund performance. The evidence reconciles the performance persistence puzzle in private equity with the persistence in LP composition across funds. An unexpected increase in the number of LPs due to the JOBS act serves as a natural experiment. A fuzzy regression discontinuity design relies on the GP's imprecise control over a fund's final close date relative to the JOBS act's effective date. Fewer and more liquid LPs exhibit positive effects on fund performance. The liquidity of LPs influences GP's effort and choice of portfolio companies.

In the second essay, I document a causal channel between LP composition persistence and GP performance. The paper documents significant persistence in the number, liquidity, and identities of LPs across GP-sponsored funds. Using LP stake transfers as a source of exogenous disruption in the persistence of LPs at the GP level, the paper estimates an annual decline in GP performance of 1.7% for buyout funds relative to 2.6% for venture capital funds. The results point to an important role for synergy among LPs for GP performance persistence, particularly among venture capital funds. This finding reconciles the decrease in GP performance persistence with the boom of the secondary market.

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Contents

Chapter 1

The Composition of Limited Partners in Private Equity Funds

1.1. Introduction

A long-standing puzzle in private equity is the "performance persistence puzzle": General Partners (GPs)[1] exhibit return persistence (Kaplan and Schoar (2005), Robinson and Sensoy (2016), Phalippou (2010)), although competition should eliminate differences in net-of-fees returns. One strand of the literature attributes the puzzle to heterogeneity in GP skills, albeit at odds with the lack of variation in GP compensation schemes (Gompers and Lerner (1999)). Another strand of the literature attributes the puzzle to heterogeneity in Limited Partner (LP) liquidity in addition to GP skills; skilled GPs are willing to pay higher premiums for liquid LPs (Lerner and Schoar (2004), Maurin et al. (2020)). In contrast, this paper provides evidence that persistence in the composition of LPs can alone explain the performance persistence puzzle in private equity. LPs in Private Equity (PE) have heterogeneous objectives, can negotiate different contracts with the GP to subscribe to the same fund (Begenau and Siriwardane (2020)), and are integral to the survival of the GP in the market. The composition of LPs can thus influence GP effort and choice of portfolio companies. This paper establishes first causal evidence that the composition of LPs in a private equity fund affects fund performance.

The paper overcomes the data and measurement challenges inherent in studying the effect of the composition of LPs in a private equity fund on fund performance. The first challenge is the lack of comprehensive data on the entire set of LPs that subscribe to a PE fund.[2] To overcome this challenge, the paper relies on a requirement under the 2010 Dodd-Frank Act for GPs to disclose the number of investors that subscribe to each private fund on SEC Form-ADV. The second challenge is measuring the liquidity of LPs within a PE fund without relying on their individual or aggregate commitments. To overcome this challenge, the paper uses the ratio of number of LPs to fund size, inversely related to the overall liquidity of LPs in a PE fund. The measure is based on anecdotal evidence suggesting that liquid LPs have institutional minimums, an amount below which the LP will not invest with the GP. The focus on the liquidity of LPs is consistent with the theoretical literature (Lerner and Schoar (2004) and Maurin et al. (2020)).

Endogenous GP-LP matching confounds establishing a credible causal link between LPs and fund performance. The paper overcomes this identification challenge using two sources of variation. First, variation in the number of LPs due to the Jumpstart Our Business Startups

[1] General Partners (GPs) are the fund managers and Limited Partners (LPs) are the investors in private equity funds.

[2] None of the data sources used in the literature to date (Preqin, CIQ, Venture Economics, Venture One) contain the complete list of LPs within a PE fund.

(JOBS) act. Second, variation in treatment eligibility due to GP's imprecise control over a fund's final close date relative to the 2012 JOBS act effective date. It is implausible that the GP can control the market forces that govern the number and timing of several fundraising rounds (closings) that precede the final close over 1.5-2 years. The critical implication of this institutional feature is that the eligibility of funds for treatment is effectively random near the 2012 JOBS act effective date. Random treatment eligibility is used as an instrumental variable for treatment to address the endogenous take-up of the number or liquidity of LPs (treatment) among eligible funds. It is precisely these two sources of random variation near the 2012 JOBS act effective date that allow this paper to establish a causal link between LPs and fund performance.

The paper's main finding is that the liquidity of LPs within a private equity fund is a positive and significant driver of fund performance. The liquidity of fund LPs is measured as the ratio (in percent) of the number of LPs to fund size; one additional LP per $100mn corresponds to a unit decrease in the liquidity of LPs. Results show that the number of LPs negatively affects fund performance, whereas the liquidity of LPs positively affects fund performance. Moreover, the response of fund performance to a unit change in the liquidity of fund LPs is more significant relative to a unit change in the number of fund LPs. A one-unit increase in the liquidity of LPs contributes to a 15% increase in fund performance outcomes over the fund's life. In contrast, a one-unit decrease in the number of LPs contributes to a 0.6% increase in fund performance outcomes over the fund's life. The estimated effects are relative to control funds that held a final close before the 2012 JOBS act effective date. The evidence is consistent with an important role for the composition of LPs in the trajectory of private equity fund performance.

The liquidity of LPs within a private equity fund affects fund performance through GP effort (certification) and GP choice of portfolio companies (catering). Under the *Certification* channel, liquid LPs secure capital for GP future funds and certify the GP's quality to new LPs. GPs thus exert greater effort to source deals and create value for funds with more liquid LPs. The mechanism is consistent with the theoretical literature showing that GPs work above and beyond fees to secure future funding, especially for buyout funds (Chung et al. (2012)). Under the *Catering* channel, GPs cater to the objectives and risk-capacity of underlying fund LPs. GPs thus select riskier deals for funds with more liquid LPs, catering to their risk capacity. The mechanism is consistent with recent evidence suggesting that LPs negotiate different contractual terms with the GP to subscribe to the same private equity fund (Begenau and Siriwardane (2020)). Overall, the findings from the mechanism tests support the proposition that the liquidity of LPs is integral to GP's effort and deal selection.

Identifying the contribution of LPs to fund performance relies on quasi-experimental variation in the composition of LPs in the private equity market due to the JOBS act. On April 5, 2012, the U.S. amended the threshold triggering registration for §3(c)7 funds from 500 to 2,000-investors. The reform affected 65% of all U.S. funds and 70% of all private equity funds that rely on §3(c)7 exemption under the Investment Company Act of 1940.[3] The reform especially eases fundraising constraints for large buyout funds with higher size targets in two important ways.[4] First, the eligibility of the vast majority of U.S. funds for a higher investor cap encourages the entry of new investors into the market. Consistent with this implication, the paper provides evidence that aggregate buyout fundraising rebounds from a low of $36bn in 2011 to $47bn and $101bn in 2012 and 2013, respectively.[5] Second, the reform incentivizes GPs to raise smaller amounts of capital from smaller high-net-worth investors. The threshold increase effectively quadruples the lower bound on the amount of additional capital a GP can raise from smaller high-net-worth investors from 3% ($22mn) to 12% ($97mn) of average buyout fund size.[6,7] Consistent with this implication, the paper finds that the liquidity of LPs in PE funds decreases in response to the 2012 JOBS act.

A regression discontinuity design (RDD) isolates random variation in treatment eligibility due to GP's imprecise control over a fund's final close date relative to the act's effective date. The fundraising process for a private equity fund is a long 1.5-2 years, with several closings that precede the final close. It is implausible that the GP can control the market forces that govern the number and timing of interim closings that precede the final close. The critical consequence of this institutional feature is that eligibility for treatment is effectively random near the 2012 JOBS act effective date. To overcome the possibility of self-selection among funds who take up treatment, an indicator variable for holding a final close on or after the JOBS act effective date (treatment eligibility) is used as an instrumental variable

[3]The §3(c)7 exemption requires a specific investor type. Individuals with a net worth of $5 million or institutions with at least $25 million in private capital ('qualified purchasers').

[4]Regulatory Compliance Watch (PEI): https://www.regcompliancewatch.com/jobs-act-likely-to-benefit-buyouts-biz-2/

[5]The 2012 sharp rebound in buyout fundraising and entry of new LPs to the asset class has been documented in the news: PEI (https://www.buyoutsinsider.com/mega-firms-power-strongest-fundraising-year-since-crisis/), Pitchbook (https://pitchbook.com/newsletter/buyout-fundraising-boost), Capital Dynamics (https://www.capdyn.com/news/fy-2012-summary-private-equity-review-and-outlook/).

[6]High-net-worth investors typically contribute $50,000 to $250,000. The calculation is based on the lower bound of $50,000 for a high-net-worth investor. The average number of LPs in a §3(c)7 buyout fund before the reform was about 65 LPs and the average fund size was $840mn. The lower bound thus increases from $21.75mn (435 LPs × $50,000) or about 3% of average buyout fund size to $96.75mn (1,935 LPs × $50,000) or about 12% of average buyout fund size.

[7]Major GPs in the buyout asset class increased their commitments from high-net-worth investors (e.g., Blackstone by 3.7× from 2011 to 2014 and Carlyle by 2.7× from 2012 to 2020).

for the number and liquidity of LPs in PE funds (treatment). This approach isolates a causal effect because it effectively compares buyout funds based on randomly assigned treatment eligibility rather than actual (endogenous) treatment take-up. The instrumental variable setup leads to a fuzzy regression discontinuity design (RDD) around the 2012 JOBS act effective date.[8] An additional advantage of this design is that treatment and control funds have access to the same funding opportunities (deals) and are managed by the same GP cohort. This advantage lends credibility to the identifying assumption that treatment and control funds would exhibit similar performance absent the reform.

In support of the validity of the RDD design, the paper implements a battery of identification checks against endogenous sorting, GP anticipatory effects, and interference with respect to fund performance. First, the McCrary density test provides no evidence for bunching around the 2012 JOBS act effective date. The finding is consistent with GP's imprecise control over a fund's final close date relative to the act's effective date. Second, balance tests on minimum commitment, target fund size, and GP ability are consistent with no GP anticipatory effects. GPs could not strategically respond through a decrease in minimum commitment or an increase in target fund size in an attempt to capture more LPs. The more important evidence points to balance on GP ability, albeit through a proxy measure defined as the top 100 GPs by capital raised in 2006-2010. Third, the paper relies on Fisherian randomization inference to show that the identified effect on fund performance is robust to the possibility of interference between treatment and control funds. Overall, the findings from these tests lend credibility to the identification assumptions behind the design.

1.1.1. Literature Review

The private equity literature has been predominantly concerned with the relationship between GPs and their portfolio companies. Within this GP-portfolio company relationship, GPs act as the investor entity. In contrast, this paper investigates the relationship between the LPs within a private equity fund and the GP. Within this LP-GP relationship, LPs act as the investor entity. The investment decision is sequential, LPs invest capital with the GP and the GP invests this capital in portfolio companies. An important distinction is that this paper is not concerned with GPs as investors in portfolio companies but rather with LPs as investors in funds raised by the GP. LPs and GPs are two distinct investor entities in their function, characteristics, and incentives. LPs are the source of the capital, whereas GPs are

[8] The running variable is the final close date for a private equity fund and the cutoff is the JOBS act effective date. GPs who happen to close PE funds on or right after the JOBS act effective date are in a market of a larger number of LPs (treatment) relative to right before (control) due to the 2012 JOBS act reform.

merely deploying capital on behalf of the LPs. LPs are integral to the GP's survival and ability to fund the portfolio companies. LP characteristics thus have an important bearing on GP decisions. The key contribution of this paper to the literature is attributing GP investment choices and performance to LP characteristics.

While the active and value-adding role of the GP in portfolio company performance is well-established, the process determining GP choice of and value-creation efforts for portfolio companies constitutes a significant gap. GPs are actively involved in the management of their portfolio companies. Sahlman (1990), Gorman and Sahlman (1989), Sapienza (1992), Sapienza and Gupta (1994), and Lerner (1995) show that GPs exert significant effort and time on value-adding activities that shape the growth trajectory of their portfolio companies.[9] An active strand of this literature examines whether GP value-adding activities result in better company performance. Bottazzi et al. (2008) and Puri and Zarutskie (2012) find that these value-adding activities lead to fewer failures and more successful exits. Hellmann and Puri (2002) find that GP-backed companies exhibit professionalization patterns that improve performance. An important gap within this strand of the literature is the factors that influence GP choice of portfolio companies and the specific value-creation efforts for each portfolio company. Sørensen (2008) shows that GPs draw on their experience as well as the option value of future learning. This paper shows that the liquidity of LPs within a fund influences GP choice of portfolio companies and value-creation efforts.

A long-standing challenge in the existing literature is attributing causal effects to GP characteristics, albeit LP characteristics are more pertinent when LPs ultimately shape GP investment decisions. The literature has so far pointed to four key GP characteristics that correlate with performance: GP Reputation (Hsu (2004), Nahata (2008), Tian et al. (2011), Atanasov et al. (2012), Cumming et al. (2009)), GP Experience (Bottazzi et al. (2008), Zarutskie (2010), Dimov and Shepherd (2005)), GP Specialization (Gompers et al. (2009)), and GP Network (Lindsey (2008), Gompers and Xuan (2009), Sunesson (2009), Hochberg et al. (2007)). Despite some strides (Sørensen (2007), Fitza et al. (2009), Baum and Silverman (2004)), attributing causal effects to these GP characteristics is difficult due to the endogenous matching between GPs and portfolio companies. When LP characteristics ultimately shape GP investment decisions, attributing causal effects to the LPs becomes first order. A similar challenge arises in attributing causal effects to LP characteristics, the endogenous matching between LPs and the GP. The paper overcomes this challenge by relying on quasi-experimental variation in the number of LPs within a private equity fund due to

[9] These activities range from fundraising and recruitment to mentoring founders, providing strategic advice, and serving as board members for the portfolio company.

the 2012 JOBS act. In overcoming this challenge, this paper is the first to attribute a causal effect to investors in the private equity market.

The finding that fund size and aggregate fundraising are the most pertinent fund characteristics to fund performance could be driven by the source rather than the amount of capital. Kaplan and Schoar (2005), Phalippou and Gottschalg (2009), Robinson and Sensoy (2016), Gompers and Lerner (2000), Harris et al. (2014), Kaplan and Stromberg (2009) investigate whether fund size, fund sequence number, and aggregate fundraising correlate with fund-level returns. Overall, the evidence suggests that fund-level returns have a concave relationship with fund size, a weak relationship with fund sequence number, and a cyclical relationship with aggregate fundraising. Driessen et al. (2012) show that fund-level beta, not alpha, increases with fund size. The findings in this paper suggest that the correlation of fund-level returns with fund size and aggregate fundraising could be driven by the characteristics of the investors contributing the capital.

A rich strand of the literature documents a performance persistence puzzle in private equity with no consensus over an explanation. Robinson and Sensoy (2016), Kaplan and Schoar (2005), Phalippou (2010), and Harris et al. (2020) investigate GP-level persistence. Lerner et al. (2007), Dyck and Pomorski (2016), and Cavagnaro et al. (2019) investigate LP-level persistence. Overall, the findings are consistent with some return persistence at the GP-level and at the LP-level. The persistence in GP returns is considered a puzzle given that variation in net-of-fees returns should be eliminated through competition.[10] One explanation put forth by the literature is the heterogeneity in GP skills, albeit at odds with the lack of variation in GP compensation schemes (Gompers and Lerner (1999), Hochberg et al. (2014), Marquez et al. (2010), Glode and Green (2011)). Another explanation is that skilled GPs screen for liquid LPs that are better able to withstand liquidity shocks (Lerner and Schoar (2004), Maurin et al. (2020)).

The causal link between LPs and fund performance established in this paper offers an alternative explanation for the performance persistence puzzle, the persistence in the composition of LPs across funds. Given that GPs predominantly rely on incumbent LPs to raise capital for new funds, there is a high degree of persistence in the composition of LPs across funds. The persistence in the composition of LPs at the GP-level and at the LP-level can thus explain the performance persistence puzzle in private equity. LPs contribute to fund performance through two channels: *Certification* and *Catering*. Liquid LPs prompt greater GP effort to secure future funding (certification) and influence GP choice of portfolio

[10]Such persistence is absent from other asset classes such as mutual funds (Chevalier and Ellison (1997)).

companies (catering). In support of the *Catering* view, Begenau and Siriwardane (2020) find evidence consistent with different contractual terms for LPs that subscribe to the same private equity fund. In support of the *Certification* view, Chung et al. (2012) theoretically show that GPs work above and beyond fees to secure future funding and that fundraising incentives are stronger than fee incentives for buyout funds.

The paper is organized as follows. Section 1.2 describes the institutional details that govern the composition of limited partners in private equity funds. Section 1.3 discusses the measurement of LP liquidity and the data used in the estimation. Section 1.4 explains the strategy used to identify the contribution of LPs to PE fund performance. Section 1.5 estimates the effect of the number and liquidity of LPs on fund performance outcomes and reports a battery of identification checks. Section 1.6 tests potential mechanisms for the causal effect of LPs on fund performance. Section 1.7 concludes and discusses the implications of the findings.

1.2. Institutional Setting: LPs in Private Equity Funds

The typical lifecycle of a PE fund spans 10-12 years and undergoes four overlapping stages: fundraising, deal selection (investment), value-creation and deal exit (harvesting), and liquidation. GPs raise capital for the fund, select and manage portfolio companies (deals), and choose when to invest or exit these deals. LPs contribute capital to the fund and serve on an advisory board. GPs may also contribute a small percentage (1-5%) of the fund's initial capital to signal vested interest to LPs. Throughout the fund's life, GP calls committed capital from LPs on a deal-by-deal basis (capital calls) and distributes the proceeds back to the LPs upon deal exit (distributions). In addition to an annual management fee, LPs compensate the GP with a fraction of the fund's profit (carried interest). While all LPs sign the same Limited Partner Agreement (LPA) for a fund, each LP can separately negotiate and amend the terms of the LPA with a 'side letter'. LP-level returns within the same PE fund may differ depending on their negotiated terms (Begenau and Siriwardane (2020)).

Determinants of LP Composition in Private Equity Funds

Several institutional features govern the composition of LPs in PE funds. The first feature is that LPs join a PE fund in several fundraising rounds (closings). Each closing turns LP promises to pay into formal contractual commitments.[11] The first (initial) close occurs upon the launch of the fund after initial LP commitments are made. Over a period of six months

[11] Closings are thus necessary for the GP to start calling committed capital from the LPs to invest in portfolio companies.

to two years, subsequent closings occur when additional LPs join the fund and commit capital. The fundraising process ends with a final close when the fund achieves its target size. New LPs may informally or through the GP learn about existing LPs and base their investment decision on the identities of existing LPs.[12] The second feature is that GPs offer LPs the option to invest in a follow-on fund shortly after subscription. This feature entails that LPs decide whether to subscribe to a follow-on fund before returns on the existing fund are realized. The third feature is that LPs can subscribe to a fund directly or through a feeder fund. LPs who subscribe indirectly through a feeder fund are typically liquidity-constrained investors (e.g., high-net-worth individuals) relative to LPs who subscribe directly (e.g., sovereign wealth funds). In particular, the structure allows feeder LPs to subscribe with a lower minimum capital commitment relative to direct fund LPs. A feeder fund is typically managed by the GP or a third party and contractually acts as one LP for the PE fund.

Throughout the fund's life, LP transfers or defaults can change the composition of LPs in PE funds. Over 4-6 years from the initial closing, the GP calls the committed capital from LPs on a deal-by-deal basis. Defaults occur when the LP is unable to meet the capital call. LP defaults carry a significant reputation risk that can undermine LP's ability to subscribe to future PE funds. Therefore, it is typical that an LP will default only due to idiosyncratic factors such as dire liquidity constraints or over-allocation[13] rather than fund performance concerns. In response to an LP default, the GP can: (1) forfeit the defaulting LP's commitment to the fund reducing total fund capital and management fees, (2) reallocate the defaulting LP's interest to an existing LP or a third party (most common), or (3) acquire bridge financing to cover the capital call. Another factor that can change the composition of LPs during the fund's life is the transfer of LP interests on the secondary market.[14] Depending on the transfer clauses for a PE fund, LPs may be able to transfer their commitments to other LPs on the secondary market. In practice, the GP may preempt an LP default by facilitating a transfer to mitigate the reputational damage for the LP or delay calling capital when several fund LPs are constrained.

