Very Preliminary

Impact Investing*

Brad M. Barber
bmbarber@ucdavis.edu
Graduate School of Management
University of California, Davis

Adair Morse
morse@haas.berkeley.edu
Haas School of Business
University of California, Berkeley & NBER

Ayako Yasuda
asyasuda@ucdavis.edu
Graduate School of Management
University of California, Davis

December 7, 2015

* We are grateful for the comments of seminar participants at Oxford University Saïd Business School. Radin Ahmadian, Christina Chew, and Derek Lou provided valuable research assistance. All errors are our own.

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Abstract

We study investments in impact funds, which we define as private equity funds with a stated mandate to fund companies that generate both financial returns and positive externalities. Using data on the capital commitments of 6,000 limited partners (LPs) into 10,000 funds, we examine the effect of impact on LP's fund choice within a general fund choice model. We focus on how fund choice varies by LP type (e.g., public pensions, foundations, endowments). Generally, prior LP-general partner (GP) relationships and LP-GP proximity are, by far, the most important determinants of LP fund choice. LP demand for impact may show up in tilts toward certain industries or locations. However, like most GP and LP attributes, fund industry and location per se do not materially affect LP fund choice. Controlling for these general determinants of fund choice, being an impact fund has a positive effect on the probability that an LP invests in the fund. The effect is only reliably large for development organizations, public pension funds, and banks. Furthermore, for most LP types, the designation of the LP being a United Nations Principles for Responsible Investment (UN PRI) signatory – a measure of demand by its constituents for impact – fails to predict investment in impact. Our findings shed light on the rich heterogeneity across LP types in the general determinants of PE investment, and the importance of impact as a fund characteristic.

If a long-lived global social planner existed, a number of social and environmental problems would be on her list of items to fix. Not all social and environmental concerns would make this list, and the fixes would not likely be Pareto or Coasian because of the nature of the problems, but the social planner would nevertheless devise effective mechanisms in the interest of global welfare. The world lacks a social planner to implement mechanisms that serve the global good, but faces the same set of social and environmental problems (e.g., addressing poverty or climate change). The perennial issue is that mechanisms require capital; someone must accept the tradeoff of a financial loss for the provision of globally enjoyed positive externality. Government aid is an obvious source of capital, but many argue that government programs are inefficient and subject to capture. Philanthropies are a second source of capital, but many argue philanthropies lack enough capital to fix the problems at hand. Private capital has the scale required to address social and environmental challenges, but financial instruments (e.g., public stocks) are designed to maximize financial returns for the providers of capital rather than generate a positive externality.[2]

In this paper, we address the following questions: How do investors value the provision of positive externalities as an attribute of an investment when making investment decisions? Does the preference for the provision of a positive externality depend on the source of capital (e.g., a public pension fund vs. endowment)? Do UN PRI signatories demonstrate a greater demand for impact investment?

There is clearly interest in knowing the answer to these questions. Virtually all major consulting groups have a social impact practice to meet the growing interest in these issues. Likewise, the major investment banks all have an impact division to meet private wealth and institutional demand for social considerations in investment. Tellingly, there has been a massive response to the United Nations Principles of Responsible Investment (UNPRI) call for action. As of 2015, nearly 1400 organizations representing $59 trillion in asset under management have signed the UNPRI. World capitalization of investable assets is around $175-$200 trillion; thus this is no small scale even relative to all investment. Signatories pledge to incorporate environmental, social, and governance issues into investment analysis and decision-making processes. To date, we have only limited anecdotal evidence that these pledges materially affect investment decisions, especially in the social and environmental realms. Proponents of the initiative argue the UN PRI initiative will change how capital is deployed and benefit society by doing so. Skeptics argue that the initiative has no binding power and thus is unlikely to materially change the deployment of capital.

[2] Allocating capital to investments that generate the best risk-adjusted returns can (and often does) address pressing social problems, but the allocation of capital is only optimal if all externalities (positive and negative) are reflected in price.

In this setting, impact investment has emerged as an attempt to mobilize private capital for public good. What distinguishes impact investment from previous socially responsible investment (SRI) movements is its focus on the deployment of capital with an expressed intent to address a social and/or environmental issue through private equity funds, which represents an increasingly important part of the portfolio of many institutional investors.[3] Impact investing stands in striking contrast to the long-standing tradition of divestment, where investors sold investments in companies that engaged in objectionable practices (e.g., the divestment of South African companies during the period of apartheid, the divestment of tobacco companies by many U.S. institutions, and recently the divestment of oil companies by some university endowments). Proponents argue that funding startup or growth companies in the private domain carries the greatest opportunity for achieving both impact and close-to-market financial returns, making it an efficient mechanism for implementing fixes to pressing problems.

Our main agenda is to quantify the demand for impact, which we define as the demand for generating positive externalities when investing capital. We also explore whether the demand for impact varies by limited partner (LP) type. To measure the demand for impact, we first develop a sample of impact funds, which we define as funds with a dual objective of generating impact (e.g., reduce greenhouse gas emissions, fight poverty, or generate local job growth) and a financial return. Using this criterion, we analyze a hand-collected sample of 146 impact funds, which PE general partners (GPs) launched over the period 1989-2013.

Empirically, we develop a general model where many LPs choose from many possible funds. In this framework, we are able to control for the general factors (e.g., LP characteristics, fund characteristics, and the relation between GP and LP) that modulate the demand for certain PE funds. To estimate the model, we use a Preqin dataset of capital commitments by more than 6,000 LPs to more than 10,000 funds. We manually classify each LP into one of 11 LP types reflecting the main providers of capital to PE funds: banks, corporations, government portfolios, development organizations, endowments, foundations, high-net worth households, insurance companies, pooled assets, private pension, and public pension.

We estimate the binary choice model separately for each of the 11 LP types and separately for VC vs. other funds (including buyout, real estate, and infrastructure funds). A unit of observation in our model is an LP-fund pair. Thus, for instance, our observations include CalPERS' investment decisions regarding two funds that were raising capital in 2005: "NGEN Partners II" and "Bain Capital Venture Partners 2005." CalPERS made a capital commitment to the NGEN fund, but not the Bain fund. Thus, our key dependent variable would take on a value of one for the first LP-fund observation (CalPERS'

[3] For example, US public pensions allocate 7% ($320B) of their aggregate assets under management to private equity as of June 2015.

investment in NGEN) and zero for the second LP-fund observation (CalPERS' non-investment in Bain). In addition to host of control variables (e.g., LP and fund location, fund size, and past GP performance), we include LP fixed effects (to absorb differences in the scale of PE investments across LPs) and time fixed effects (to absorb variation in demand over time).

To set the stage, we analyze baseline investment rates and the relative importance of factors that affect the LP demand for funds. We find that among a wide array of variables that describe fund and LP characteristics, and in striking contrast to the predictions of standard asset pricing models, two variables emerge as the primary drivers of fund choice for all the LP investor types – the prior investment relationship between the LP and GP and geographic proximity between the LP and GP. While prior studies document the importance of relationship or geography in LP choice of funds (e.g., Lerner, Schoar and Wongsunwai (2007); Hochberg, Ljungqvist, and Vissing-Jørgensen (2014); Hochberg and Rauh (2014)), our results document that the economic significance of these variables is enormous, particularly when compared to a myriad of other fund and LP characteristics. For example, the partial *r*-square of the prior relationship variable accounts for over ninety percent of all explained variation, while the geographic proximity variable accounts for the majority of the remaining explained variation for most LP types.

Our main analysis augments the baseline model with the key impact variable, which is a dummy variable that takes a value of one for our impact fund sample. Three main results emerge from our analysis.

First, we generally find that impact has a positive overall effect on the probability that an LP invests in the fund. The interpretation is somewhat subtle in our choice framework; LPs exhibit higher investment rates in impact funds relative to the supply of impact funds than they do in non-impact funds relative to the supply of non-impact funds. Assuming the market for PE funds is generally complete, our results imply that the supply of impact funds is incomplete, failing to keep up with demand.