[12] After the fundraising process is complete, the GP appoints an LP Advisory Committee which consists of major institutional LPs from the pool of investors. The committee is put together to address conflict of interest transactions such as investment in portfolio companies of affiliated funds, waivers of restrictions such as investment period or partnership term extensions, and oversight issues such as approving valuations and default/litigation reports.

[13] This situation typically occurs when public equity valuations drop significantly below PE fund valuations, leaving investors over-allocated to private equity.

[14] GPs typically impose stringent limitations on the transferability of partnership interests to screen for deep-pocketed investors (Lerner and Schoar (2004)). Nonetheless, the PE secondary market has recorded significant growth in the past few years.

1.3. Measuring Liquidity of LPs and Data Description

This section discusses the measurement of the overall liquidity of LPs within a private equity fund and describes the data used in the empirical analysis. Section 1.3.1 develops a fund-level measure of the liquidity of LPs. Section 1.3.2 describes the data sources. Section 1.3.3 discusses sample construction and representativeness. Section 1.3.4 reports the descriptive statistics.

1.3.1. Measuring the Liquidity of LPs in Private Equity Funds

The paper measures the overall liquidity of LPs that subscribe to a private equity fund. The liquidity of fund LPs is important for two reasons. First, the liquidity of LPs is integral to GP's survival in the private equity market. Liquid LPs have the capacity to re-up for follow-on funds, prompting the GP to exert greater effort. Second, the liquidity of LPs influences the riskiness of fund deals. Liquid LPs have a higher risk capacity that allows the GP to select riskier deals. The focus on the liquidity of LPs is also consistent with the theoretical literature (Lerner and Schoar (2004), Maurin et al. (2020)).

LPs-to-Fund Size Measure is Inversely Related to the Liquidity of LPs

To measure the overall liquidity of LPs in a private equity fund, the paper uses the ratio of the number of LPs to fund size. In private equity, the liquidity of an LP determines its contribution to overall fund capital. Liquid institutional LPs (e.g., endowments, sovereign wealth funds) manage substantial private capital and invest significant due diligence efforts on the GP. Therefore, liquid LPs typically require a large allocation of fund capital (commitment) to consider an investment with a GP. Anecdotal evidence suggests that liquid LPs even have institutional minimums, a fund commitment amount below which an LP will not invest with the GP. The measure captures the institutional feature that more liquid LPs contribute a larger share of fund capital.

$$Liquidity of LPs = \frac{Number of LPs}{Fund Size}$$

It is important to note that the LPs-to-fund size measure is inversely related to the overall liquidity of LPs that subscribe to private equity fund. Fewer LPs for the same fund size (i.e., lower LPs-to-fund size ratio) indicate that fund LPs' overall liquidity is high. To illustrate this concept through an example, consider two funds with \$50mn in capital. Fund 'L' has 50 LPs, whereas Fund 'I' has 100 LPs. Fund 'L' has more liquid LPs than Fund 'I' because half the number of LPs contribute the full \$50mn. Using the ratio of LPs to fund size measure, Fund 'L' has a ratio of 1 (50 LPs/\$50mn) while Fund 'I' has a ratio of 2 (100 LPs/\$50mn).

Fund ‘L’ has a lower ratio and thus higher overall liquidity. Therefore, private equity funds with a low LPs-to-fund size ratio have LPs with higher overall liquidity.

1.3.2. Data Sources

A. Number of LPs from SEC Form-ADV

The challenge with studying the effect of LP composition is the lack of comprehensive data on all LP commitments to a PE fund for confidentiality reasons. The main concern is potential selection on the subset of disclosed LPs within a PE fund. In particular, none of the data sources on LP commitments used in the literature to date (Preqin, CIQ, Venture Economics, Venture One) contain the complete list of LPs within a PE fund. This paper overcomes this challenge by relying on a requirement under the 2010 Dodd-Frank Act[15] for GPs to disclose private fund information on SEC Form-ADV. The requirement to disclose private fund information on SEC Form-ADV was adopted on July 20, 2011 with an effective date of March 30, 2012.

The SEC dataset contains information on private funds that goes back to 2000-2002.[16] The form contains information about the GP’s business, ownership, clients, employees, affiliations, and any disciplinary events of the adviser or its employees. Section 7.B.(1) of Schedule D has detailed information about private funds advised by each advisory firm. GPs must indicate the type of private fund that it advises (e.g., hedge fund, private equity fund), the adviser’s services to the fund, and general information about the size and investors of the fund. GPs are required to report the number but not the identities of fund investors. The regulatory scrutiny over GP-reported information on the form ensures that the data is accurate. The paper uses the information on fund investors reported on Form-ADV to study the effect of two compositional forces, the number and liquidity of LPs in PE funds.

The paper uses the number of LPs within a PE fund as reported by the GP in question 13 of Section 7.B.(1). The reported number includes all investors that subscribe to the PE fund, either directly or through a feeder fund. Note that a ‘feeder fund’ is considered a distinct structure from ‘fund of funds’ for reporting purposes on Form-ADV. An entity that invests 100% of its assets in the master fund is considered a ‘feeder fund’, whereas an entity that invests 10% or more of its assets in other funds is considered a ‘fund of funds’. A fund-of-funds LP will thus count as one investor on Form ADV. The number on Form-ADV

[15]The 2010 Dodd-Frank act enforced narrower exemptions for private advisers. As a result, many previously unregistered and exempted advisers to private funds were required to file Form-ADV.

[16]The typical lifespan of a PE fund is 10 years and, therefore, funds active as of 2012 were launched by the GP in 2000-2002.

captures all direct investors and all investors that subscribe via a feeder fund, the complete set of investors that committed capital to each private equity fund.

The inclusion of LPs in the feeder fund is of particular importance to measuring the liquidity of LPs in a PE fund. To illustrate this through an example, consider two funds of equal size with $500mn in committed capital. Fund A has 10 direct LPs, whereas Fund B has 9 direct LPs and 1 feeder LP consisting of 50 indirect LPs. Since 10 LPs in Fund A contribute the full $500mn relative to 59 LPs in Fund B, Fund A has more liquid LPs than Fund B. If one were to observe only the direct LPs, one would falsely conclude that Fund B has more liquid investors relative to Fund A. If one were to count all indirect LPs within the feeder as one LP, one would falsely conclude that the liquidity of investors in Fund A and Fund B are comparable. It is only when the number of LPs encompasses both direct and indirect (feeder) LPs that one can correctly conclude that Fund A has more liquid LPs relative to Fund B.

B. Private Equity Fund Performance from Preqin

The paper uses performance data from Preqin. Harris et al. (2014) compares Preqin with three other sources of performance data (Burgiss, Cambridge Associates, and Venture Economics) and concludes that the dataset is unbiased, mitigating concerns about performance selection bias. Survivorship bias concerns are partially mitigated because Preqin maintains at least four sources for each fund and sources its data from both LPs and GPs. The analysis uses three metrics for fund performance – Net Internal Rate of Return (IRR), Total Value to Paid-in-Capital (TVPI) multiple, and Public Market Equivalent (PME). The three metrics constitute the most common return measures used in the private equity performance literature (Harris et al. (2014), Kaplan and Schoar (2005), Phalippou and Gottschalg (2009), Ljungqvist and Richardson (2003), Robinson and Sensoy (2016)).

The paper computes PME based on Kaplan and Schoar (2005) methodology using S&P 500 total return index as the benchmark and uses IRR and TVPI as reported by Preqin. Net IRR is a time-weighted return that accounts for distributions, contributed capital, management fees, and unrealized investments. TVPI estimates the number of times investors are likely to profit from their investment.[17] PME benchmarks the performance of the PE fund against a public index while accounting for fund cash flow timing. All fund performance metrics are measured at the same fund age in years from the first drawdown year, ensuring comparable performance across different metrics.

[17]Total value (numerator) is the sum of the distributions to investors and estimated remaining value on the fund investments. Paid-in-capital (denominator) is the amount of capital committed by LPs.

Table I. Variables Description and Sources

The table describes the variables used in the empirical analysis and their respective sources. Panel A relates to the composition of LPs in PE funds. Panel B relates to fund performance outcomes. Panel C relates to GP characteristics. GP characteristics are measured as of 2010 to capture the ability and age of the GP at the time of fundraising launch. Panel D relates to fund characteristics.

Variable Name	Variable Description	Source
Panel A: Composition of LPs in PE Funds		
Number of LPs	The number of LPs that committed capital to a PE fund	SEC
Liquidity of LPs	The ratio (in percent) of number of LPs to actual PE fund size, a lower ratio is consistent with higher liquidity of LPs	SEC & Preqin
Panel B: PE Fund Performance Outcomes		
Public Market Equivalent	PME benchmarks PE fund performance against S&P 500 index	Preqin
Net Internal Rate of Return	IRR is a time-weighted return that accounts for distributions, committed capital, management fees, and unrealized investments	Preqin
Total Value to Paid-in-Capital	TVPI is the ratio of distributions and estimated remaining fund value to total committed capital	Preqin
Panel C: GP Characteristics in 2010		
GP Ability Proxy	An indicator variable for the top 100 GPs by capital raised for the buyout asset class in 2006-2010	Preqin
GP Age	The age of the GP in years measured as of 2010	Preqin
Panel D: Fund Characteristics		
Actual Fund Size	The actual amount (in millions of U.S. dollars) of committed capital to a PE fund after fundraising is complete	Preqin
Target Fund Size	The target amount (in millions of U.S. dollars) of capital for a PE fund before fundraising	Preqin
Minimum Commitment	The minimum fund commitment amount (in millions of U.S. dollars) required from an LP	SEC
Fund Final Close Date	The date of the final fundraising (closing) round of a PE fund	Preqin
Number of Fund Deals	The number of PE fund investments in portfolio companies	Preqin
Mean Fund Deal Size	The average size of a fund's investment in a portfolio company	Preqin

1.3.3. Sample Construction: U.S. Buyout Funds With North American Focus

The focus of the analysis is U.S.-based buyout funds with a North American geographic focus. The study is restricted to buyout funds for two reasons. First, the focus on buyout funds ensures a representative sample of funds. Preqin sources most of its performance data through FOIA requests. These requests apply only to the subset of funds where a public pension fund is an investor. Public pension funds are active investors in the class of buyout funds, as these funds allow for larger investments relative to VC funds. Second, the 2012 JOBS act reform was binding for most private equity funds due to their reliance on §3(c)7 for exemption under the Investment Company Act of 1940. In contrast, venture capital funds predominantly rely on §3(c)1 for exemption. The focus on U.S.-based funds is because the 2012 JOBS act reform was specific to the U.S. market. The focus on funds with a North American geographic focus ensures that all funds in the sample have comparable performance. In particular, North American funds are on a different performance trajectory relative to funds with other geographic focus.

The analysis uses the Preqin-SEC merged sample based on the name of the buyout fund and sponsoring GP. The sample excludes funds without a final close date. Table II gauges representativeness based on the full sample. There are 1,190 U.S.-based buyout funds with a North American geographic focus that held a final close between 2005 and 2016. Of these, roughly 83% (990 funds) have LP composition data available in SEC and 46% (457 funds) have performance data available in Preqin. The subset of funds with LP composition and performance data is 428 buyout funds with a first drawdown year (vintage) between 2004 and 2017. This subsample of 428 funds represents about 77% of aggregate commitments based on the full sample of 1,190 funds, suggesting that the sample is tilted towards larger buyout funds. The RD design uses observations closest to the cutoff; the largest MSE-optimal bandwidth uses two years around the JOBS act effective date. There are 442 U.S.-based buyout funds within this window with a North American geographic focus that held a final close between 2010 and 2014. Of these, roughly 88% (390 funds) have LP composition data available in SEC and 41% (182 funds) have performance data available in Preqin. The subset of funds with LP composition and performance data is 173 buyout funds with a first drawdown year (vintage) between 2008 and 2016, representing about 78% of aggregate commitments. Roughly 90% (152 funds) of these funds are §3(c)7 funds, subject to the 2012 JOBS act threshold increase.

Table II. Sample Representativeness

The table shows the representativeness of the sample of funds used in the empirical analysis relative to the full sample. The first line shows the mean fund size and the second line shows the standard deviation of fund size in parentheses. Aggregate capital and fund size are in millions of U.S. dollars. Panel A reports statistics for funds closed between 2005 and 2016. Panel B reports statistics for the funds closed between 2010 and 2014, within a two-year bandwidth of the 2012 JOBS act. Columns (2) and (3) report the percentage of the number of funds and aggregate capital relative to the full sample in Column (1). §3(c)7 funds are subject to the 2012 JOBS act threshold increase. The sample consists of buyout funds located in the U.S. with a North American geographic focus.

	(1)	(2)		(3)	
	All U.S.-Based	Funds with Performance and LP Composition Data			
	Buyout Funds	All Funds		3(c)7 Funds	
Panel A: Funds Closed in 2005 - 2016					
Fund Size	978.6	1,926.5		2,114.4	
	(2,212.7)	(3,188.4)		(3,334.7)	
Number of Funds	1,190	428	36%	374	31%
Aggregate Capital	1,064,717	818,773	77%	784,428	74%
Panel B: Funds Closed in 2010 - 2014					
Fund Size	829.7	1,502.10		1,655.3	
	(1,803.7)	(2,482.3)		(2,604.8)	
Number of Funds	442	173	39%	152	34%
Aggregate Capital	331,890	258,366	78%	249,951	75%

1.3.4. Descriptive Statistics at the Fund-Age Level: 2010 - 2014

The analysis is based on a panel of annual performance and LP composition observations at the fund-age level for funds closed in 2010-2014. Table III reports the descriptive statistics for the variables used in the estimation. The sample consists of §3(c)7 U.S. buyout funds with a North American geographic focus closed between 2010 and 2014, with a first drawdown year (vintage) between 2008 and 2016. The average difference between close year and drawdown year is zero and the maximum is 2 years. Interim fund performance is observed for years 1-10 for PME and TVPI and years 3-10 for IRR.[18] The average final close year for funds in the sample is 2012, the year of the reform. The sample's average number of LPs in a buyout fund is 89 LPs with a median of 63 LPs. The average liquidity of LPs ratio is 10 LPs per $100mn fund size with a median of 7 LPs per $100mn fund size. The average minimum commitment

[18]Preqin does not compute IRR for the first three years of a PE fund's lifecycle.

per LP is $6mn with a median of $5mn. The average fund size before fundraising (target) is $1,448mn, whereas the average fund size after fundraising (actual) is $1,655mn. About 30% of the funds in the sample are raised by high-ability GPs, measured as the top 100 GPs by capital raised in the buyout asset class in 2006-2010. The average age of the GP in the sample is 15 years, measured as of 2010. In terms of fund performance, the average PME, Net IRR, and TVPI are 1, 17%, and 1.4, respectively.

Table III. Descriptive Statistics

The table provides the descriptive statistics for the variables used in the empirical analysis. Panel A relates to the composition of LPs in PE funds. Panel B relates to fund performance outcomes. Panel C relates to GP characteristics. GP characteristics are measured as of 2010 to capture the ability and age of the GP at the time of fundraising launch. Panel D relates to fund characteristics. The statistics are computed based on a sample of funds closed in 2010 - 2014, within two years of the 2012 JOBS act reform effective date. The unit of observation is fund-age, where fund age is measured in years from the first drawdown year. The sample consists of §3(c)7 buyout funds located in the U.S. with a North American geographic focus.

	(1)	(2)	(3)	(4)	(5)	(6)
					Percentiles	
	N	Mean	SD	p10	p50	p90
Panel A: Composition of LPs in PE Funds						
Number of LPs	1,520	88.6	95.8	25.0	62.5	165.0
Liquidity of LPs	1,510	9.7	10.1	3.0	6.7	18.0
Panel B: PE Fund Performance Outcomes						
Public Market Equivalent (PME)	1,098	1.0	0.3	0.7	1.0	1.3
Net Internal Rate of Return (IRR)	719	16.9	11.8	6.1	15.4	31.7
Total Value to Paid-in-Capital (TVPI)	1,039	1.4	0.5	1.0	1.3	2.0
Panel C: GP Characteristics in 2010						
GP Ability Proxy	1,520	0.3	0.5	0.0	0.0	1.0
GP Age	1,520	14.7	12.7	2.0	12.0	27.0
Panel D: Fund Characteristics						
Actual Fund Size ($, mn)	1,510	1,655.3	2,597.0	288.0	735.0	3,750.0
Target Fund Size ($, mn)	1,490	1,448.1	2,113.8	275.0	700.0	3,750.0
Minimum Commitment ($, mn)	1,520	5.9	6.1	0.0	5.0	10.0
Fund Close Year	1,520	2012	1.5	2010	2013	2014
Number of Fund Deals	1,490	26.4	20.7	8.0	22.0	52.0
Fund Deals (% of Fund Size)	1,480	3.3	3.5	0.7	2.2	7.1
Mean Deal Size (% of Fund Size)	1,190	37.5	95.4	6.2	19.9	55.8

1.4. Identification: JOBS Act as a Natural Experiment

The primary challenge in identifying the effect of LP composition on PE fund performance is the endogenous matching between GPs and LPs. That is, it is difficult to disentangle the contribution of LPs from GP ability. A comparison of performance for funds with different number or liquidity of LPs would yield biased estimates given that the number and liquidity of LPs in a PE fund is likely correlated with unobserved GP ability. The ideal experiment would be to randomize new funds at the time of first close (launch) into treated and control groups.[19] Unlike control funds, treated funds are exposed to the entry of new LPs and are eligible to increase the number of LPs through a higher investor cap. To overcome the possibility of self-selection among treated funds, randomly assigned treatment eligibility is used as an instrument for treatment. The design ensures that treated and control funds are balanced on unobservable and observable characteristics. The proximity in time ensures that treated and control funds have access to the same funding opportunities (deals) and are managed by the same GP cohort. The paper relies on a fuzzy regression discontinuity design around the 2012 JOBS Act to proxy for such an ideal experiment.

1.4.1. The 2012 JOBS Act Reform

On April 5, 2012, the U.S. enacted the Jumpstart Our Business Startups (JOBS) Act into law to ease restrictions on private capital formation. Title §V and §VI of the JOBS Act raise the threshold triggering registration under §12(g) of the Securities Exchange Act of 1934 ('Exchange Act') from 500 to 2,000 investors.[20] Unlike other sections of the JOBS act, §V and §VI were effective immediately as of April 5, 2012. The threshold increase was binding for the majority of private equity funds due to their reliance on the exemption under §3(c)7 of the Investment Company Act of 1940 ('1940 Act').[21] To the surprise of market participants, the act had a quick route along the legislation path. The House of Representatives introduced

[19] The first close (launch) constitutes the first out of several fundraising rounds (closings) for a private equity fund. The fundraising process for a private equity fund concludes with a final close.

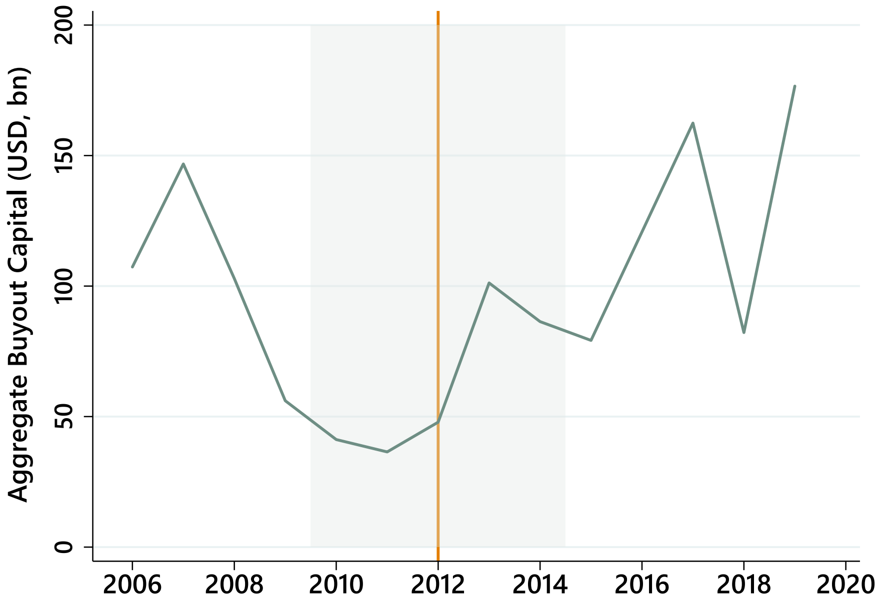
[20] Although the trigger under Title §V is either 2,000 holders of record or 500 non-accredited investors, the latter threshold does not apply. Private funds are effectively limited to accredited investors to comply with requirements under Regulation D for private offerings.

[21] PE funds may rely on §3(c)1 or §3(c)7 under the 1940 Act to avoid registration and reporting requirements for investment companies. The type of investors in the PE fund determines the applicable section for exemption. §3(c)1 funds consist of individuals with a net worth of $1 million or entities with at least $5 million in assets ('accredited investors'). In contrast, §3(c)7 funds consist of individuals with a net worth of $5 million or institutions with at least $25 million in private capital ('qualified purchasers'). The 1940 Act limits §3(c)1 funds to 100 investors but provides no explicit limit on the number of investors in §3(c)7 funds. Despite the lack of an explicit limit under the 1940 Act, §3(c)7 funds were practically subject to a pre-JOBS act limit of 499 record holders under §12(g) of the Exchange Act.

the act on March 1 and the President signed the act into federal law on April 5.[22] The one-month lag between the introduction of the act and its effectiveness left market participants with no time to strategically respond to the reform. The paper formally tests and presents empirical evidence consistent with this observation in section 2.4.

Figure 1. Aggregate Capital Raised: Buyout Funds

The figure shows the aggregate capital raised for buyout funds around the 2012 reform. The sample consists of U.S.-based buyout funds with a North American geographic focus. Data Source: Preqin.



The 2012 JOBS act led to variation at the intensive margin in the number of LPs per fund due to the entry of new LPs into the PE market. The JOBS act encouraged the entry of new LPs for two reasons. First, the JOBS act affected all §3(c)7 funds in the U.S. market and thus encouraged the entry of §3(c)7 type investors. About 65% of all U.S. funds and 70% of all private equity funds are §3(c)7 funds. The §3(c)7 exemption requires a specific investor type, individuals with a net worth of \$5 million or institutions with at least \$25 million in private capital ('qualified purchasers'). Consistent with the entry of new LPs, Figure 1 provides evidence that aggregate buyout fundraising rebounds from a low of \$36bn in 2011 to \$47bn (31% y/y increase) in 2012 and \$101bn (115% y/y increase) in 2013.[23] Second, the

[22] The House of Representatives introduced the act on March 1 and passed it on March 8. The Senate then passed the act on March 22 with an amendment to §III. The House accepted the proposed Senate amendment on March 27 and the President signed the act into federal law on April 5.

[23] The 2012 sharp rebound in buyout fundraising and entry of new LPs to the asset class has been documented in the news: PEI (https://www.buyoutsinsider.com/mega-firms-power-strongest-fundraising-year-since-crisis/), Pitchbook (https://pitchbook.com/newsletter/buyout-fundraising-boost), Capital Dynamics (https://www.capdyn.com/news/fy-2012-summary-private-equity-review-and-outlook/).

threshold increase incentivizes GPs to raise smaller amounts of capital from smaller high-net-worth (HNW) investors. The threshold increase effectively quadruples the lower bound on the amount of additional capital a GP can raise from HNW investors from 3% ($22mn) to 12% ($97mn) of average buyout fund size.[24,25] Consistent with this implication, Section 1.5.1 provides evidence that the 2012 JOBS act had a negative effect on the liquidity of LPs in private equity funds.

1.4.2. Identification Strategy: Fuzzy RDD Around the 2012 JOBS Act

A regression discontinuity design (RDD) around the 2012 JOBS act isolates random variation in treatment eligibility due to GP's imprecise control over a fund's final close date relative to the act's effective date. The fundraising process for a private equity fund is a long 1.5-2 years, with several closings that precede the final close. It is implausible that the GP can control the market forces that govern the number and timing of interim closings that precede the final close. In support of this institutional feature, Section 2.4 provides evidence against endogenous sorting and GP anticipatory effects around the 2012 JOBS act effective date. The RDD running variable is the final close date for a private equity fund and the cutoff is the JOBS act effective date. GPs who happen to close PE funds on or right after the JOBS act effective date are in a market of a larger number of LPs (treatment) relative to right before (control). The identifying assumption is that, in the absence of the 2012 reform, funds closed in the days right before and right after the effective date would exhibit the same performance outcomes. This assumption is plausible since funds closed in the days right before and right after the JOBS act have access to the same funding opportunities (deals) and are managed by the same GP cohort.

To address endogenous take-up of treatment, random treatment eligibility is used as an instrumental variable for treatment. An indicator variable for holding a final close on or after the JOBS act effective date (treatment eligibility) is used as an instrumental variable for the number and liquidity of LPs in PE funds (treatment). Given GP's imprecise control over a fund's final close date, funds that held a final close on or after the JOBS act (treatment eligibility) are randomly assigned to treatment. The effect of random treatment eligibility on

[24]HNW LPs typically contribute $50,000 to $250,000. The calculation is based on the lower bound of $50,000 per HNW LP. The average number of LPs in a §3(c)7 buyout fund before the reform was about 65 LPs and the average fund size was $840mn. The lower bound thus increases from $21.75mn (435 LPs × $50,000) or about 3% of average buyout fund size to $96.75mn (1,935 LPs × $50,000) or about 12% of average buyout fund size.

[25]Major GPs in the buyout asset class increased their commitments from HNW investors (e.g., Blackstone by 3.7× from 2011 to 2014 and Carlyle by 2.7× from 2012 to 2020).

outcomes ('intent-to-treat') is an uncontroversial causal effect because it effectively compares funds based on randomized eligibility rather actual treatment take-up. To identify the causal effect of treatment on outcomes, the reduced-form ('intent-to-treat') effect can then be scaled by the first-stage effect of treatment eligibility on treatment (see Section 1.5.1 for first-stage and reduced-form effects). Using randomly assigned treatment eligibility as an instrumental variable for treatment thus eliminates the possibility of self-selection among funds who take up treatment. With non-binary treatment, the average causal response (ACR) theorem shows that LATE is a weighted average of causal responses to a unit change in treatment for funds affected by the instrument (Angrist and Imbens (1995)). The instrumental variable set-up leads to a fuzzy regression discontinuity design (see Section 1.5.2 for the second-stage IV effect).

Given independence, the exclusion restriction, monotonicity, and the existence of a first stage, the conditions for the local average treatment effect (LATE) and the average causal response (ACR) theorems are satisfied (Angrist and Pischke (2008)). The existence of a first stage is a testable assumption (see Section 1.5.1 for first stage results). The independence assumption requires that final close timing for a PE fund is as good as randomly assigned relative to the act's effective date. This assumption is violated if the GP can precisely time the final close date. It is highly implausible that the GP can manipulate the market forces that govern the number and timing of multiple closing rounds over 1.5 to 2 years leading up to the final close. The exclusion restriction assumption requires that fund final close timing relative to the act's effective date affects fund performance outcomes only through the number of LPs. Increased competition in the market due to the JOBS act does not violate the exclusion restriction since it is a downstream consequence of the increase in the number of LPs in PE funds. The monotonicity assumption requires that all funds affected by the act were affected in the same direction (i.e., through a positive increase in the number of LPs). It is unlikely that the eligibility of all PE funds in the U.S. market for a cap increase would result in an increase for some funds and a decrease for other funds.

1.5. The Contribution of LPs to Fund Performance

In this section, I estimate the effect of the number and liquidity of LPs on private equity fund performance using a fuzzy regression discontinuity design around the 2012 JOBS act. The running (score) variable is the final close date for a PE fund and the cutoff is the JOBS act effective date of April 5th, 2012. The design thus compares funds closed right before (control) and right after (treatment) the JOBS act effective date of April 5th, 2012. The analysis is based on a panel of performance and LP composition observations at the fund-age year level.[26] In Section 1.5.1, I estimate the effect of the 2012 JOBS act on the composition of LPs (first-stage) and fund performance outcomes (reduced-form). In Section 1.5.2, I present the main findings of the effect of LP composition on fund performance outcomes (second-stage IV). In Section 2.4, I present a battery of identification checks against endogenous sorting, GP anticipatory effects, fund inflows, and interference (SUTVA violation) with respect to fund performance outcomes.

1.5.1. Effect of 2012 JOBS Act on LP Composition and Fund Performance

This subsection demonstrates the effect of the 2012 JOBS act on the composition of LPs in private equity funds (first-stage) and fund performance (reduced-form). To identify the effect of the 2012 JOBS Act on fund LP composition and fund performance outcomes, I estimate non-parametric local polynomial approximations of the form:

$$Y_{it} = \alpha + \Gamma \cdot 1(t_i^{FinalClose} \geq 0) + f(t_i^{FinalClose}) + 1(t_i^{FinalClose} \geq 0) \cdot f(t_i^{FinalClose}) + \epsilon_{it} \quad (1.1)$$

where Y_{it} represents $FundLPs_{it}$ (first-stage) and $FundPerformance_{it}$ (reduced-form). $FundLPs_{it}$ represents the composition of LPs in PE funds: $NumberofLPs_{it}$ is the number of LPs in a buyout fund and $LiquidityofLPs_{it}$ is the ratio of LPs-to-fund size (in percent) for a buyout fund. $FundPerformance_{it}$ represents fund performance metrics measured t years from the first drawdown year: PME_{it} is the public market equivalent benchmarked against the S&P500 total return index, IRR_{it} is the net internal rate of return, and $TVPI_{it}$ is the total value to paid-in-capital multiple. $t_i^{FinalClose}$ is the final close date of PE fund i normalized such that the 2012 JOBS act effective (cutoff) date of April 5th, 2012 is at $t = 0$. The estimation uses robust bias corrected (RBC) standard errors (Cattaneo et al. (2019)) for

[26] The results are robust to estimation at the fund level. Since the running (score) variable is discrete, the number of mass points (i.e., final close dates shared by more than one fund) matters for the estimation. The canonical continuity-based RD approach is deemed appropriate only when the number of mass points is sufficiently large, whereas the local randomization inference approach is valid with few mass points. Therefore, the paper estimates the canonical continuity-based RD approach at the fund-age level to ensure a sufficiently large number of mass points. The estimates at the fund level using local randomization inference are in Appendix 1.8.

inference, local linear polynomial regressions (Gelman and Imbens (2019)), and a triangular weighting kernel. The sample consists of §3(c)7 buyout funds located in the U.S. with a North American geographic focus. The panel consists of Fund-by-Age observations, where fund age is measured in years from the first drawdown year. Standard errors are clustered at the fund level.

Table IV. Effect of 2012 JOBS Act on LP Composition and Fund Performance

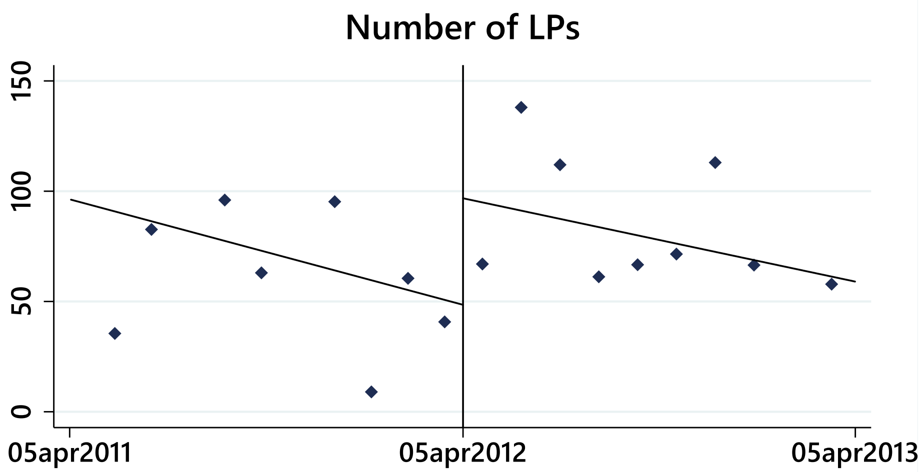
The table reports the effect of the 2012 JOBS act on the composition of LPs (first-stage) and private equity fund performance (reduced-form). The liquidity of LPs is inversely related to its measure − the number of LPs to fund size ratio, a higher ratio is consistent with lower LP liquidity. The unit of observation is fund-age, where fund age is measured in years from the first drawdown year. The sample consists of §3(c)7 buyout funds located in the U.S. with a North American geographic focus. All specifications use a local linear polynomial and a triangular weighting kernel. All coefficients are estimated within the same bandwidth of 455 days, corresponding to the MSE-optimal bandwidth for the first specification. Robust bias-corrected standard errors (reported in parentheses) are clustered at the fund level. ***, **, and * denote significance at the 1%, 5%, and 10%, respectively.

	First-Stage Fund LP Composition		*Reduced-Form* Fund Performance		
	(1)	(2)	(3)	(4)	(5)
	Number of LPs	Liquidity of LPs	Public Market Market Equivalent (PME)	Internal Rate of Return (IRR)	Total Value to Paid-in-Capital (TVPI)
$1(t_i^{FinalClose} \geq 0)$	40.96***	2.682***	-0.297***	-8.455***	-0.253***
	(3.190)	(0.504)	(0.012)	(2.784)	(0.017)
Controls	N	N	N	N	N
Bandwidth (days)	455	455	455	455	455
Control Funds Mean	49.393	7.480	1.192	23.350	1.625
Observations	590	590	462	303	434

Table IV reports the corresponding regression results. First-stage and reduced-form effects are estimated within a fixed bandwidth to ensure comparability across specifications. Specifically, the fixed bandwidth of 455 days corresponds to the MSE-optimal bandwidth for the number of LPs. The first-stage effects are consistent with an increase in the number of LPs and a decrease in the liquidity of LPs as a result of the 2012 JOBS Act. Relative to funds closed before April 5, 2012 (control funds), the first-stage effects correspond to an increase of 82.9% (40.96/49.393) in the number of LPs in PE funds and 35.9% (2.682/7.480) in the LPs-to-Fund Size ratio measure of LP liquidity. The liquidity of LPs is inversely related to its measure − the number of LPs to fund size ratio. Therefore, the increase in the number of LPs to fund size ratio measure corresponds to a decrease in LP liquidity. In terms of fund performance outcomes, the reduced-form effects correspond to a decrease of 24.9% (0.297/1.192) in PME, 36.2% (8.455/23.35) in IRR, and 15.6% (0.253/1.625) in TVPI. Figures 2 and 3 show graphical results corresponding to the first-stage and reduced-form effects, respectively. Overall, the results are consistent with a significant discontinuity in the composition of LPs and fund performance outcomes at the JOBS act effective date.

Figure 2. First Stage: Composition of LPs in Private Equity Funds

The figures show the first-stage effect of the 2012 JOBS act on the number and liquidity of LPs in PE funds. Bandwidth is 365 days around the JOBS act effective date of April 5, 2012. The number of LPs is winsorized at the 10% level. The first-stage effect of the 2012 JOBS act is an increase of 48 (97-49) in the number of LPs in PE funds and 3 (10-7) LPs per $100mn fund size for the liquidity of LPs in PE funds. The liquidity of LPs is inversely related to its measure – the number of LPs to fund size ratio, a higher ratio is consistent with lower LP liquidity. The sample consists of §3(c)7 buyout funds located in the U.S. with a North American geographic focus.



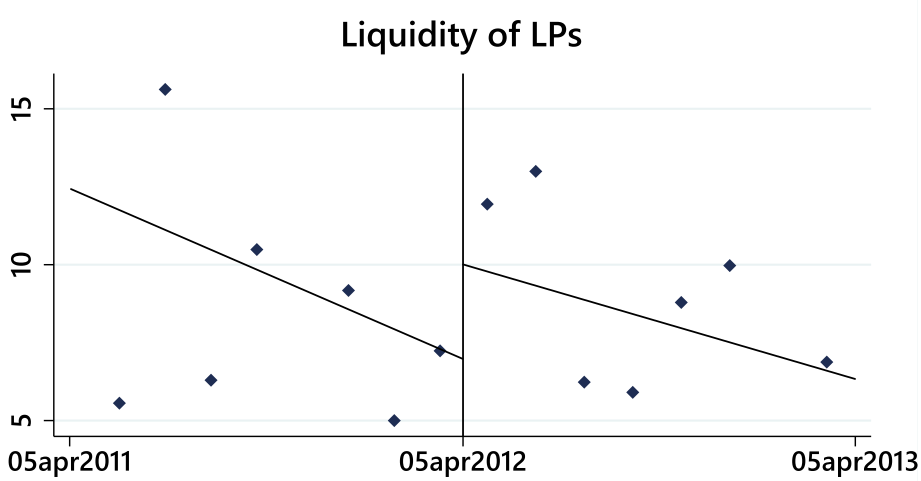
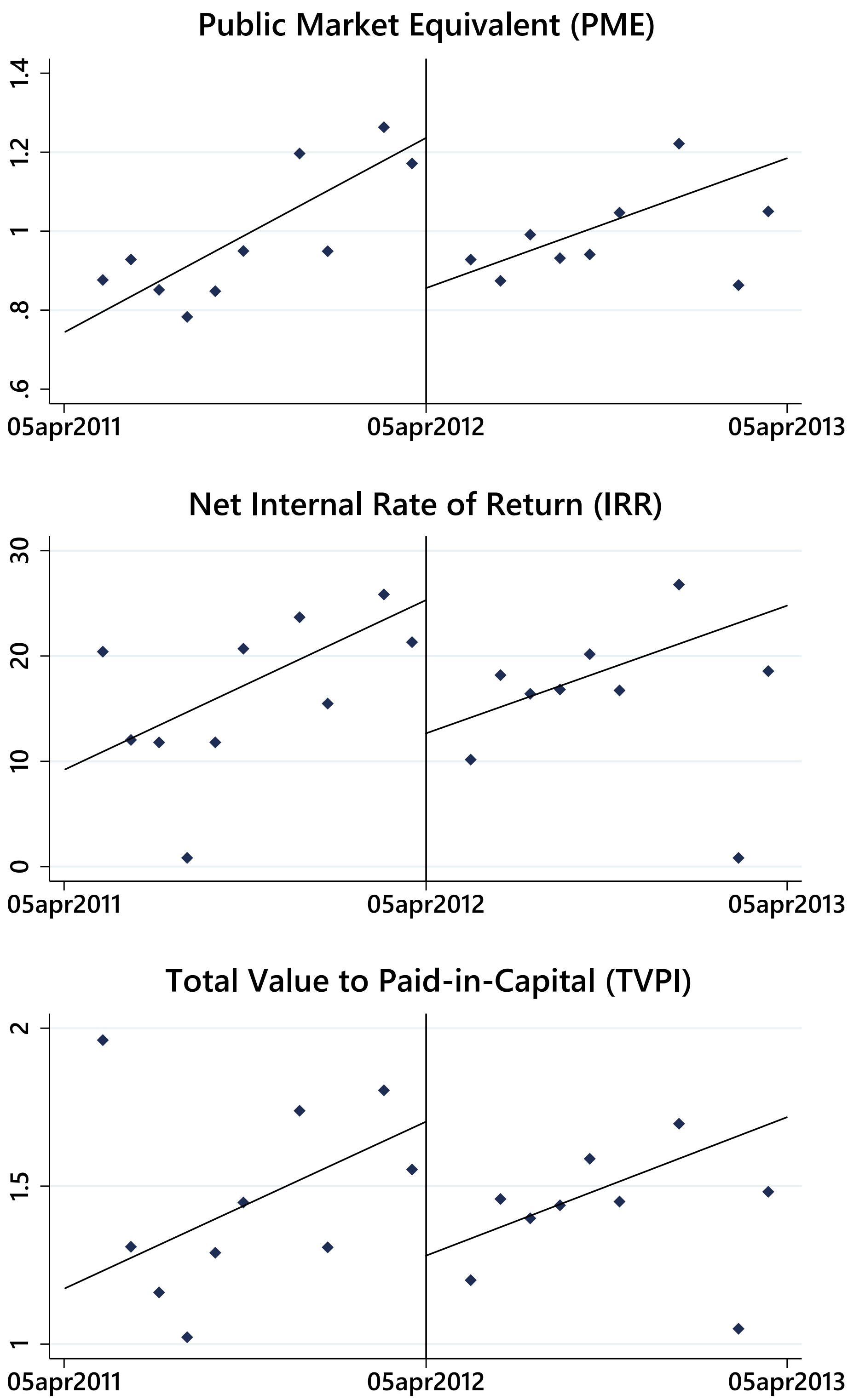


Figure 3. Reduced-Form: Private Equity Fund Performance

The figures show the reduced-form effect of the 2012 JOBS act on fund performance outcomes. Bandwidth is 365 days around the JOBS act effective date of April 5, 2012. The reduced form effect of the 2012 JOBS act is a decline of 0.3 (1.2-0.9) for PME, 12% (25-13) for IRR, and 0.4 (1.7-1.3) for TVPI. The sample consists of §3(c)7 buyout funds located in the U.S. with a North American geographic focus.