Second, there is meaningful variation in the demand for impact across LP types. Demand for impact funds and thus a willingness to accept financial tradeoffs for externalities is large for development organizations, public pension funds, and banks. In contrast, the results for foundations are surprisingly mixed. We discuss how different LP types likely have different motives and face different institutional and/or regulatory constraints when investing that lead to the observed variation in the demand for impact. Development organizations often have a stated objective that is aligned with impact. The constituents of public pensions often value impact – both in the generation of economic opportunity in the region they serve and addressing more global concerns (e.g., climate change), which might affect economic growth. U.S. banks face regulatory requirements imposed by the Community Reinvestment Act to invest in the communities in which they serve. These cultural, regulatory, and political issues all likely combine to affect the demand for impact. Foundations run programs that are mandated to generate impact (e.g., through grants); however, our results suggest that the foundation investments are managed separately from program operations and are not generally invested in a way that generates impact.

Third, we document that UN PRI signatories are generally no more likely to invest in impact than non-signatories. We emphasize that this result does not mean the UN PRI initiative has had no material effect on investor behavior, but rather that the effect on investment, if any, has not been different for signatories and non-signatories. Nonetheless, this result suggests that being a signatory does not correlate with an increased demand for impact and raises several obvious questions. Why do so many institutions sign the UN PRI if their investments do not obviously reflect the environmental and social principles espoused? What factors cause an institution to sign the UN PRI initiative?

Our paper connects to the literature on variation in institutional preferences for securities in public markets. For example, Gompers and Metrick (2001) document the growth in institutional ownership in public markets and the resulting increased demand for large stocks. Bennett, Sias, and Starks (2003) document that over time the institutional appetite for small and risky stocks has grown. As in public markets, we show that the demand for private equities in general and that for impact in particular depends on the composition of investor (LP) types.

Our paper also relates to the growing private equity literature. Demand is central to our analysis, with a motivation akin to Lerner, Schoar and Wongsunwai (2007) who write "investors vary in their sophistication and potentially their investment objectives." While we focus on the demand for impact in our analysis, our analysis contributes more broadly to the literature on the determinants of the demand for private equity. Lerner et al. (2007) and Sensoy, Wang and Weisbach (2014) compare choices by one LP type – endowments, which historically have enjoyed preferential access to funds. In contrast, we analyze 11 LP types and the capital commitments of 6,000 LPs to more than 10,000 funds, and focus on understanding the importance of qualitative fund attributes (other than returns) as determinants of the demand for private equity.

Our contributions also extend to testing the demand for (and frictions against) impact investments, across LP types. There is now a burgeoning literature, spread across multiple disciplines, on socially responsible investing (SRI) that dates back as far as Milton Friedman's doctrine on responsible investing.[4] A survey by Renneboog, Ter Horst, and Zhang (2008) highlights the tension of SRI investing, concluding that investors in SRI funds may (but not with certainty) be willing to knowingly forego some financial returns for social or moral considerations. Consistent with the idea that investors in SRI funds value attributes other than performance, Benson and Humphrey (2008) show that SRI fund flows are less

[4] "The Social Responsibility of Business is to Increase Its Profits," The New York Times Magazine, September 13, 1970.

sensitive to performance than non-SRI flows. Similarly, Hong and Kacpercyzk (2009) hypothesize that stocks subject to widespread negative investment screens earn strong returns. Consistent with this notion, sin stocks (e.g., tobacco and gambling stocks) sport attractive valuation ratios and earn high returns. These findings are consistent with the notion that some investors are willing to sacrifice returns for other investment characteristics.

We contribute to this extant literature by inferring investor demand for impact from the fund choices in their private equity portfolios. To the best of our knowledge, our paper is the first to manually collect data on impact funds and to examine investor demand for funds within a broad fund choice framework. In particular, we shed light on rich heterogeneity among LPs in their preference towards impact as inferred from their fund choices. Finally, we are also the first to use the UNPRI signatory designations of institutional investors to measure demand for impact by end-constituents and examine whether this demand by end-constituents is reflected in the actual PE fund choices made by the signatories.

The remainder of the paper is organized as follows. Section I describes the private equity industry, impact funds, and the research hypotheses to be examined. Section II describes the data. Section III specifies the empirical model. Section IV presents and discusses the estimation results. Section V concludes.

I. IMPACT FUNDS IN THE PRIVATE EQUITY INDUSTRY

The Global Impact Investing Network (the "GIIN") defines impact investments as "those investments made into companies, organizations, and funds with the intention to generate social and environmental impact alongside a financial return. Impact investments can be made in both emerging and developed markets, and target a range of returns from below market to market rate, depending upon the circumstances."[5] In practice impact investment vehicles are often organized as private equity funds; another common format is a credit fund that provides below-market-return subsidized loans to enterprises.

We take this definition of impact funds in our paper. In particular, impact investments require active pursuit of positive externalities, not just avoidance negative externalities (sin stocks such as firearms, tobacco, etc.). Thus, impact investments can be thought of a segment of socially responsible investment (SRI) but is not synonymous with it. It is also important to note that for impact funds positive externality is a goal in of itself; it is not a by-product of return maximization, nor is it pursued because it is thought to boost returns. In contrast, we consider non-impact PE funds to be investment vehicles with a single stated objective of (risk-adjusted) return maximization. For example, a sector-focused fund that

[5] http://www.impactbase.org/info/about-impact-investing

invests primarily in alternative energy companies for the sole purpose of exploiting growth and profit opportunities in the sector is a *non-impact* fund, even though as a by-product of its profit maximization it may contribute to replacement of fossil fuel consumption with alternative fuel usage.

Bridges Ventures is an example of a PE firm that manages several impact funds in our sample. On the firm's website, it describes itself as "a UK-based private equity firm with the aim of combining financial returns with social and environmental impact."[6] Its limited partners include university endowments, banks, pension funds, and high-net-worth investors. Another example of an impact PE firm is Leapfrog Financial Inclusion Fund, which "invests capital, people and knowledge in purpose-driven businesses, helping them to grow, to be profitable and to have real social impact."[7] It counts among its limited partners a foundation, development organizations, an insurance company, and a pension fund.

A. Fund/Investor Characteristics and Fund-Investor Matches

In order for us to examine what types of investors demand impact investors, we need to also understand what other fund and GP characteristics investors consider when making PE fund investment decisions in general. What could explain the matches we observe in the data between PE funds and their investors? It is expected that, ceteris paribus, investors have higher demand for funds managed by GPs with better past performance than those with poor performance. Thus, good past performance should boost the likelihood of investment.

While some investors aim to hold well-diversified PE portfolios across countries/regions and sectors, others may exhibit tilts towards certain segments, e.g., geographic proximity may increase likelihood of investments for some investors. This could be due to information advantage, familiarity bias[8], or because investors desire generation of positive spillover effect on the local economy. Corporations may invest more heavily in PE funds that focus on sectors of strategic importance to them, e.g., pharmaceutical companies may invest more heavily in biotech VC funds than IT VC funds.

Before committing capital to a given fund, prospective limited partners incur costs in assessing the fund manager's current and past fund outcomes and the stated investment strategy/thesis of the follow-on fund that the fund manager is raising. This due diligence process is costlier if you have never invested in the manager's previous funds, whereas if you are an incumbent investor in the previous funds, you already have established personnel networks and communication channels with the fund manager, and thus you have an information advantage over outside investors in evaluating the prospective follow-on fund. Likewise, fund managers welcome incumbent investors' investments in follow-on funds, in part

[6] http://bridgesventures.com/about-us
[7] http://www.leapfroginvest.com
[8] See Atanasova and Chemla (2014) for evidence of familiarity bias in corporate pensions' investment patterns.

because their decisions to re-up send positive signals to outside investors and allow the manager to raise a larger follow-on fund than otherwise. Thus, the previous investment relationship, all else equal, is expected to increase the likelihood of investment.

To summarize, we want to control for these fund/GP, LP, and GP-LP characteristics so as to be able to isolate the effect of being an impact fund on the investor's demand.