1.5.2. Effect of LP Composition on Private Equity Fund Performance

This subsection presents the main findings of the effect of the number and liquidity of LPs in private equity funds on fund performance outcomes (second-stage). To identify the effect of the composition of LPs on fund performance outcomes, I estimate the following first-stage and second-stage specifications:

$$FundLPs_{it} = \alpha + \Gamma \cdot 1(t_i^{FinalClose} \geq 0) + f(t_i^{FinalClose}) + 1(t_i^{FinalClose} \geq 0) \cdot f(t_i^{FinalClose}) + \gamma \cdot X_{it} + \epsilon_{it}$$

$$FundPerformance_{it} = \alpha + \beta \cdot \widehat{FundLP}s_{it} + \gamma \cdot X_{it} + \epsilon_{it}$$

where $t_i^{FinalClose}$ is the final close date of PE fund i normalized such that the 2012 JOBS act effective (cutoff) date of April 5th, 2012 is at $t = 0$. $FundLPs_{it}$ represents the composition of LPs in PE funds: $NumberofLPs_{it}$ is the number of LPs in a buyout fund and $LiquidityofLPs_{it}$ is the ratio of LPs-to-fund size (in percent) for a buyout fund. $\widehat{FundLP}s_{it}$ represents the fitted values from the first stage regression. $FundPerformance_{it}$ represents fund performance metrics measured t years from the first drawdown year: PME_{it} is the public market equivalent benchmarked against the S&P500 total return index, IRR_{it} is the net internal rate of return, and $TVPI_{it}$ is the total value to paid-in-capital multiple. X_{it} denotes a vector of control variables. GP-level controls include: $GPAbilityProxy_i$ is an indicator for the top 100 GPs by capital raised in 2006-2010 and $GPAge_i$ is the age of GP in years as of 2010.[27] Fund-level controls include fixed effects for fund close year, fund industry, and years since the first drawdown.

The results are based on a mean square error (MSE)-optimal point estimator and robust bias-corrected (RBC) standard errors for inference (Cattaneo et al. (2019)). Relative to a fixed bandwidth, an MSE-optimal bandwidth ensures that the RD point estimator is consistent and has minimal asymptotic MSE. The robust bias correction (RBC) ensures that the MSE-optimal bandwidth can be used for optimal point estimation and valid statistical inference. The estimation uses local linear polynomial regressions as recommended by Gelman and Imbens (2019) and a triangular weighting kernel since it is the MSE-optimal choice for point estimation. The sample consists of §3(c)7 buyout funds located in the U.S. with a North American geographic focus. The panel consists of Fund-by-Age observations, where fund age is measured in years from the first drawdown year. Standard errors are clustered at the fund level.

[27] GP-level controls are measured as of 2010 to account for GP ability and GP age at the time of fundraising launch. The fundraising process for a private equity fund spans 1.5 to 2 years from fundraising launch to final close. Funds closed in the days around the 2012 reform were launched by the GP in 2010.

Table V presents the results from the estimation. Columns (1)-(3) show the first-stage estimates from regressing the number of LPs in a PE fund on an indicator for holding a final close on or after April 5th, 2012. Columns (4)-(6) show the first-stage estimates from regressing the liquidity of LPs in a PE fund on an indicator for holding a final close on or after April 5th, 2012. All first-stage estimates are positive and strongly significant under the MSE-optimal bandwidth, consistent with the results from the fixed bandwidth in section 1.5.1. The results are consistent with an increase in the number of LPs and a decrease in the liquidity of LPs in response to the 2012 JOBS act reform. Given that the liquidity of LPs is inversely related to its measure – the number of LPs to fund size ratio, a higher ratio is consistent with lower LP liquidity. The strong first-stage results allow for identifying the effect of LP composition on fund performance outcomes.

Number of LPs in Private Equity Funds

Columns (1)-(3) of Table V show the effect of the number of LPs in a private equity fund on fund performance. The second-stage estimates are from regressing fund performance outcomes on the instrumented first-stage number of LPs in a PE fund. The estimates suggest a strongly significant negative relationship between the number of LPs in a private equity fund and fund performance. Relative to funds that held a final close before April 5th, 2012 (control funds), an increase of 1 LP in a private equity fund reduces PME by 0.6% (0.00725/1.202), Net IRR by 0.8% (0.193/25.312), and TVPI by 0.4% (0.00696/1.584). Overall, the findings suggest that a decrease of 1 LP in a private equity fund contributes to a 0.6% average increase in fund performance over the fund's life.

Liquidity of LPs in Private Equity Funds

Relative to the number of LPs, the liquidity of LPs is a significant driver of private equity fund performance. Columns (4)-(6) of Table V show the effect of the liquidity of LPs in a private equity fund on fund performance. The second-stage estimates are from regressing fund performance outcomes on the instrumented first-stage liquidity of LPs in a PE fund. Given that the liquidity of LPs is inversely related to its measure – the number of LPs to fund size ratio, the estimates suggest a strongly significant positive relationship between the liquidity of LPs in a private equity fund and fund performance. Relative to funds that held a final close before April 5th, 2012 (control funds), an increase of 1 LP per $100mn fund size corresponding to 1 unit decrease in the liquidity of LPs reduces PME by 16.1% (0.199/1.236), Net IRR by 18.4% (4.649/25.304), and TVPI by 10.6% (0.181/1.705). Overall, the findings suggest that a 1 unit increase in the liquidity of LPs in a private equity fund contributes to a 15% average increase in fund performance over the fund's life.

Table V. Effect of LP Composition on Fund Performance

The table investigates the effect of the composition of LPs in PE funds on fund performance outcomes. The first-stage estimates are from regressing LP composition features on an indicator for holding a final close on or after April 5, 2012. The liquidity of LPs is inversely related to its measure – the number of LPs to fund size ratio, a higher ratio is consistent with lower LP liquidity. The unit of observation is fund-age, where fund age is measured in years from the first drawdown year. The sample consists of §3(c)7 buyout funds located in the U.S. with a North American geographic focus. All specifications use a local linear polynomial with an MSE-optimal bandwidth based on Calonico et al. (2014) and a triangular weighting kernel. Robust bias-corrected standard errors (reported in parentheses) are clustered at the fund level. ***, **, and * denote significance at the 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Public Market Equivalent (PME)					
First-Stage	43.295***	11.316***	53.931***	1.880***	2.684***	4.688***
	(2.508)	(2.511)	(5.763)	(0.484)	(0.380)	(0.437)
$\widehat{NumberofLPs}_{it}$	-0.00725***	-0.0192***	-0.00906***			
	(0.001)	(0.005)	(0.001)			
$\widehat{LiquidityofLPs}_{it}$				-0.199**	-0.136***	-0.110***
				(0.054)	(0.023)	(0.011)
GP-level Controls	N	Y	Y	N	Y	Y
Fund-level Controls	N	N	Y	N	N	Y
Bandwidth (days)	427	540	486	372	381	398
Control Funds Mean	1.202	1.155	1.176	1.236	1.231	1.220
Observations	438	611	580	380	400	432
	Panel B: Net Internal Rate of Return (IRR)					
First-Stage	65.128***	26.961***	74.617***	2.673***	4.211***	5.479***
	(4.486)	(4.059)	(8.306)	(0.574)	(0.487)	(0.711)
$\widehat{NumberofLPs}_{it}$	-0.193***	-0.313***	-0.265***			
	(0.035)	(0.088)	(0.035)			
$\widehat{LiquidityofLPs}_{it}$				-4.649***	-3.643***	-3.380***
				(1.180)	(0.593)	(0.500)
GP-level Controls	N	Y	Y	N	Y	Y
Fund-level Controls	N	N	Y	N	N	Y
Bandwidth (days)	366	459	361	369	332	453
Control Funds Mean	25.312	23.300	25.324	25.304	25.336	23.370
Observations	247	303	241	247	211	303
	Panel C: Total Value to Paid-in-Capital (TVPI)					
First-Stage	20.625***	38.812***	73.053***	2.371***	4.034***	5.269***
	(3.645)	(5.650)	(9.347)	(0.542)	(0.348)	(0.381)
$\widehat{NumberofLPs}_{it}$	-0.00696***	-0.0102***	-0.00830***			
	(0.002)	(0.002)	(0.001)			
$\widehat{LiquidityofLPs}_{it}$				-0.181***	-0.129***	-0.116***
				(0.044)	(0.014)	(0.010)
GP-level Controls	N	Y	Y	N	Y	Y
Fund-level Controls	N	N	Y	N	N	Y
Bandwidth (days)	590	384	308	363	311	314
Control Funds Mean	1.584	1.689	1.710	1.705	1.710	1.711
Observations	615	375	289	355	298	298

1.5.3. Identification Checks

This subsection discusses potential threats to the identification. The first potential threat to identification is the possibility of endogenous sorting or GP strategic response to benefit from the reform. Section A presents evidence consistent with the imprecise control of the GP over the fund final close timing. Section B provides evidence for balance on GP ability and against GP anticipatory effects. The endogenous sorting and balance tests are based on the full sample of buyout funds that filed for exemption under section §3(c)7 of the 1940 Investment Company Act, regardless of whether their performance data is available. The second potential threat to identification is the possibility that the negative effect on fund-level returns is driven by fund inflows. Section C provides evidence against this possibility through balance on fund size around the 2012 JOBS act effective (cutoff) date. The third potential threat to identification is the possibility that performance outcomes for the control group are confounded by competition with the treatment group, violating the well-known stable unit treatment value assignment (SUTVA) assumption. Section D shows that the results are robust to the possibility of interference between treatment and control funds with respect to fund performance.

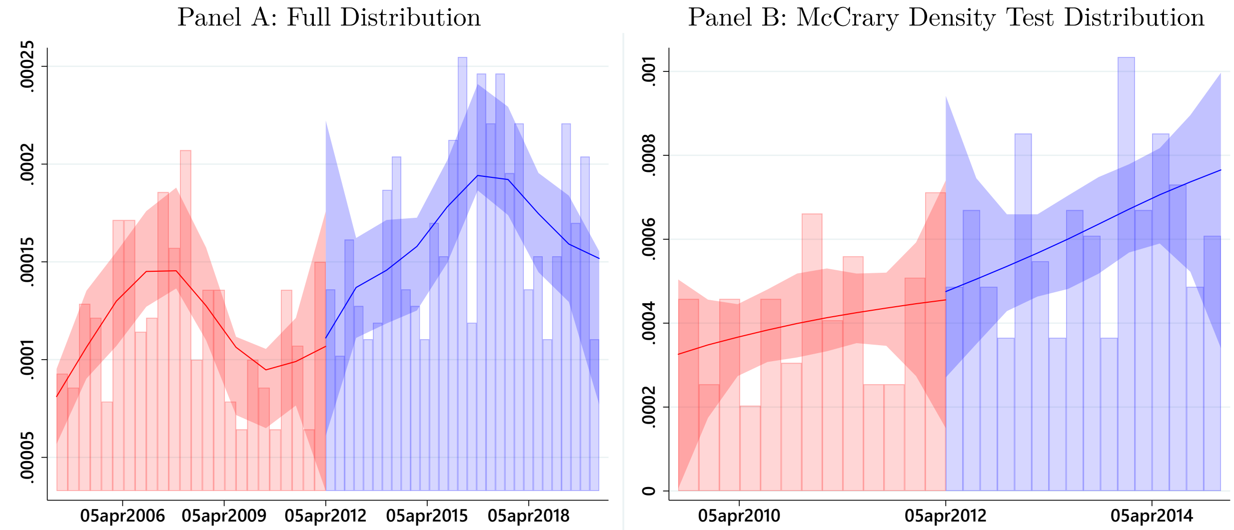
A. Endogenous Sorting

Identification relies on the imprecise ability of the GP to time the final close date of a PE fund. The fundraising process for a PE fund spans 1.5 to 2 years, with several closing rounds that precede the final close. It is implausible that the GP can control the market forces that govern the number and timing of closings that precede the final close. In addition, longer fundraising periods constitute a strong negative signal for GP ability and delay the fund's investment schedule. If GPs can precisely time the final close date, one would expect to observe bunching of funds closed at the 2012 JOBS act effective date. The McCrary (2008) density test provides direct evidence against this possibility. It is important to note that endogenous sorting concerns matter for the number of funds *closed* not raised due to the imprecise control of the GP over the timing of the final *close* for a PE fund.

McCrary (2008) Density Test. The test separately estimates the density of the number of funds closed to the left and to the right of the cutoff date and tests whether the density of the running variable (final close date) is continuous at the cutoff. Figure 4 implements the test at the fund level since the fund is the relevant unit for endogenous sorting. Based on an MSE-optimal bandwidth of two years around the 2012 JOBS act effective date, the resulting statistic is 0.68 with a p-value of 0.50. The test fails to reject the null hypothesis of no difference between control and treated observations at the cutoff. The test further validates the identification assumption that GPs do not have precise control over the final close date timing relative to the act's effective date.[28] Evidence against endogenous sorting is robust under local randomization inference (see Table VIII, Appendix 1.8.2).

Figure 4. Endogenous Sorting: McCrary Density Test

The test separately estimates the density of observations (number of funds closed) to the left and right of the 2012 JOBS act effective (cutoff) date. The null hypothesis is that the running variable's density (final close date) is continuous at the cutoff. The unit of observation is the buyout fund. Panel A shows the full distribution. Panel B shows the distribution used in the McCrary density test based on an MSE-optimal bandwidth. Confidence intervals are not centered around the point estimates because they are bias-corrected. The sample consists of §3(c)7 buyout funds located in the U.S. with a North American geographic focus.



B. GP Anticipatory Effects

Identification relies on the quick enactment of the 2012 JOBS act, leaving GPs with no time to strategically respond to the reform. Given the one-month lag between the introduction of the 2012 JOBS act and its effectiveness, it is implausible that GPs were able to strategically respond to benefit from the reform. If GPs were able to anticipate the effects of the JOBS act, one would expect to observe a decrease in minimum commitment or an increase in target fund size in an attempt to capture more LPs into their PE funds. Table VI shows the results from a balance test using specification (1.1) with minimum commitment and target fund size as outcomes Y_{it}. The point estimates for minimum commitment and target fund size are close to zero and none are statistically significant. The evidence is consistent with the identification assumption that GPs were left with no time to anticipate and strategically respond to the reform.

[28]The results are robust to a smaller bandwidth. Based on a 450-day bandwidth around the 2012 JOBS act effective date, the resulting p-value of the statistic is 0.43.

A critical assumption for identification is the randomization of GP ability around the 2012 JOBS act effective (cutoff) date. The more important evidence from Table VI points to balance on GP ability. GP ability is an indicator for the top 100 GPs by capital raised for buyout funds in 2006 - 2010, a proxy for GP competitiveness when the funds are launched.[29] In particular, the point estimates are small and none are significantly different from zero. Overall, Table VI points to balance on GP and fund characteristics around the cutoff. Evidence for balance on GP and fund characteristics is robust under local randomization inference (see Figure 5 and Table IX, Appendix 1.8.2).

Table VI. Balance Test on GP and Fund Characteristics

This table formally tests for systematic differences between control and treated funds on GP and fund characteristics. The unit of observation is fund-age, where fund age is measured in years from the first drawdown year. All specifications use an MSE-optimal bandwidth, local linear polynomial, and a triangular weighting kernel. Robust bias-corrected standard errors are clustered at the fund level. The sample consists of §3(c)7 buyout funds located in the U.S. with a North American geographic focus. ***, **, and * denote significance at the 1%, 5%, and 10%, respectively.

Variable	Type	MSE-Optimal Bandwidth	RD Estimator	Robust Inference P-Value	Robust Inference CI	Effective Observations
Minimum Commitment (log)	Placebo	560	1.049	0.246	[-1.021 ; 3.979]	1,550
Target Fund Size (log)	Placebo	484	0.169	0.758	[-0.479 ; 0.657]	1,200
Actual Fund Size (log)	Placebo	482	0.447	0.188	[-0.252 ; 1.280]	1,300
GP Ability Proxy	Covariate	466	0.025	0.986	[-0.168 ; 0.171]	1,240
GP Age	Covariate	447	3.227	0.069*	[-0.303 ; 8.239]	1,150

C. Fund Inflows

The possibility that fund inflows is driving the negative effect on performance is a potential threat to identification. To provide evidence against this possibility, Table VI provides evidence for balance on actual fund size around the 2012 JOBS act effective date. The point estimate for actual fund size is not statistically significant. This result can be attributed to the fact that the JOBS act encouraged the entry of smaller LPs into the private equity market. The sharp increase in aggregate capital in 2013 can thus be reconciled by the increase in the number of funds rather than fund size. Because the contribution of LPs to fund performance is identified at the 2012 JOBS act effective date (cutoff), the later increase in the number of funds does not pose a threat to identification.

[29]The fundraising process for a PE fund from launch to final close spans 1.5 to 2 years. Funds closed in the days around the 2012 reform were thus launched in 2010.

D. Interference (SUTVA Violation)

The possibility of spillovers to the control group through a competition channel constitutes another potential threat to identification. This threat violates the stable unit treatment value assignment (SUTVA) assumption, requiring no interference between treatment and control funds. There is no potential for interference with respect to fundraising outcomes since the final close date essentially concludes the fundraising stage for a PE fund. However, there is potential for interference with respect to fund performance outcomes. Since funds closed right before the act (control) are chasing deals at the same time as funds closed right after the act (treatment), the competition with the treatment group likely confounds outcomes for the control group.

To address this possibility, the paper shows that the effects are robust under (Fisherian) randomization inference that tests the sharp null of a zero treatment effect for each unit. Because the null of no treatment effect for each unit implies no interference between units, testing the sharp null does not require SUTVA. The null of no treatment effect for each unit is sharp because missing potential outcomes can be imputed as equal to observed outcomes. This property allows for constructing the randomization distribution, the set of all test statistics for each possible treatment assignment vector. The Fisher exact p-value corresponds to the proportion of test statistics under the randomization distribution as large or larger than the observed test statistic under actual treatment assignment. This p-value represents the likelihood that chance could have produced the observed difference between treated and control funds. Table XI in Appendix 1.8.3 reports the Fisher exact p-values that correspond to the effect of the 2012 JOBS act on fund performance outcomes. The p-values are computed for funds at the same age to ensure that performance is comparable for treated and control funds. The key finding is that the reported p-values reject the sharp null of no treatment effect.