B. The Effect of Impact Fund

Having controlled for these various fund/investor characteristics, what incremental effect would being an impact fund have on the investors' demand for that fund? Does this effect vary across different types of investors? For what types of investors is this likely a positive (negative) attribute?

In the U.S., the federal guideline supplementing the 1974 Employee Retirement Income Security Act (ERISA) states that ERISA fiduciary ".. may never subordinate the economic interests of the plan to unrelated objectives, and may not select investments on the basis of any factor outside the economic interest_of the plan",[9] though non-financial factors can be considered when they do not_adversely affect risk or returns. This strict interpretation of fiduciary duty is likely to dis-incentivize pension investors to invest in impact funds, for fear of being seen as sacrificing financial returns in return for positive externality. In other words, frictions against impact investments may operate particularly strongly for private pensions.

Private pensions are directly subject to ERISA, whereas state (public) pensions are subject to state-level regulations. In practice, state regulations often closely follow ERISA, so they may behave similarly to private pensions with respect to impact funds. At the same time, public pensions are often pressured to serve the political interests of their boards, which are often pro-labor and consider local job creation as an important policy goal. Thus, public pension investors may face a tension between the boards that pressure them to serve the local economy (e.g., by investing in impact funds that target improving welfare and employment conditions of underserved neighborhoods in the state, for example) on one hand, and the strong form of fiduciary duty that they are bound by. Net effect is therefore ambiguous for public pensions. Interestingly, impact funds are often loath to admit the existence of any trade-offs between positive externality they generate and the financial return they earn. It is possible that the rhetoric used by impact funds is in response to these fiduciary investors' needs to appear uncompromising in their search for financial returns. On the balance, we expect private pension funds to be less likely to invest in impact funds than in non-impact funds, whereas the direction is ambiguous for public pension funds.

[9] Johnson (2014).

In the U.S., commercial banks are subject to the Community Reinvestment Act (CRA), which is "intended to encourage depository institutions to help meet the credit needs of the communities in which they operate, including low- and moderate-income neighborhoods, consistent with safe and sound operations."[10] The CRA requires that each depository institution's record in helping meet the credit needs of its entire community be evaluated by the appropriate Federal financial supervisory agency periodically, and a bank's CRA performance record is taken into account in considering an institution's application for deposit facilities.[11] In efforts to satisfy this CRA requirement, banks are known to give grants to community-based organizations; thus it is also plausible that banks invest in impact funds that target improving credit access for low-income neighborhoods.

Foundations are non-profit organizations with explicit organizational missions that often overlap with the social and environmental goals of impact funds. Thus it is possible that foundations tilt positively towards impact funds in their PE portfolio choices. However, two potential institutional frictions exist. In the U.S., IRS requires foundations to maintain 5% annual payout rate to keep their tax exemption status. In particular, foundations can make investments designated as program-related investments (PRIs) and count these investments towards the 5% tax-exempt eligibility requirement if (i) The investment furthers the foundation's organization missions and (ii) Financial return is not a primary purpose of the investment. In practice, PRI investors are required to demonstrate that conventional investors maximizing returns would not invest at the same term as their investment terms. This is simple if the financial instrument used is a below-market return debt security, and precisely for this reason, below-market-return loan is a popular format for PRIs. In contrast, equity format is used much more rarely, possibly because of the perceived risk of violating the IRS eligibility requirement if it makes too much profit ex post. Loss of tax-exemption status is costly for foundations, and the risk of losing tax-exempt status may suppress foundations' demand for impact investments below where it would be otherwise.

Of course, foundations also manage their endowment portfolios and they could potentially invest in impact funds via their endowment portfolios. Mission-related investments (MRIs), when they exist, are distinct from PRIs and are part of endowment investments. However, historically endowment investment decisions have tended to be completely detached from pursuit of the organizational mission for the foundations, and investment staff and grant-giving staff rarely if ever are in contact with each other. A few high-profile foundations such as Gates Foundation are blurring the asset management side and the grant-giving side of foundation business, but their practice seems to remain the exceptions rather than

[10] http://www.federalreserve.gov/communitydev/cra_about.htm
[11] Ibid.

norms.[12] To summarize, while foundations seem to be the obvious entities to invest heavily in impact funds, in practice these frictions make their net effect ambiguous.