The paper also constructs confidence intervals proposed by Rosenbaum (2007) that are robust to any structure of interference between units (see Appendix 1.8.4). To illustrate the idea behind the methodology, consider a placebo trial where units are randomly assigned to treatment and control groups, but treatment is withheld from all units. The key insight behind the methodology is that under the placebo trial, the particular value of the test statistic is unknown, but the distribution of the test statistic is known. Because the sharp null holds by construction under the placebo trial, missing potential outcomes can be imputed as equal to observed outcomes and the randomization distribution can be constructed. The differential change in outcomes for treated and control units between the actual experiment and the placebo trial recovers a treatment effect range under any arbitrary interference structure between units. Figure 6 in Appendix 1.8.4 shows the 95% confidence intervals for fund performance outcomes under the possibility of arbitrary interference between funds. The important observation is that the estimated effects on performance due to the 2012 JOBS act are robust to the possibility of arbitrary interference.

1.6. How do LPs Contribute to Fund Performance?

In this section, I investigate two mechanisms that drive the causal effect of the composition of LPs on private equity fund performance. A key motivation for these mechanisms is that LPs are highly heterogeneous, can negotiate different contracts with the GP to subscribe to the same fund (Begenau and Siriwardane (2020)), and are integral to the survival of the GP in the market. The first mechanism is a *certification* channel where the GP exerts greater effort for funds with more liquid LPs. The second mechanism is a *catering* channel where the GP allocates riskier deals to funds with more liquid LPs.

1.6.1. Certification

The liquidity of LPs can influence GP effort for the fund. LPs are critical to the survival of a GP in the private equity market. The minimum length of a GP-LP relationship is 10 years, as GPs predominantly rely on LPs that subscribed to prior funds to raise capital for new funds. Liquid LPs have the capacity to provide capital for future funds and can certify the quality of the GP to new LPs. To retain liquid LPs for future funds, the GP will exert greater effort to achieve premium returns for the current fund. In support of this view, Chung et al. (2012) theoretically show that GPs work above and beyond fees to secure future funding, especially for buyout funds. The evidence is consistent with a certification channel; GPs exert greater effort for LPs that can re-up for future funds and certify GP quality.

1.6.2. Catering

The characteristics of LPs in a PE fund can influence the characteristics of fund deals. LPs are heterogeneous with respect to their liquidity, regulatory and tax constraints, and governance. These factors influence their risk capacity and investment objectives. The underlying characteristics of fund LPs can thus influence GP deal selection, an important determinant of fund performance. In support of this view, Begenau and Siriwardane (2020) find evidence consistent with different contractual terms for LPs that subscribe to the same private equity fund. The evidence is consistent with a catering channel; GPs cater to LPs' risk-capacity and investment objectives.

1.6.3. Suggestive Evidence for Certification and Catering Channels

To test these mechanisms, I identify the effect of the liquidity of LPs on the number and size of fund deals. More deals for funds with more liquid LPs provide evidence for the certification and catering channels. In support of certification, more deals entail greater GP effort to source the deals and more deal managers allocating more hours to create value for these deals. The ratio of the number of deals-to-fund size is used as a proxy for GP effort. The idea is that the GP will allocate more resources and value-creation efforts for funds with a large number of deals relative to funds with a small number of deals. The prediction is consistent with Kandel et al. (2011) who theoretically show that GP monitoring cost is too high. In support of catering[30], a larger portfolio of deals is also consistent with greater GP risk-taking. The prediction is consistent with Fulghieri and Sevilir (2009) and Kanniainen and Keuschnigg (2004), showing that the GP constructs larger portfolios when portfolio companies are perceived to have a high probability of failure.

Table VII. Effect of Liquidity of LPs on Fund Deal Characteristics

The table investigates the effect of the liquidity of LPs in PE funds on characteristics of fund deals. The first-stage estimates are from regressing the liquidity of LPs measure on an indicator for holding a final close on or after April 5, 2012. The liquidity of LPs is inversely related to its measure – the number of LPs to fund size ratio, a higher ratio is consistent with lower LP liquidity. The unit of observation is fund-age, where fund age is measured in years from the first drawdown year. The sample consists of §3(c)7 buyout funds located in the U.S. with a North American geographic focus. All specifications use a local linear polynomial with an MSE-optimal bandwidth based on Calonico et al. (2014) and a triangular weighting kernel. Robust bias-corrected standard errors (reported in parentheses) are clustered at the fund level. ***, **, and * denote significance at the 1%, 5%, and 10%, respectively.

	(1) Number of Fund Deals	(2) Mean Deal Size (% Fund Size)	(3) Number of Fund Deals (% Fund Size)
First-Stage	5.531***	3.939***	5.899***
	(0.101)	(0.165)	(0.069)
$\widehat{Liquidity of LPs}_{it}$	-1.958***	30.64***	-0.511***
	(0.089)	(2.46)	(0.023)
GP-level Controls	Y	Y	Y
Fund-level Controls	Y	Y	Y
Bandwidth (days)	409	373	283
Control Funds Mean	27.5	36.3	4.6
Observations	560	440	370

[30]The ideal test for this mechanism is to show that funds with more liquid LPs have a higher fraction of (ex-ante) high-risk deals but it is difficult to identify the ex-ante riskiness of fund deals.

Table VII provides evidence consistent with the certification and catering channels for LP contribution to fund performance. The second-stage estimates are from regressing fund deal characteristics on the instrumented first-stage liquidity of LPs in a PE fund. Columns (1)-(2) show that the liquidity of LPs in a PE fund has a strong positive relationship with the number of fund deals and a negative relationship with deal size. Relative to funds that held a final close before April 5, 2012 (control funds), an increase of 1 LP per $100mn fund size corresponding to a 1 unit decrease in the liquidity of LPs decreases the number of fund deals by 7.1% (1.958/27.5) and increases average deal size by 84.4% (30.64/36.3). Column (3) shows the effect of LP liquidity on the proxy for GP effort, the ratio of number of fund deals to fund size. Relative to funds that held a final close before April 5, 2012 (control funds), an increase of 1 LP per $100mn fund size corresponding to a 1 unit decrease in the liquidity of LPs decreases the ratio of fund deals to fund size by 11.1% (0.511/4.6). Overall, the significant and positive effect of the liquidity of LPs on the number of deals at the fund level points to certification and catering channels for LPs.

1.7. Summary and Implications

This paper provides first causal evidence of the contribution of LPs to private equity fund performance. To establish this causal claim, the paper relies on two sources of variation. First, variation in the composition of LPs due to the 2012 JOBS act. Second, variation in treatment eligibility as a consequence of GP's imprecise control over a fund's final close date relative to the act's effective date. The liquidity of fund LPs is measured as the ratio (in percent) of the number of LPs to fund size; one additional LP per $100mn corresponds to a unit decrease in the liquidity of LPs. Fund performance is inversely related to the number of investors and directly related to the liquidity of investors. The liquidity of investors is a significant driver of fund performance. One additional LP contributes to a 0.6% decrease in fund performance, whereas one additional LP per $100mn contributes to a 15% decrease in fund performance. The paper provides suggestive evidence consistent with two mechanisms for the contribution of LPs to fund performance: *Certification* and *Catering*.

The contribution of LPs to fund performance has several important implications. First, the persistence in the composition of LPs across funds can explain the performance persistence puzzle in private equity. GPs predominantly rely on prior fund LPs to raise capital for new follow-on funds. This institutional feature results in significant persistence in the composition of LPs across funds. The causal channel between LPs and fund performance attributes the persistence in fund performance to the persistence in LP composition. Second, it alerts GPs, LPs, and portfolio companies that the ultimate source of fund capital constitutes an important determinant of their performance.[31] Third, policymakers and regulators should consider the implications of new policy changes on the overall composition of investors that contribute to aggregate capital. The causal link between LPs and fund performance is likely to apply beyond buyout funds. Quantifying the contribution of LPs to Venture Capital (VC) funds is a fruitful avenue for future research.

[31] A portfolio company considering a GP investment should not only consider the quality of the GP but the overall quality of ultimate fund LPs. An LP considering a fund investment with a GP should consider the quality of existing and potential LPs. A GP raising a fund should prioritize the quality of fund capital.

1.8. Appendix: Robustness to Fisherian Randomization Inference

The local randomization approach to RD analysis essentially treats units closest to the cutoff as-if randomly assigned in a randomized experiment. Adopting the randomization assumption explicitly allows leveraging the statistical tools built for randomized experiments within a local neighborhood around the cutoff. Fisher and Neyman developed the two leading methods for statistical inference for randomized experiments.[32] Fisherian inference tests the sharp null of no treatment effect for each unit, is finite-sample exact, and leads to correct inferences even with few observations. Neyman inference tests the weak null of no average treatment effect, relies on large-sample approximations, and requires a sufficiently large number of observations. Neyman method allows for point estimation since it is concerned with the *average* rather than the *individual* treatment effect.[33] Fisher method is particularly valid in small samples, a setting where the Fisher exact null placebo (randomization) distribution can significantly deviate from the Neyman approximating Student's t distribution. The Fisherian approach is thus particularly relevant to the analysis at the fund level, given the small number of fund observations. The focus of this section is the application of Fisherian inference methods.

1.8.1. Continuity-based vs. Local Randomization Approach

There are important conceptual differences between the canonical continuity-based RD approach and the local randomization approach. First, the continuity-based RD approach treats potential outcomes as random variables due to random sampling, whereas randomization-based methods treat potential outcomes as non-stochastic. The source of uncertainty in estimates essentially shifts from hypothesized random sampling from a (large) population under the continuity-based approach to random treatment assignment under randomization inference.[34] Second, the fact that treatment assignment is 'as good as random' in a neighborhood around the cutoff is used as a heuristic device under the continuity-based approach but explicitly under the local randomization approach. In particular, identification relies on the

[32]Both methods do not assume that the data is a random sample from a large population.

[33]Fisherian methods cannot be utilized to perform inference for the average treatment effect (ATE) because the null of no ATE is not *sharp* in the sense that it does not allow imputation of missing potential outcomes. Neyman methods relying on large sample approximations to the ATE distribution are thus more appropriate for point estimation.

[34]Note that randomization inference is also very different from bootstrapping. Under bootstrapping, the source of uncertainty pertains to which observations are used from the sample, whereas uncertainty under randomization inference pertains to which observations are assigned to treatment.

continuity and differentiability of regression functions under the continuity-based approach and explicit randomization assumptions under the local randomization approach.

The local randomization approach offers several advantages relative to the continuity-based RD approach. First, the local randomization RD approach allows for analysis at the fund level. The continuity-based RD requires a sufficiently large number of mass points when the running variable is discrete. In contrast, the local randomization approach is appropriate with only a few mass points, rendering the analysis at the fund level possible. Second, estimation is finite-sample exact and does not rely on large-sample approximations or modeling assumptions for outcomes. These properties lead to correct inferences even when there is a small number of observations. Third, the construction of confidence intervals under arbitrary interference is possible under local randomization. The continuity-based approach assumes that the stable unit treatment value assignment (SUTVA) assumption holds. Under local randomization, interference confidence intervals can be constructed under a counterfactual statistic where treatment is withheld from all funds. The approach, suggested by Rosenbaum (2007), essentially compares the relative deviation of treated and control funds from a zero-effect scenario where treatment is withheld from all funds.

1.8.2. Identification and Window Selection

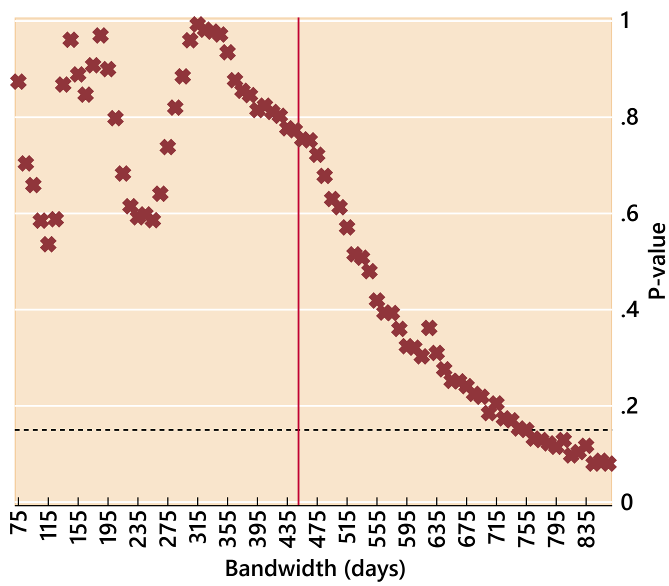
The local randomization approach requires two assumptions – *as-if random assignment* and an exclusion restriction. The *as-if random assignment* requires that funds closed in the days around the cutoff (locally) are assigned to treatment and control as in a randomized experiment. It is highly implausible for the GP to precisely time several closing rounds for a PE fund over 1.5-2 years leading to the final close date. Therefore, PE funds' final close timing relative to the act's effective date is as good as randomly assigned, satisfying the first assumption. The exclusion restriction requires that the value of the running variable (final close date) cannot affect potential outcomes, except through treatment assignment. In particular, potential fund performance outcomes depend on the final close date only through the increase in the number or liquidity of LPs (treatment) rather than through the particular value of the final close date. The assumption ensures no systematic differences between funds closed in the days right after (treatment) and right before (control) the effective date of the JOBS act. This assumption is also satisfied since the particular final close date of the PE fund (e.g., 4/2/2012 vs. 4/7/2012) cannot directly influence potential fund performance outcomes. Given the running variable's discreteness and to ensure consistency with the continuity-based approach, the paper relies on a first-order polynomial transformation of outcomes and a triangular weighting kernel.

A. Window Selection: Balance Test on GP Ability

Implementation of Fisherian inference tests requires a window around the cutoff where the local randomization assumption holds and a treatment assignment mechanism. The paper relies on a covariate balance test identifying the largest window around the cutoff where balance holds. The focus of the test is GP ability given that it constitutes the most important covariate for identifying the effect of LPs. The iterative procedure starts with a small window around the cutoff and tests the null hypothesis of balance on GP ability. As long as the p-value is greater than 0.15, the test fails to reject the null and selects a larger window. The procedure iterates until it reaches an alpha level of 0.15. Figure 5 shows the results from the window selection procedure. At the recommended alpha level of 0.15 (dotted line), the largest window is 750 days around the cutoff. Inference uses a more conservative and smaller window of 450 days around the cutoff. The paper uses a fixed margin assignment for the treatment assignment mechanism to avoid the possibility of few or no treated observations under *Bernoulli* assignment.[35]

Figure 5. Window Selection: Balance Test on GP Ability

The figure shows the window selection procedure for the local randomization approach. The procedure starts with the smallest window and tests the null hypothesis of balance on GP ability. As long as the p-value is greater than 0.15 (dotted line), the test fails to reject the null and selects a larger window. The procedure iterates until it identifies the largest window where balance holds. The vertical line corresponds to the chosen bandwidth of 450 days. The test uses a first-order polynomial transformation and a triangular weighting kernel. The sample consists of §3(c)7 buyout funds located in the U.S. with a North American geographic focus.



[35]This possibility arises under *Bernoulli* assignment because each unit has an equal probability of being assigned to treatment or control. However, it can never arise under *fixed margin* assignment because each treatment assignment vector has a fixed number of treated units, corresponding to the number under observed assignment.

B. Endogenous Sorting

Bernoulli Density Test. This test is finite-sample exact, investigates whether the density of observations in a small neighborhood around the cutoff is consistent with the density observed from a series of unbiased coin flips (i.e., 50% probability of being assigned to treatment). Table VIII reports the results from the test. Within all bandwidth windows, the observed probabilities of success are in the range of 0.53-0.55 and the p-values are large. The p-values entail that the test fails to reject the null hypothesis that the true probability of success is equal to 0.5.

Table VIII. Endogenous Sorting: Bernoulli Density Test

The table reports the results from a Bernoulli test within bandwidths of 450, 350, and 250 days. The test investigates whether the density of observations within the bandwidth is consistent with the density observed from a series of unbiased coin flips, with 50% probability of being assigned to treatment. The table shows the treatment probability based on the observed treatment assignment within the bandwidth. The p-value corresponds to a test of the null hypothesis that treatment probability is equal to 0.5. The unit of observation is the buyout fund. The sample consists of §3(c)7 buyout funds located in the U.S. with a North American geographic focus. ***, **, and * denote significance at the 1%, 5%, and 10%, respectively.

Bandwidth	All Funds	Treated Funds	Observed Treatment Probability	Bernoulli Test p-value
450	116	63	0.543	0.403
350	97	53	0.546	0.417
250	66	35	0.530	0.712

C. GP Anticipatory Effects

If GPs were able to anticipate the effect of the JOBS act, one would expect to observe a decrease in minimum commitment or an increase in target fund size in an attempt to capture more LPs into their funds. Table IX shows the results from a balance test under local randomization inference. The Fisherian p-values for minimum commitment and target fund size are not statistically significant, even as the bandwidth shrinks closer to the cutoff. The evidence is consistent with the identification assumption that GPs could not foresee the precise timing of the JOBS act and the corresponding variation on the intensive margin as a result of LP entry. The more important evidence from the table points to balance on GP ability. GP ability is an indicator for the top 100 GPs by capital raised for buyout funds in 2006 - 2010, a proxy for GP competitiveness at the time the funds are launched. In particular, the Fisherian p-values for GP ability are not statistically significant. The results provide direct evidence for randomization of GP ability on both sides of the cutoff, a critical assumption for identification. Overall, the test points to balance on GP and fund characteristics around the cutoff.

Table IX. Balance Test on GP and Fund Characteristics

This table formally tests for systematic differences between control and treated funds on GP and fund characteristics. Fisher exact p-values correspond to the effect of the 2012 JOBS act on GP and fund characteristics at the fund-level. The p-values are calculated within bandwidths of 450, 350, and 250 days. The *sharp null* hypothesis tests whether treatment has no effect on GP and fund characteristics. The Fisher p-value corresponds to the proportion of values of the difference-in-means test statistic under the randomization distribution that are as large or larger than the observed value. To ensure consistency with the continuity-based approach, inference uses a local linear polynomial and a triangular weighting kernel. The sample consists of §3(c)7 buyout funds located in the U.S. with a North American geographic focus. ***, **, and * denote significance at the 1%, 5%, and 10%, respectively.

Variable	Bandwidth	Control Mean	Treated Mean	Diff-in-Means Statistic	Fisherian p-value	Effective Observations
Minimum Commitment (log)	450	12.49	12.30	1.369	0.243	116
Target Fund Size (log)	450	5.93	6.39	0.187	0.483	100
GP Ability Proxy	450	0.17	0.27	0.023	0.753	116
GP Age	450	13.17	12.42	3.226	0.080*	115
Minimum Commitment (log)	350	12.37	12.14	1.575	0.224	97
Target Fund Size (log)	350	5.92	6.25	0.313	0.267	83
GP Ability Proxy	350	0.14	0.25	0.005	0.946	97
GP Age	350	11.50	12.06	3.965	0.067*	96
Minimum Commitment (log)	250	11.93	12.91	0.110	0.949	66
Target Fund Size (log)	250	5.91	6.20	-0.043	0.895	59
GP Ability Proxy	250	0.13	0.23	-0.049	0.571	66
GP Age	250	9.74	10.68	5.560	0.021**	65

1.8.3. Fisher Exact P-Values for the First-Stage and Reduced-Form Effects

Under Fisherian inference, the focus is not point estimation but rather testing the *sharp null* hypothesis of a zero treatment effect for each unit. The null of no treatment effect for each unit is *sharp* because missing potential outcomes can be imputed as equal to observed outcomes, allowing for the construction of the placebo (randomization) distribution. In contrast, the null of no average treatment effect (ATE) required for unbiased point estimation of the treatment effect is not sharp and thus necessitates the use of asymptotic approximations. In addition, the TSLS estimator necessary to obtain estimates of the (direct) second-stage effect of the composition of LPs in PE funds on fund performance outcomes relies on asymptotic approximations. Therefore, the paper relies on the continuity-based approach for point estimation and uses Fisherian inference to test the sharp null. The key advantage of the Fisherian approach is that it leads to correct inferences with a small number of observations, rendering the analysis at the fund level possible. In addition, it does not rely on sample size, statistical model, or asymptotic approximation assumptions. This section reports the Fisher exact p-values that correspond to the first-stage and reduced-form effects of the 2012 JOBS act on the composition of LPs in PE funds and fund performance outcomes.

Two properties of the *sharp null* allow for the construction of the randomization distribution. First, the unknown unit counterfactual potential outcome is equal to its observed outcome under the sharp null. That is, potential outcomes are no longer stochastic under the sharp null of a zero treatment effect for each unit. Second, potential outcomes are independent of treatment assignment under the sharp null. That is, counterfactual potential outcomes are the same as observed outcomes under any treatment assignment vector. These two properties allow for the construction of a placebo (randomization) distribution, the set of all test statistics for each possible treatment assignment vector. In practical terms, Fisherian inference boils down to generating the set of all possible treatment assignment vectors within a local window around the cutoff and calculating a unique test statistic for each possible assignment vector. The Fisher exact p-value corresponds to the proportion of test statistics under the placebo (randomization) distribution as large or larger than the observed test statistic under actual treatment assignment. This p-value represents the likelihood that chance could have produced the observed difference between treated and control funds.

Table X reports the Fisher exact p-values that correspond to the first-stage effect of the 2012 JOBS act on the composition of LPs in PE funds. The *sharp null* hypothesis is that there is no treatment effect for each fund and the p-values represent the likelihood that chance could have produced the estimate. Estimates are based on bandwidths of 450, 350, and 250 days around the 2012 JOBS act. The p-values for the number of LPs are very close to zero and highly statistically significant. The results are similar for the liquidity of LPs within the 250 bandwidth but not within the 350 and 450 bandwidths. Note the p-value is less than the critical value of 0.15 for the 350 bandwidth.[36] Overall, the results provide evidence against the no-difference null between treated and control funds with respect to the composition of LPs in PE funds.

[36] A large effect size is required for enough statistical power to detect an effect in small samples. The weaker results within the 450 and 350 bandwidths can be attributed to the small effect size in an already small sample due to the fund-level estimation. The results are stronger when the effect size doubles from about 3 within the 350-450 bandwidth to 6 within the 250 bandwidth.

Table X. Fisher Exact P-Values: Composition of LPs in PE Funds

The table reports the Fisher exact p-values that correspond to the first-stage effect of the 2012 JOBS act on the composition of LPs in PE funds within bandwidths of 450, 350, and 250 days. The *sharp null* hypothesis tests whether the 2012 JOBS act has a zero effect on the composition of LPs for *each* fund. The p-value corresponds to the proportion of values of the difference-in-means test statistic under the placebo distribution as large or larger than the observed value. The unit of observation is the buyout fund. To ensure consistency with the continuity-based approach, inference uses a local linear polynomial and a triangular weighting kernel. The sample consists of §3(c)7 buyout funds located in the U.S. with a North American geographic focus. ***, **, and * denote significance at the 1%, 5%, and 10%, respectively.

	Number of LPs		Liquidity of LPs	
	Effect Size	Fisher p-value	Effect Size	Fisher p-value
Bandwidth of 450 (Funds = 58)	41.5	0.01**	2.7	0.167
Bandwidth of 350 (Funds = 45)	60.1	0.00***	3.3	0.109
Bandwidth of 250 (Funds = 33)	74.5	0.00***	6.3	0.001***

Table XI reports the Fisher exact p-values that correspond to the reduced-form effect of the 2012 JOBS act on fund performance outcomes. Comparing fund performance outcomes at the same fund age ensures comparable performance for treated and control funds. Under PME, all reported p-values are close to zero and statistically significant. Under IRR, all but two p-values (age 3 for the 450 bandwidth and age 7 for 250 bandwidth) are close to zero and statistically significant. Under TVPI, all but three p-values (age 2-3 for the 450 bandwidth and age 3 for the 350 bandwidth) are close to zero and statistically significant. The Fisher p-values are closer to zero and are more statistically significant for age 4 or older funds, suggesting stronger effects among mature funds. The results are stronger at all fund ages within the smaller bandwidths of 350 and 250 days around the cutoff. Overall, the reported p-values reject the sharp null of no treatment effect with respect to fund performance outcomes. In addition, the small p-values suggest an almost-zero likelihood that chance could have produced the observed difference between treated and control funds.

Table XI. Fisher Exact P-Values: Private Equity Fund Performance

The table reports the Fisher exact p-values that correspond to the reduced-form effect of the 2012 JOBS act on fund performance outcomes within bandwidths of 450, 350, and 250 days. The *sharp null* hypothesis tests whether the 2012 JOBS act has a zero effect on performance outcomes for *each* fund. The p-value corresponds to the proportion of values of the difference-in-means test statistic under the placebo distribution as large or larger than the observed value. The unit of observation is the buyout fund and p-values are estimated for fund performance outcomes at the same fund age, measured in years from the first drawdown year. To ensure consistency with the continuity-based approach, inference uses a local linear polynomial and a triangular weighting kernel. The sample consists of §3(c)7 buyout funds located in the U.S. with a North American geographic focus. ***, **, and * denote significance at the 1%, 5%, and 10%, respectively.

	Buyout Fund Age							
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
				Bandwidth of 450 (Funds = 58)				
PME	0.000***	0.000***	0.028**	0.000***	0.000***	0.000***	0.000***	0.000***
IRR			0.311	0.005***	0.036**	0.002***	0.006***	0.061*
TVPI	0.004***	0.118	0.912	0.027**	0.001***	0.009***	0.018**	0.001***
				Bandwidth of 350 (Funds = 45)				
PME	0.000***	0.000***	0.001***	0.000***	0.000***	0.000***	0.000***	0.000***
IRR			0.023**	0.000***	0.007***	0.000***	0.003***	0.011**
TVPI	0.000***	0.007***	0.105	0.000***	0.000***	0.000***	0.002***	0.000***
				Bandwidth of 250 (Funds = 33)				
PME	0.000***	0.000***	0.007***	0.000***	0.004***	0.011**	0.012**	0.007***
IRR			0.013**	0.000***	0.046**	0.010**	0.110	0.000***
TVPI	0.010**	0.002***	0.050*	0.000***	0.002***	0.013**	0.053*	0.000***

1.8.4. Rosenbaum (2007) Interference Confidence Intervals

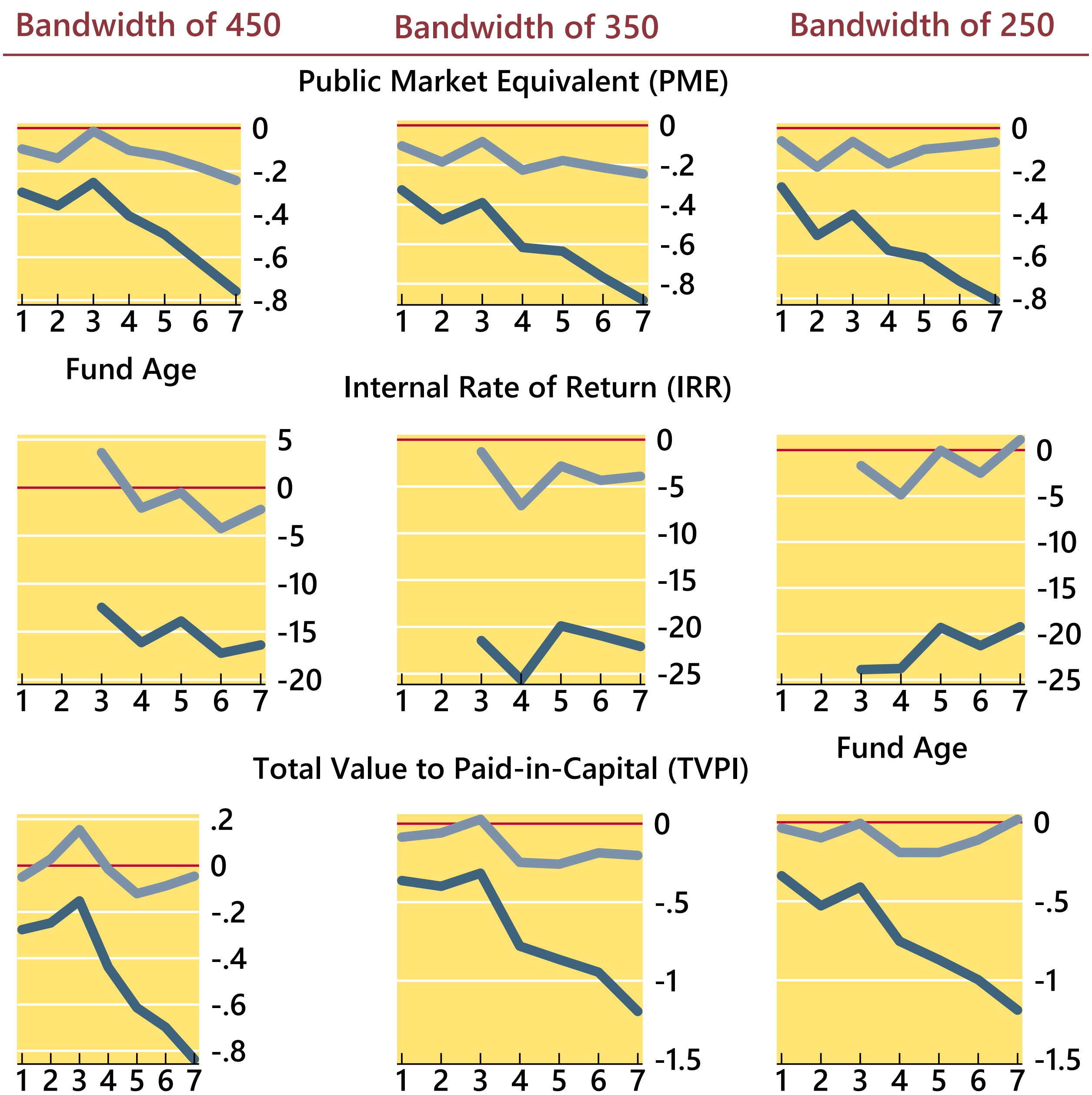
The construction of exact confidence intervals under arbitrary interference constitutes an important advantage of Fisherian inference. Interference refers to the possibility that a unit outcome response is affected by the treatment assignment of other units, violating the well-known stable unit treatment value assignment (SUTVA) assumption. The potential for interference entails that each unit can have many potential outcomes depending on the treatment assignment of other units. Rosenbaum (2007) proposes a methodology to construct confidence intervals that are robust to any structure of interference between units. To illustrate the idea behind the methodology, consider a placebo trial where units are randomly assigned to treatment and control groups, but treatment is withheld from all units. The key insight behind the methodology is that under the placebo trial, the particular value of the test statistic $\mathcal{T}_p$ is unknown, but the distribution of $\mathcal{T}_p$ is known given that the sharp null hypothesis of no effect holds by construction. Let a random variable $\triangle$ denote the difference in the values of the test statistic under the actual experiment $\mathcal{T}_a$ and the placebo trial $\mathcal{T}_p$. A confidence interval for the random variable $\triangle$ can be constructed using the $\alpha/2$ (κ_1) and $1-\alpha/2$ (κ_2) quantiles of $\mathcal{T}_p$ known randomization distribution for some level α. The confidence interval is thus $\triangle \in [\mathcal{T}_a - \kappa_1, \mathcal{T}_a - \kappa_2]$ with probability $1-\alpha$ and represents the relative average deviation of treated and control funds from the placebo zero-effect case.

The possibility of interference is relevant for fund performance outcomes (reduced-form) but not for the composition of LPs in PE funds (first-stage). There is no potential for interference between treated and control funds with respect to fundraising outcomes since the final close date concludes the fundraising process for a private equity fund. Funds that held a final close right after the act (treatment) cannot affect fundraising outcomes for funds that held a final close right before the act (control). There is, however, the potential for interference with respect to fund performance outcomes since funds closed right before the act (control) are chasing deals at the same time as funds closed right after the act (treatment). Treated funds that raised more capital from a larger set of LPs will raise market equilibrium deal prices, confounding observed fund performance returns for control funds. The paper, therefore, constructs the confidence intervals under interference for fund performance outcomes.

Figure 6 shows the 95% confidence intervals under interference for fund performance outcomes within bandwidths of 450, 350, and 250 days of the effective date. The confidence intervals under arbitrary interference represent a range for the excess benefit for treated funds relative to control funds, benchmarked against a placebo trial where treatment is withheld from all funds. Under PME and TVPI, the response range in fund performance outcomes to a change in composition is small in the early 1-3 years of the fund's lifecycle. The effects of the change in the composition of LPs in PE funds are more pronounced in the later years of the fund's lifecycle. For example, the confidence interval range for PME under the 450 bandwidth widens from [-0.01,-0.3] in year 3 to [-.24,-.76] in year 7 with similar trends for TVPI and across bandwidths. Under interference, the confidence interval is not a confidence interval for the point estimate given its construction as the difference between observed and placebo test statistics. The confidence interval range can thus be interpreted as the excess treatment benefit relative to the placebo trial under the possibility of arbitrary interference.

Figure 6. Interference Confidence Intervals: PE Fund Performance

The figures show the 95% confidence interval constructed under arbitrary interference based on Rosenbaum (2007) within 450, 350, and 250 days around the JOBS act effective date. The sample consists of §3(c)7 buyout funds located in the U.S. with a North American geographic focus.



1.9. Appendix: Fuzzy RDD Robustness Checks for Number of LPs

1.9.1. Sensitivity to Bandwidth Choice

This subsection investigates the sensitivity of estimates as funds are added or removed at the endpoints of the bandwidth window. Table XII shows the sensitivity of the fuzzy RD estimates to varying CER and MSE-optimal one-sided and two-sided bandwidths. 'msesum' minimizes the MSE of the sum of the regression coefficients while 'mserd' and 'msetwo' optimize the MSE of their difference. 'msecomb2' is the median of 'msetwo', 'mserd', and 'msesum'. CER bandwidths are defined analogously. The RD point estimates are broadly stable and highly statistically significant across all bandwidth types.

Table XII. Robustness: Sensitivity to Bandwidth Choice

		RD	Robust Inference		Bandwidth		
Outcome	BW Type	Estimator	p-val	CI	Left	Right	Observations
PME	cerrd	-0.006	0	[-.007 ; -.005]	328.739	328.739	315
IRR	cerrd	-0.153	0	[-.207 ; -.089]	255.199	255.199	164
TVPI	cerrd	-0.007	0	[-.009 ; -.005]	464.22	464.22	467
PME	certwo	-0.004	0	[-.005 ; -.004]	620.309	156.07	406
IRR	certwo	-0.219	0	[-.288 ; -.146]	496.328	288.063	278
TVPI	certwo	-0.010	0	[-.011 ; -.009]	518.354	136.784	323
PME	msetwo	-0.004	0	[-.005 ; -.004]	849.071	213.627	625
IRR	msetwo	-0.308	0	[-.434 ; -.136]	673.039	390.624	396
TVPI	msetwo	-0.008	0	[-.009 ; -.007]	708.573	186.98	461
PME	cersum	-0.007	0	[-.009 ; -.007]	431.359	431.359	448
IRR	cersum	-0.196	0	[-.265 ; -.118]	389.729	389.729	266
TVPI	cersum	-0.008	0	[-.008 ; -.006]	346.025	346.025	333
PME	msesum	-0.009	0	[-.015 ; -.007]	590.439	590.439	653
IRR	msesum	-0.215	0.008	[-.356 ; -.053]	528.486	528.486	401
TVPI	msesum	-0.007	0	[-.009 ; -.004]	473.006	473.006	476
PME	msecomb2	-0.011	0	[-.014 ; -.006]	590.439	449.974	554
IRR	msecomb2	-0.246	0	[-.340 ; -.111]	528.486	390.624	346
TVPI	msecomb2	-0.011	0	[-.014 ; -.004]	634.573	473.006	553
PME	cercomb2	-0.007	0	[-.008 ; -.006]	431.359	328.739	358
IRR	cercomb2	-0.195	0	[-.250 ; -.133]	389.729	288.063	223
TVPI	cercomb2	-0.008	0	[-.009 ; -.006]	464.22	346.025	391

1.9.2. Placebo Cutoffs

This subsection investigates whether the treatment effect holds at placebo cutoff points. Table XIII shows the results for placebo cutoff points using treatment and control funds separately. In particular, the alternative cutoffs of 500 and 700 days use treated funds only while the cutoffs of -500 and -700 days use control funds only. This sample restriction ensures that the estimation uses similar observations in their treatment status (i.e., 'no contamination' due to treatment). Almost all point estimates are not statistically significant from zero. At the cutoff of -700, the TVPI point estimate is statistically significant but the PME and IRR point estimates are insignificant. The paper uses the 500 alternative cutoff as a minimum to allow enough observations for the estimation. The broad conclusion is that fund performance metrics do not jump discontinuously at the placebo cutoffs.

Table XIII. Robustness: Placebo Cutoffs

	Alternative	RD	Robust Inference		MSE-Optimal	Observations	
	Cutoff	Estimator	p-val	CI	Bandwidth	Left	Right
PME	500	0	0.94	[-.002 ; .002]	116.742	98	53
IRR	500	0.632	0.761	[-16.3 ; 11.9]	89.459	52	18
TVPI	500	0.043	0.263	[-.532 ; .145]	94.57	79	27
PME	700	0.003	0.102	[.000 ; .005]	120.407	105	89
IRR	700	-0.252	0.683	[-1.06 ; .692]	216.45	92	69
TVPI	700	0.002	0.459	[-.002 ; .005]	145.36	107	90
PME	900	0.001	0.588	[-.002 ; .004]	333.618	220	162
IRR	900	0.013	0.898	[-.068 ; .077]	262.216	83	66
TVPI	900	0.002	0.368	[-.002 ; .007]	337.004	208	149
PME	-500	0.006	0.508	[-.020 ; .039]	492.965	285	267
IRR	-500	0.118	0.603	[-.784 ; .455]	235.457	87	98
TVPI	-500	0.003	0.161	[-.010 ; .002]	237.609	111	132
PME	-700	-0.003	0.108	[-.010 ; .001]	621.808	459	333
IRR	-700	0.137	0.719	[-.300 ; .436]	200.167	105	78
TVPI	-700	0.003	0.038	[.000 ; .009]	292.613	165	166
PME	-900	-0.051	0.582	[-2.19 ; 1.23]	205.524	123	140
IRR	-900	0.344	0.149	[-.422 ; 2.79]	294.729	147	155
TVPI	-900	0.003	0.4	[-.005 ; .014]	396.605	258	229

1.9.3. Sensitivity to Observations near Cutoff

This subsection investigates the sensitivity of the results to fund observations that are very close to the cutoff. The approach ensures that the results are robust to the extrapolation involved in the local polynomial estimation. Table XIV varies the radius from 15-55 days around the cutoff. The results from radius 15 and 55 are omitted since the number of excluded observations is the same as those of radius 25 and 45. Note that the results from the 25 and 35-day radius do not exclude any treated observations. Therefore, the most relevant radius is the 45/55 day radius, excluding both treated and control funds closest to the cutoff. The magnitude, sign, and statistical significance remain broadly stable under the 45/55 day radius test. The results further validate the baseline estimates from the fuzzy RDD design.