Finally, we expect development organizations (e.g., government development banks) to have positive tilts towards impact funds. They are typically non-profit entities with explicit organizational goal of generating positive externalities for a given region or country they serve. So for them there is no tension between their organizational goals and potential trade off between impact and returns.

C. UNPRI Signatories vs. Non-signatories

While in the previous section we discussed several hypotheses regarding the variation in the LP propensity to invest in impact funds *across* different LP types, we are also interested in examining any variation *within* an LP type. In particular, if an LP is an UNPRI signatory, does it significantly affect its likelihood of investing in an impact fund, relative to non-signatories of the same LP type? For example, among banks, do UNPRI signatory banks and non-signatory banks behave differently towards impact funds?

UNPRI pledge states the followings: "*As institutional investors, we have a duty to act in the best long-term interests of our beneficiaries. In this fiduciary role, we believe that environmental, social, and corporate governance (ESG) issues can affect the performance of investment portfolios (to varying degrees across companies, sectors, regions, asset classes and through time). We also recognize that applying these Principles may better align investors with broader objectives of society. Therefore, <u>where consistent with our fiduciary responsibilities</u>, we commit to the following:*

1. *We will incorporate ESG issues into investment analysis and decision-making processes.*
2. *We will be active owners and incorporate ESG issues into our ownership policies and practices.*
3. *We will seek appropriate disclosure on ESG issues by the entities in which we invest.*
4. *We will promote acceptance and implementation of the Principles within the investment industry.*
5. *We will work together to enhance our effectiveness in implementing the Principles.*
6. *We will each report on our activities and progress towards implementing the Principles*.

It is possible that there is heterogeneity among investors in their demand for impact funds, and that variation is positively correlated with their decision to sign the UNPRI. For example, some asset managers (e.g., Robeco) specialize in catering to end investors that demand SRI in their portfolio choices. For such institutional investors, being an UNPRI signatory elevates their credibility as asset managers in the eyes of their target audience, whereas for more conventional asset managers the cost associated with UNPRI compliance may be too high relative to its benefits. In this case, a separating equilibrium may be

[12] Strom (2011).

observed where signatories are more heavily tilted towards impact funds, reflecting the underlying demand by end investors.

Alternatively, UNPRI is signed by investors for reasons other than their demand for positive externality, e.g., some sort of "cheap talk" to satisfy their constituency for regulatory or marketing purposes. If the latter effect is dominant enough, then we may not see much correlation between UNPRI signatory and their likelihood to invest in impact funds relative to non-signatories of the same LP type. A third, non-mutually exclusive possibility is that larger investors tend to sign UNPRI with higher frequency than smaller investors, because the cost of compliance is more affordable for larger investors than for their smaller counterparts. Again, this effect will likely weaken any relationship between being an UNPRI signatory and being an impact investor, ceteris paribus. Thus the overall prediction is a priori ambiguous for this question.

II. DATA

We employ two primary datasets. We use Preqin data to identify LP investments in funds (the fund-LP dataset). Because of their differing nature, we separately analyze venture capital (VC) and other funds. The other funds are primarily buyout funds, but also include other fund types (e.g., real estate and infrastructure). For expositional ease, we refer to this category as buyout funds. For VC funds, the Preqin dataset contains information on about 3,000 LPs and 4,500 funds, which result in about 21,000 LP capital commitments. For the buyout sample, there are about 3,700 LPs, 5,900 funds, and almost 52,000 capital commitments. This dataset contains detailed information of LPs (including LP name and location) and funds (including fund name, size, industry, and type – venture v. buyout).

We marry this primary dataset with a hand-collected dataset of 146 impact funds (75 VC and 71 buyout funds). The key feature of this second dataset is the identification of funds that explicitly seek to address an environmental or social concern when deploying capital as, at a minimum, a dual objective alongside earning a financial return. We supplement the two primary datasets with a list of UN PRI signatories. In this section, we describe the key features of these datasets in more detail.