Table XIV. Robustness: Sensitivity to Observations near the Cutoff

	Donut	RD	Robust Inference		MSE-Optimal		Excluded Obs	
	Radius	Estimator	p-val	CI	Bandwidth	Observations	Left	Right
PME	45/55	-0.017	0.003	[-.047 ; -.010]	490.517	538	37	6
IRR	45/55	-0.308	0.051	[-.688 ; .001]	480.209	325	21	4
TVPI	45/55	-0.012	0.020	[-.035 ; -.003]	489.578	505	34	6
PME	35	0.009	0	[.005 ; .014]	759.083	878	29	0
IRR	35	4.182	0.886	[-20.1 ; 23.3]	588.800	418	15	0
TVPI	35	0.010	0	[.007 ; .018]	754.363	823	26	0
PME	25/15	-0.008	0	[-.009 ; -.005]	454.274	447	15	0
IRR	25/15	-0.210	0	[-.242 ; -.148]	383.641	253	7	0
TVPI	25/15	-0.007	0	[-.010 ; -.005]	431.749	407	14	0

Chapter 2

Does LP Composition Persistence Drive GP Performance Persistence in Private Equity?

2.1. Introduction

General Partner (GP) performance persistence remains an outstanding puzzle in the private equity literature (Kaplan and Schoar (2005), Robinson and Sensoy (2016), Phalippou (2010), Harris et al. (2020)). Return persistence at the GP level is considered a puzzle because variation in net-of-fees returns should be eliminated through competition. One strand of the literature attributes the puzzle to the heterogeneity in GP skills, albeit at odds with the lack of variation in GP compensation schemes (Gompers and Lerner (1999)). Another strand of the literature attributes the puzzle to the heterogeneity in LP liquidity in addition to GP skill (Lerner and Schoar (2004), Maurin et al. (2020)). The contribution of this paper is attributing the source of performance persistence at the GP-level to the persistence in the composition of Limited Partners (LPs) across GP-sponsored funds. An exogenous disruption in the persistence of LPs across GP-sponsored funds due to LP stake transfers results in a decline in GP performance. The evidence points to an important role for synergy among fund LPs for GP performance persistence. This finding reconciles the recent decline in performance persistence (Harris et al. (2014)) with the rise of the secondary market.

The paper documents significant persistence in the composition of LPs across GP-sponsored funds. Using the identities of fund LPs from Preqin, the paper documents that the majority of consecutive GP-LP investments are within 1-4 years. In terms of consecutive GP-LP investments, twice as many GP-LP pairs reinvest within two years in venture capital funds (42.1%) relative to buyout funds (21.7%).[1] Conditional on an initial GP-LP match, the probability of a future match is 43% for buyout funds relative to 45% for venture capital funds. The probability of a future GP-LP match increases from 6% and 2% within one year to 35% and 26% within four years for venture capital and buyout funds, respectively. Using the total number of fund LPs from SEC Form-ADV, the paper develops a measure for the overall liquidity of fund LPs. Previous fund, second previous fund, and third previous fund LP composition have a strong positive relationship with current fund LP composition.

The key endogeneity challenge in studying the role of LP persistence in GP performance is that the degree of LP persistence is endogenous to GP ability. To establish a credible causal link between LP persistence and GP performance, the paper relies on quasi-experimental variation in the persistence of LPs due to LP stake transfers. A transfer involves an LP selling its fund stake to one or more buyers. Because an LP stake transfer undermines LP's ability to subscribe to future funds, an LP will typically engage in a transfer due to an idiosyncratic liquidity shock rather than GP performance concerns. Because the GP will

[1]The shorter delay between consecutive GP-LP investments in VC funds is in part due to the shorter time it takes the GP to raise a venture capital fund relative to a buyout fund.

not ask the transferring LP to re-up for a follow-on fund, an LP stake transfer disrupts the persistence in the composition of LPs across GP-sponsored funds. The identification assumption is that the occurrence and timing of an idiosyncratic liquidity shock to the LP that results in a fund stake transfer is plausibly exogenous with respect to GP performance.

The identification assumption is violated if the GP can strategically time the LP transfer date or if the LP transfer affects the timing and sequencing of fund investments. The first possibility of strategic timing of an LP stake transfer arises if the GP perceives an LP stake transfer as a negative fundraising signal for the follow-on fund. In this case, the GP may have an incentive to delay the LP transfer until the final close of the follow-on fund. To address this possibility, the paper uses the final close date rather than the LP transfer date as the treatment date since the GP cannot anticipate a future LP transfer at the time of the fund's final close. The second possibility is that an LP transfer would affect fund performance by delaying or back-loading the fund's investment schedule. Delaying or back-loading the fund's investment schedule is highly unlikely for two reasons. First, the GP can acquire bridge financing or withhold LP distributions to cover interim capital calls. Second, changes to the fund's investment schedule would risk the GP's track record and its ability to garner future commitments. To address this possibility, the paper shows that the negative effect on GP performance is robust to excluding the fund that experiences the LP transfer from the sequence of GP-sponsored funds.

Using a local randomization regression discontinuity design, the paper estimates the effect of LP persistence on GP performance. In response to a disruption in LP persistence, the estimates translate to a 1.7% average decline in buyout per-year performance relative to a 2.6% average decline in venture capital per-year performance. The running variable is the fund series number and the cutoff is the fund series number corresponding to the first instance of an LP stake transfer at the GP level. The analysis compares the performance of funds closed right before (control) relative to right on or after (treatment) the first GP incidence of an LP stake transfer. The cutoff uses the final close date of the fund with the first incidence of an LP stake transfer rather than the actual transfer date. Using the final close date rather than the actual LP transfer date as the treatment date ensures that the sequencing of GP-sponsored funds relative to the first incidence of an LP transfer is effectively random. Two facts lend credibility to this assumption. The first fact is that the GP cannot foresee a future LP transfer at the time of fund final close. The second fact is that occurrence and timing of an LP idiosyncratic shock that results in a stake transfer are plausibly exogenous with respect to GP performance.

The causal channel between LP persistence and GP performance has two important implications. The first implication is that LP contribution to fund performance involves an element of synergy. Identifying the determinants of synergy among fund LPs would yield valuable insights into the economics of value-creation that drive the performance of private equity and venture capital funds. The second implication is that the persistence in LP performance (Lerner et al. (2007), Dyck and Pomorski (2016), Cavagnaro et al. (2019)) may also be driven by the persistence in the composition of LPs across LP-selected funds. The paper presents evidence (see Appendix 2.7) that unique LP pairs tend to invest together in the cross-section and over time. Establishing causal evidence between LP persistence and LP performance would reconcile performance persistence at the LP level with the persistence in the composition of LPs.

This paper contributes to a rich strand of the literature investigating the performance persistence puzzle in private equity. Robinson and Sensoy (2016), Kaplan and Schoar (2005), Phalippou (2010), and Harris et al. (2020) investigate GP-level persistence. Lerner et al. (2007), Dyck and Pomorski (2016), and Cavagnaro et al. (2019) investigate LP-level persistence. The persistence in returns at the GP-level is considered a puzzle given that variation in net-of-fees returns should be eliminated through competition. Chevalier and Ellison (1997) show that such persistence is absent from mutual funds, a liquid asset class. One explanation put forth by the literature is the heterogeneity in GP skills. The explanation is inconsistent with the lack of variation in GP compensation schemes (Gompers and Lerner (1999)). Hochberg et al. (2014), Marquez et al. (2010), and Glode and Green (2011) theoretically rationalize this inconsistency with asymmetric information about GP skills. Another explanation put forth by the literature is GP screening; GPs screen for liquid LPs that are better able to withstand liquidity shocks (Lerner and Schoar (2004) and Maurin et al. (2020)). The explanation rationalizes the persistence in GP performance with the willingness of skilled GPs to pay higher premiums for liquid LPs. The causal channel between LP persistence and GP performance established in this paper suggests the source of performance persistence is the persistence in the composition of LPs across funds.

The paper is organized as follows. Section 2.2 describes the data used in the analysis. Section 2.3 provides stylized facts about persistence in the composition of LPs across GP-sponsored funds. Section 2.4 describes the identification strategy used to isolate the effect of LP persistence on GP performance. Section 2.5 estimates the effect of persistence in the overall composition of LPs on GP performance. Section 2.6 concludes and discusses the implications of the findings.

2.2. Data

This section provides an overview of the data used in the empirical analysis. Subsection 2.2.1 describes the data, sources, and variable construction. Subsection 2.2.2 presents the descriptive statistics for the variables used in the estimation.

2.2.1. Data Description and Sources

Fund Performance: Preqin. The paper uses performance data from Preqin. Harris et al. (2014) compares Preqin with three other performance data sources (Burgiss, Cambridge Associates, and Venture Economics) and concludes that the dataset is unbiased, mitigating concerns about performance selection bias. Survivorship bias concerns are in part mitigated by the fact that Preqin maintains at least four sources for each fund and sources its data from both LPs and GPs. The analysis uses two metrics for fund performance – Total Value to Paid-in-Capital (TVPI) multiple and Public Market Equivalent (PME). TVPI estimates the number of times investors are likely to profit from their investment, used as reported by Preqin.[2] PME benchmarks the performance of the PE fund against a public index while accounting for fund cash flow timing, computed based on Kaplan and Schoar (2005) methodology using S&P 500 total return index. All fund performance metrics are measured at the same fund age in years from the first drawdown year, ensuring that fund performance is comparable across different performance metrics.

Investor Stake Transfers: Preqin. The paper uses a dataset of fund secondary transactions from Preqin. These transactions capture LP fund stakes sold on the secondary market after the final close date for a private equity or a venture capital fund. A fund may experience more than one secondary transaction throughout its life. Preqin collects secondary market transactions for a subset of funds.[3] For each transaction, the dataset discloses (when available) the buyer, seller, date, and type of transaction. The analysis is restricted to 'sole fund interest' and 'portfolio' type transactions, comprising 90% of all transactions. A sole fund interest transaction indicates fund-level LP liquidation, whereas a portfolio transaction indicates portfolio-level LP liquidation. The empirical estimation restricts the analysis to GPs that experience an LP stake transfer and uses the first instance of an LP stake transfer at the GP level.

Identities of Fund Investors: Preqin. The paper uses data on the identities of LPs that subscribe to a fund from Preqin. The dataset discloses the name, type, commitment

[2] Total value (numerator) is the sum of the distributions to investors and estimated remaining value on the fund investments, and paid-in-capital (denominator) is the amount of capital committed by LPs.

[3] Funds that are absent from the dataset may have experienced LP transfers that were not disclosed.

amount, and country of each investor that subscribes to a private equity or venture capital fund. It is important to note that the disclosed investors constitute only a subset of all investors that subscribe to a fund. As a result, persistence in the set of disclosed investors underestimates the degree of persistence in the overall set of investors. To gauge persistence based on the overall composition of LPs, the paper complements the data on the identities of LPs from Preqin with data on the overall number of LPs from SEC Form-ADV.

Number of Fund Investors: SEC. The 2010 Dodd-Frank Act required GPs to disclose private fund information on SEC Form-ADV. The requirement to disclose private fund information on SEC Form-ADV was effective March 30, 2012. Section 7.B.(1) of Schedule D has detailed information about private funds advised by each advisory firm. GPs must indicate the type of private funds advised, the adviser's services to the fund, and general information about the size and investors of the fund. The regulatory scrutiny over GP-reported information on the Form ensures that the data is accurate. The paper uses the number of LPs within a PE fund as reported by the GP in question 13 of Section 7.B.(1).[4] The reported number includes all investors that subscribe to the PE fund, either directly or through a feeder fund.

Liquidity of Fund Investors: Preqin & SEC. The paper uses the ratio of the number of LPs to fund size to capture the overall liquidity of investors that subscribe to a fund. The number of LPs is from SEC Form-ADV and fund size is from Preqin. It is important to note that the LPs-to-fund size measure is inversely related to the overall liquidity of LPs that subscribe to a private equity fund. Fewer LPs for the same fund size (i.e., lower LPs-to-fund size ratio) indicate that fund LPs' overall liquidity is high. The measure is motivated by the fact that the liquidity of an LP determines its contribution to overall fund capital. Liquid institutional LPs manage substantial private capital and invest significant due diligence efforts on the GP. To consider an investment with a GP, liquid LPs typically require a large allocation of fund capital. Anecdotal evidence suggests that liquid LPs even have institutional minimums, a fund commitment amount below which an LP will not invest with the GP. The measure thus captures the institutional feature that liquid LPs contribute a larger share of fund capital.

$$Liquidity of LPs = \frac{Number of LPs}{Fund Size}$$

[4]Note that a 'feeder fund' is considered a distinct structure from 'fund of funds' for reporting purposes on Form-ADV. An entity that invests 100% of its assets in the master fund is considered a 'feeder fund,' whereas an entity that invests 10% or more of its assets in other funds is considered a 'fund of funds.' A fund-of-funds LP will thus count as one investor on Form ADV.

2.2.2. Descriptive Statistics

The sample consists of buyout and venture capital funds located in the U.S. with a North American geographic focus, with a first drawdown year (vintage) before 2011. The focus on U.S.-based funds with a North American geographic focus ensures that funds have comparable performance. The focus on funds with vintages before 2011 ensures that the majority of cash flows are realized. The sample is restricted to GPs who experienced an LP stake transfer. The analysis separately compares buyout and venture capital funds. The unit of observation is the fund-age year. Table I presents the descriptive statistics. Venture Capital funds have fewer and less liquid LPs relative to buyout funds. The average number of LPs in buyout funds is 95 LPs relative to 59 LPs in venture capital funds. The average liquidity of LPs is 7 LPs per $100mn for buyout funds relative to 14 LPs per $100mn for venture capital funds, suggesting the VC funds have less liquid investors. PME and TVPI are similar on average for buyout and venture capital funds. The median fund size is $985mn for a buyout fund relative to $300mn for a venture capital fund.

Table I. Descriptive Statistics

The table provides the descriptive statistics for the variables used in the empirical analysis. The unit of observation is fund-age, where fund age is measured in years from the first drawdown year. The sample consists of buyout and venture capital funds with a vintage year before 2011 based in the U.S. with a North American geographic focus. The sample of funds is restricted to GPs that experienced an LP stake transfer.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Buyout Funds						
				Percentiles		
	N	Mean	SD	p10	p50	p90
Number of LPs	1,425	95.4	114.5	10.0	61.0	220.0
Liquidity of LPs	1,425	7.2	7.5	0.7	5.5	13.5
Public Market Equivalent (PME)	1,383	1.2	0.8	0.7	1.1	1.7
Total Value to Paid-in-Capital (TVPI)	1,317	1.5	0.9	0.8	1.3	2.2
Actual Fund Size ($, mn)	1,425	2,205.8	3,135.8	260.0	985.0	5,000.0
Vintage Year	1,425	2001	5	1994	2000	2007
Panel B. Venture Capital Funds						
Number of LPs	952	58.7	63.5	10.0	46.0	104.0
Liquidity of LPs	952	13.5	9.6	3.3	12.2	24.8
Public Market Equivalent (PME)	914	1.2	0.8	0.6	1.0	1.8
Total Value to Paid-in-Capital (TVPI)	910	1.5	1.4	0.6	1.1	2.8
Actual Fund Size ($, mn)	952	505.4	508.2	140.0	300.0	1,000.0
Vintage Year	952	2000	5	1994	2000	2007

2.3. Persistence in LP Composition at the GP-Level

This section investigates the degree of persistence in the composition of LPs across GP-sponsored funds. Subsection 2.3.1 investigates persistence in the identities of fund LPs using fund LP commitments from Preqin. Because the disclosed fund LPs in Preqin constitute only a subset of all LPs that commit capital to a fund, the documented persistence underestimates the full extent of persistence in the overall composition. To gauge persistence in the overall composition, the paper relies on the GP-disclosed total number of LPs that subscribe to a private fund on SEC Form-ADV. The paper then uses the ratio of the number of LPs to fund size to measure the liquidity of fund LPs. Subsection 2.3.2 investigates persistence in the overall number and liquidity of fund LPs using data from SEC Form-ADV.

2.3.1. Persistence in the Identities of Fund LPs

Figure 1 shows the gap between two consecutive investments by the same GP-LP for buyout and venture capital funds separately. The first important observation is that the majority of consecutive GP-LP investments are within 1-4 years. The second important observation is that twice as many GP-LP pairs reinvest within two years in VC funds (42.1%) relative to buyout funds (21.7%). The shorter delay between GP-LP investments for VC funds can in part be attributed to the shorter time it takes the GP to raise a VC fund due to its smaller size relative to a buyout fund. In particular, the average time it takes the GP to raise a follow-on fund in the sample is three years for a VC fund relative to four years for a buyout fund. The front-loaded investment pattern is consistent with a high degree of persistence between GP-LP pairs.

Figure 1. Gap in Years Between Consecutive GP-LP Investments

The figure shows the gap in years between two consecutive investments by the same GP-LP pair. The analysis conditions on GPs with at least two funds and LPs with at least two investments across years. The sample consists of U.S.-based buyout and venture capital funds with a North American geographic focus.

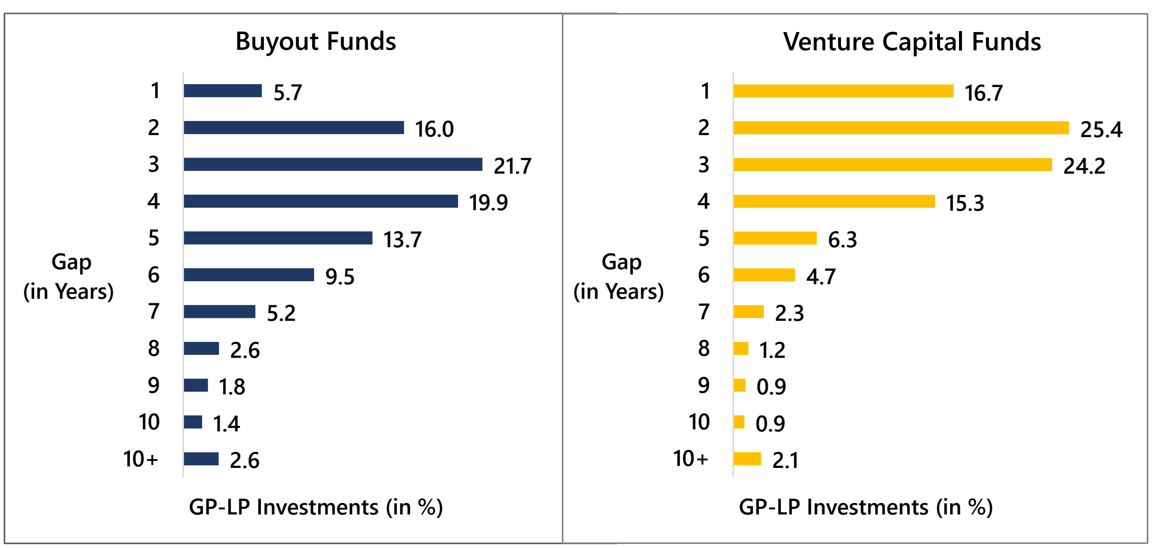
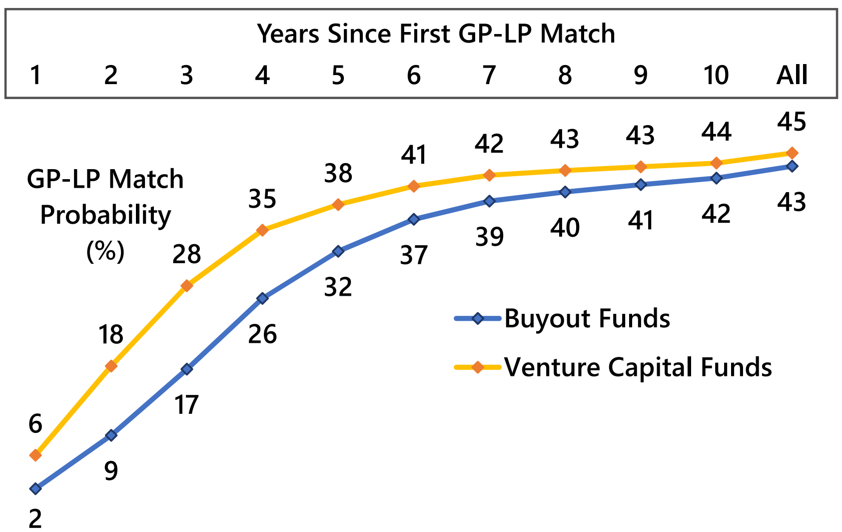


Figure 2 shows the probabilities of a future GP-LP match conditional on an initial match. The probability of a future GP-LP match conditional on an initial match is 43% for buyout funds and 45% for venture capital funds. From the first GP-LP match, the gap between VC and buyout funds widens in the early years (1-5) and narrows later (6-10). Within three years, the probability of a GP-LP match is 28% for VC funds relative to 17% for buyout funds. Within five years, the probability of a GP-LP match increases to 38% for VC funds relative to 32% for buyout funds. Overall, the evidence is consistent with a high probability of a subsequent match in the early years of a GP-LP relationship.

Figure 2. Transition Probabilities: GP-LP Match

The figure shows the probabilities of a future GP-LP match within 1-10 years conditional an initial match. There are 5,683 GP-LP pairs for VC funds and 11,462 GP-LP pairs for buyout funds. The analysis conditions on GPs with at least two funds and LPs with at least two investments across years. The sample consists of U.S.-based buyout and venture capital funds with a North American geographic focus.



2.3.2. Persistence in the Number and Liquidity of Fund LPs

Table II provides evidence consistent with strong persistence in fund LP composition across GP-sponsored funds. Panel A is based on regressions of the liquidity of fund LPs on lagged liquidity of fund LPs, controlling for the final close year. Liquidity of LPs is defined as the ratio of the number of LPs to fund size; a higher ratio is consistent with lower LP liquidity. Panel B is based on regressions of the number of fund LPs on lagged number of fund LPs, controlling for the final close year. Columns (1)-(4) show the results for Buyout funds, while Columns (5)-(8) show the results for Venture Capital funds. The coefficients on the lagged number and liquidity of LPs are positive and strongly significant. Previous fund, second previous fund, and third previous fund LP composition are statistically significantly related to current fund LP composition. Overall, the evidence is consistent with strong persistence in the overall composition of LPs across GP-sponsored funds.

Table II. Persistence in the Number and Liquidity of LPs

The table investigates the degree of persistence in the composition of LPs across GP-sponsored funds. Panel A investigates persistence in the liquidity of LPs, defined as the ratio of the number of LPs to fund size. Panel B investigates persistence in the number of LPs. $LiquidityofLPs_{t-1}$, $LiquidityofLPs_{t-2}$, and $LiquidityofLPs_{t-3}$ represent the lagged liquidity of LPs for previous funds of a given GP. $NumberofLPs_{t-1}$, $NumberofLPs_{t-2}$, and $NumberofLPs_{t-3}$ represent the lagged number of LPs for previous funds of a given GP. The sample consists of buyout and venture capital funds located in the U.S. with a North American geographic focus. Standard errors (reported in parentheses) are clustered at the GP level. ***, **, and * denote significance at the 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. Dependent Variable: $LiquidityofLPs_t$							
	Buyout Funds				Venture Capital Funds			
$LiquidityofLPs_{t-1}$	0.41***			0.17**	0.37***			-1.07***
	(0.09)			(0.08)	(0.14)			(0.18)
$LiquidityofLPs_{t-2}$		0.27***		0.23**		1.17***		0.93***
		(0.06)		(0.10)		(0.03)		(0.06)
$LiquidityofLPs_{t-3}$			0.15***	0.04			1.57***	1.67***
			(0.05)	(0.05)			(0.04)	(0.13)
Close Year F.E.	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.27	0.15	0.03	0.14	0.10	0.44	0.59	0.86
No. of GPs	188	118	71	71	156	99	58	57
No. of Observations	477	288	168	168	414	261	163	161
	Panel B. Dependent Variable: $NumberofLPs_t$							
	Buyout Funds				Venture Capital Funds			
$NumberofLPs_{t-1}$	0.69***			0.36*	0.47***			0.59***
	(0.08)			(0.18)	(0.15)			(0.08)
$NumberofLPs_{t-2}$		0.72***		0.50**		0.31*		-0.12
		(0.09)		(0.24)		(0.17)		(0.10)
$NumberofLPs_{t-3}$			0.60***	0.05			0.54***	0.45**
			(0.10)	(0.11)			(0.07)	(0.18)
Close Year F.E.	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.41	0.41	0.27	0.49	0.24	0.07	0.20	0.45
No. of GPs	188	119	72	72	162	103	61	61
No. of Observations	479	290	169	169	443	282	179	179

2.4. Identification Strategy: LP Stake Transfers

The primary challenge in identifying the effect of the persistence in the composition of LPs on GP performance is that the degree of persistence is endogenous to GP ability. A high degree of persistence in the composition of LPs across funds is likely correlated with GP ability, a significant driver of fund performance persistence. The ideal experiment in this setting would be to randomly disrupt the degree of LP persistence at the GP level to identify the effect of LP persistence on GP performance. To proxy for such an experiment, the paper relies on within-GP variation in the persistence of LPs as a result of LP stake transfers. LP stake transfers involve an LP selling its fund stake to one or more buyers and typically occur in the mid-stages of a fund's life. LP transfers bear significant reputational risk that undermines an LP's ability to subscribe to future funds. In particular, LP transfers signal a lack of the long-term illiquidity tolerance required to invest in the PE/VC asset class. It is, therefore, typical that an LP will engage in a transfer due to idiosyncratic factors such as unexpected liquidity constraints or over-allocation rather than GP performance concerns. The key identifying assumption is that the occurrence and timing of an idiosyncratic liquidity shock to the LP are plausibly exogenous with respect to GP performance.

An LP stake transfer disrupts the persistence in the composition of LPs at the GP-level on one important dimension - synergy. GPs typically rely on prior fund LPs to raise capital for a new fund. This feature leads to significant persistence in the composition of LPs across GP-sponsored funds over time. LPs are typically offered the opportunity to subscribe to the GP's next fund shortly after subscription and before fund returns on the current fund are realized. The critical feature of this structure is that GP fund-to-fund persistence in the composition of LPs is not contingent on prior fund performance. If an LP transfers its stake in a prior fund, the GP will not ask this LP to re-up for a new fund. For the fund that experiences an LP transfer, the GP is likely to transfer the LP commitment to one or more existing LPs given the time constraints of fund capital calls and the long due diligence process required for new LPs. For the consecutive fund to the LP transfer fund, the GP is likely to recruit new LPs to diversify its investor base and secure capital for future follow-on funds.[5] The composition of LPs will thus differ for the fund that experiences an LP transfer and consecutive funds. An important contribution of this setting is identifying whether LP contribution to performance depends on other fund LPs – involves an element of synergy. Synergies in fund LPs' contribution to performance may arise from

[5]The possibility of offering larger allocations to prior fund LPs in a follow-on fund is not feasible from a diversification standpoint. GPs want to diversify their financing sources to withstand systemic liquidity shocks and LPs want to maximize their return potential through diversifying their investment portfolios.

complementarities in investment objectives or expertise across fund target industries. The distinction identifies whether the persistence in GP performance is driven by the persistence in the overall composition or the specific identities of fund LPs.

2.4.1. Potential Threats to Identification

The first threat to identification is the possibility of strategic timing of an LP transfer date for an existing fund relative to the final close date of GP's next fund. GPs typically hold a final close on a new fund within 3-4 years of the final close of a prior fund. If the GP perceives the LP transfer as a negative signal for fundraising, GPs may have an incentive to delay the LP transfer date on an existing fund until the final close of the new fund. Evidence from secondary market transactions suggests that 40% of LP transfers occur within 3-5 years from the final close year of a PE/VC fund. The potential delay between the LP informing the GP of its intent to sell its fund stake and the actual sell (transaction) date matters for treatment timing. In particular, the GP may know that an LP will not retain its fund stake before the actual transaction date and not ask this LP to re-up for the new fund. Although the final close date of the new fund may precede the LP transfer date on the prior fund, the new fund will still experience a shock to LP persistence due to GP's knowledge about a future LP transfer. To address this possibility, the analysis uses the final close date rather than the LP transfer date as the treatment date. The GP cannot anticipate a future LP transfer on an existing fund at the time of the final close and does not have precise control over the order of the fund that experiences an LP idiosyncratic shock relative to its sequence of funds. Using the final close date instead of the LP transfer date as the treatment date ensures that the order of GP funds with respect to the first LP transfer is as-good-as-random.

The second threat to identification is the rare possibility that the LP transfer can affect the timing and sequencing of fund investments. First, an LP transfer could potentially delay the fund's investment schedule. The GP calls the committed capital from the LP on a deal-by-deal basis. If the LP informs the GP of its intent to sell its stake and refuses to meet a capital call, the delay could theoretically disrupt the fund's investment schedule. In practice, however, the GP is likely to acquire bridge financing to cover the capital call or withhold the capital call amount from the LP's distribution. Second, an LP transfer could alter the set or sequence of investment opportunities for the fund. In anticipation of an LP transfer, the GP may allocate the fund a smaller percentage of a new deal or back-load larger deals. In practice, however, the GP is unlikely to risk their performance track record. Although both possibilities are improbable, the paper excludes funds that experience an LP transfer as a robustness check. The results are broadly similar when excluding funds that experienced an LP transfer, suggesting that such possibility is remote.

2.5. The Role of LP Persistence in GP Performance

This section estimates the effect of persistence in the composition of LPs on GP performance using a local randomization regression discontinuity design.[6] The running (score) variable is the fund series number and the cutoff is the fund series number corresponding to the first GP incidence of an LP interest transfer. An LP interest transfer disrupts the persistence in the composition of LPs as the GP will not ask an LP that sold its stake in a prior fund to re-up for the next fund. The fund series number is constructed based on the chronological order of the final close dates of private equity funds raised by the GP. The analysis thus compares the performance of funds closed right before (control) and right on or after (treatment) the first GP incidence of an LP stake transfer. The cutoff uses the final close date of the fund with the first incidence of an LP interest transfer rather than the actual transfer date for two reasons. First, there may be a potential delay between LP informing GP of its intent to sell its stake and the actual sell date. Second, the GP cannot foresee a future LP transfer at the time of fund final close. Identification relies on the as-good-as-random order of GP-sponsored funds relative to its first incidence of an LP stake transfer. That is, the occurrence and timing of an LP idiosyncratic liquidity shock that results in a fund stake transfer are plausibly exogenous with respect to GP performance.

To identify the effect of the persistence in the composition of LPs on GP-level performance, the paper estimates a reduced-form local randomization specification of the form:

$$Performance_{ijt} = \alpha + \Gamma \cdot 1(t_{ij}^{FundSeries} \geq 0) + f(t_{ij}^{FundSeries}) + 1(t_{ij}^{FundSeries} \geq 0) \cdot f(t_{ij}^{FundSeries}) + \epsilon_{ijt}$$

where $t_{ij}^{FundSeries}$ is the fund series number based on the final close date of fund i normalized such that the first fund with the incidence of an LP interest transfer for GP j is at $t = 0$. $Performance_{ijt}$ represents fund performance metrics measured t years from the first drawdown year: PME_{ijt} is the public market equivalent benchmarked against the S&P500 total return index and $TVPI_{ijt}$ is the total value to paid-in-capital multiple. The panel consists of Fund-by-Age observations, where fund age is measured in years from the first drawdown year.

The sample consists of buyout and venture capital funds located in the U.S. with a North American geographic focus. Given that the analysis relies on within-GP variation, the estimation includes GPs with at least two funds in the sample. To ensure that performance is comparable across funds, the sample is restricted to funds with a first drawdown year

[6] The canonical continuity-based regression discontinuity design (RDD) does not apply to a setting with few mass points in a discrete running variable. The difference-in-differences (DiD) design is not applicable because control GPs may have experienced LP transfers that were not disclosed in the dataset.

(vintage) before 2011 to ensure that the majority of cash flows are realized. Given that the running variable – fund series number – is discrete, a parametric functional form for the relationship between outcomes and the running variable is required to extrapolate from the nearest mass points to the cutoff. The estimation uses a first-order polynomial (Gelman and Imbens (2019)) and a triangular weighting kernel. The estimation uses previous and consecutive funds to an LP transfer fund for the same set of GPs.

Table III shows the effect of LP persistence on GP performance. The estimates correspond to the reduced-form effect of an LP transfer on GP fund performance outcomes. Large sample (Neyman) p-values reported in curly brackets correspond to the *weak null* of no average treatment effect required for unbiased point estimation of the treatment effect. The effects are robust under finite-sample exact (Fisherian) p-values reported in brackets, corresponding to the *sharp null* of no treatment effect for each fund. The first column is estimated using first previous fund (control) and LP transfer fund (treatment). The second column excludes LP transfer funds, uses first previous fund (control) and first consecutive fund (treatment) to the LP transfer fund. The third and fourth columns include LP transfer funds and extend the treatment window to second consecutive fund.

The important observation from Table III is the strong negative relationship between a disruption in the persistence of LPs at the GP-level and GP performance. The estimated negative effects are robust to excluding LP transfer funds in the second column. Relative to buyout funds closed right before an LP transfer (control funds), the reduced-form estimates correspond to a decrease of 16% in PME and 17% in TVPI over the fund's life. Relative to VC funds closed before an LP transfer (control funds), the reduced-form estimates correspond to a decrease of 21% in PME and 31% in TVPI over the fund's life. In response to a disruption in LP persistence, the estimates translate to a 1.7% average decline in buyout per-year performance relative to a 2.6% decline in VC per-year performance. The greater decline in VC performance is consistent with a more significant role for synergy among LPs that subscribe to VC funds relative to buyout funds. Overall, the findings are consistent with a significant role for LP persistence in GP performance.

Table III. Effect of LP Composition Persistence on GP Performance

The table investigates the effect of persistence in the composition of LPs in PE funds on GP performance using local randomization inference. The estimates correspond to the reduced-form effect of an LP stake transfer on fund performance outcomes. The first GP incidence of an LP interest transfer is based on the fund's final close date rather than the transfer transaction date. The unit of observation is fund-age, where performance is measured in years from the first drawdown year. The first column is estimated using first previous fund (control) and LP transfer fund (treatment). The second column is estimated using first previous fund (control) and first consecutive fund (treatment) to the LP transfer fund. The third and fourth columns include LP transfer funds and extend the treatment window to second consecutive fund. The sample consists of buyout and venture capital funds located in the U.S. with a North American geographic focus. The analysis is restricted to GPs that have at least two funds. All specifications use a local linear polynomial and a triangular weighting kernel. Finite sample p-values are reported in brackets and large sample p-values are reported in curly brackets. ***, **, and * denote significance at the 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Buyout Funds							
	Public Market Equivalent (PME)				Total Value to Paid-in-Capital (TVPI)			
$1(t_{ij}^{FundSeries} \geq 0)$	-0.235***	-0.204**	-0.266***	-0.258***	-0.260***	-0.266***	-0.254***	-0.295***
	{0.001}	{0.013}	{0.003}	{0.002}	{0.001}	{0.001}	{0.007}	{0.001}
	[0.000]	[0.016]	[0.000]	[0.000]	[0.000]	[0.002]	[0.000]	[0.000]
Control Mean	1.282	1.282	1.282	1.282	1.541	1.541	1.541	1.541
Control S.D.	1.302	1.302	1.302	1.302	1.369	1.369	1.369	1.369
Estimation Window	[-1,0]	[-1], [1]	[-1,1]	[-1,2]	[-1,0]	[-1], [1]	[-1,1]	[-1,2]
Observations	724	579	949	1,057	693	546	898	1,004
	Panel B: Venture Capital Funds							
	Public Market Equivalent (PME)				Total Value to Paid-in-Capital (TVPI)			
$1(t_{ij}^{FundSeries} \geq 0)$	-0.197***	-0.246***	-0.147*	-0.162**	-0.406***	-0.470***	-0.343***	-0.387***
	{0.000}	{0.000}	{0.067}	{0.024}	{0.000}	{0.000}	{0.005}	{0.001}
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Control Mean	1.165	1.165	1.165	1.165	1.524	1.524	1.524	1.524
Control S.D.	0.711	0.711	0.711	0.711	1.277	1.277	1.277	1.277
Estimation Window	[-1,0]	[-1], [1]	[-1,1]	[-1,2]	[-1,0]	[-1], [1]	[-1,1]	[-1,2]
Observations	422	362	572	672	413	360	569	676

2.6. Summary and Implications

This paper investigates the role of LP composition persistence in GP performance. Using LP stake transfers as a source of exogenous disruption to the persistence of LPs across GP-sponsored funds, the paper documents a decline in GP performance following a disruption in the persistence of LPs. The effects are economically larger for Venture Capital funds relative to Buyout funds. The reduced-form estimates correspond to a decrease of 17% in Buyout performance relative to 26% in Venture Capital performance over the fund's life. The finding reconciles the performance persistence puzzle in private equity with the persistence in the composition of LPs across GP-sponsored funds. Overall, the results point to an important role for synergy among LPs within a fund in GP performance and performance persistence.

The contribution of LP persistence to GP performance point to several important avenues for future research. The first avenue is identifying the determinants of synergy among fund LPs to develop insights into the economics of value-creation in private equity and venture capital funds. Understanding these determinants would influence the decisions of LPs, GPs, and portfolio companies and advance our understanding towards an optimal composition of LPs within a fund for performance. The second avenue is identifying whether the persistence in LP composition also drives the persistence in LP performance. The fact that certain pairs of LPs tend to invest together (see Appendix 2.7) in the cross-section and over time may explain the observed persistence in the performance of LPs in the private equity market. Quantifying the causal channel between LP persistence and LP performance is a fruitful avenue for future research. In addition, identifying persistent LP clusters would shed light on LP investment patterns and its contribution to LP performance.

2.7. Appendix: Persistence in LP Composition at the LP-Level

2.7.1. Cross-Section and Time-Series Persistence

Table IV shows the degree of cross-sectional and time-series persistence in the identities of fund LPs. Conditional on an LP-LP match, the probability of another LP-LP match in the same vintage (cross-section) is 30% for buyout funds relative to 28% for venture capital funds. Conditional on an initial LP-LP match, the probability of another LP-LP match in a future vintage (time-series) is 45% for buyout funds relative to 40% for venture capital funds. It is important to note that the estimated transition probabilities underestimate the true degree of persistence in the composition of fund LPs because it is based on the set of disclosed LPs that may constitute only a subset of all LPs that subscribe to a private equity or venture capital fund. Overall, the findings are consistent with significant persistence in the composition of LPs in the cross-section and over time.

Table IV. Transition Probabilities: LP-LP Match

The table investigates the degree of LP-LP persistence in the cross-section and over time. Conditional on an initial LP-LP match, the cross-section probabilities correspond to another LP-LP match in the same vintage and the time-series probabilities correspond to a another LP-LP match in a future vintage. The sample consists of buyout and venture capital funds with vintages 1992-2014 and a North American geographic focus. The analysis is restricted to LPs that invested in at least two funds.

Panel A. Buyout Funds

Time-Series LP-LP Pairs			Cross-Section LP-LP Pairs		
	Probability	Frequency		Probability	Frequency
Match	44.85	51,161	Match	30.49	37,844
No Match	55.15	62,905	No Match	69.51	86,258
Total	100%	114,066	Total	100%	124,102

Panel B. Venture Capital Funds

Time-Series LP-LP Pairs			Cross-Section LP-LP Pairs		
	Probability	Frequency		Probability	Frequency
Match	40.06	18,330	Match	28.06	10,029
No Match	59.94	27,432	No Match	71.94	25,708
Total	100%	45,762	Total	100%	35,737

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