A. LP Data

Much of our analysis focuses on how the demand for PE in general and impact funds in particular varies across different LP types. To categorize LP Types, we conduct web searches for all LPs and categorize them into one of 11 LP types (Bank, Corporation, Development Organization, Government Portfolio, High Net Worth, Insurance, Pooled Assets, Private Pension, and Public Pension). Development organizations include multinational, national, and regional organizations that invest with development purposes in mind (e.g., International Finance Corporation, Ireland Strategic Investment Fund, and New

Mexico State Investment Council). Government portfolios currently include a heterogeneous mix of government agencies and primarily Chinese state-owned corporations, so we plan to recode in subsequent versions of the paper. High net worth LPs include family offices (e.g., Sobrato Family Holdings) or advisers who serve high net worth clients (e.g., BNY Mellon Wealth Management). LPs with pooled assets have broad client base (e.g., Blackrock). Private pensions are primarily corporate pensions, while public pensions include city, state, and national pension funds. The remaining LP types (banks, corporations, and insurance) are self-explanatory.

In figure 1, we plot the frequency of LPs by type separately for venture and buyout. For both venture and buyout, the top four LPs are foundations, pooled assets, private and public pensions. Corporations and development organizations are somewhat more active in venture than buyout. Perhaps because of the different scale of venture vs. buyout, large asset owners (e.g., public/private pensions, pooled assets, and foundations) tilt toward buyout.

In figure 2, we plot the frequency of LPs across eight broad regions. For both venture and buyout, LPs are heavily concentrated in North America and Europe, though the concentration is more pronounced for buyout.

The composition of LP types varies by region. For each of the eight regions (and the world) we calculate the percentage of LPs that fall into each of the 11 LP type categories separately for VC (figure 3) and buyout (figure 4). When we compare figure 3 to figure 4, there are modest differences in the composition of VC versus buyout; the biggest difference between VC and buyout emerges in Africa and South America where banks and corporations are more active in VC, while pooled assets and private pensions are more active in buyout. In contrast, there is large variation in the composition of LPs across regions. For example, in North America foundations and public/private pensions are the most prevalent LPs, while in Europe pooled assets are the most common LP type.

As discussed above, the majority of LPs are in North American and Europe, but the concentration of LPs varies considerably by LP type. We present the distribution of LP Regions by LP Type (i.e., summing across regions yields 100%) in figure 5 for VC and figure 6 for buyout. The composition of LPs is similar for venture and buyout. Foundations and endowments are heavily concentrated in North America. Public and private pension funds are also predominantly in North America. In contrast, banks, high net worth, and pooled assets are more prevalent in Europe.

In addition to the type and location of LP, we measure the experience and size of LPs. To measure LP size, we calculate the number of funds to which an LP committed capital over a rolling three-year window (*NUM_FUND*). To measure LP experience, we calculate the number of years since the LP first invested in a fund (*EXPER*). We separately construct the variables for venture and buyout. We also construct a dummy variable (*EXPERDUM*) that takes a value of one for LPs with more than 10 years of experience in venture (or buyout). Summary statistics on these variables are presented in table 1. On average, public pensions are investing in the largest number of funds (3.3 venture and 2.8 buyout funds) and have the most experience (8.68 and 8.80 years in venture and buyout). Nearly 40% of public pensions have invested in PE for 10 years or more. At the other end of the spectrum, corporations invest in relatively few venture or buyout funds (< 0.5 per year) and are relatively inexperienced (< 3 years of experience).

B. Fund Data

We analyze capital commitments to about 4500 venture and almost 6000 buyout funds with vintage years from 1985 to 2014, though about 75% of VC and 80% of buyout funds have vintage years of 2000 or later. We present descriptive statistics on funds in table 2. Buyout funds tend to be larger than venture funds and a higher proportion of venture funds are first-time funds. We define a GP of fund i raised in vintage year t as a top-tercile GP if the past fund performance of the GP is ranked in the top tercile among all GPs that raised at least one fund in year t; mid- and bottom-tercile GPs are analogously defined.

We use Preqin codes to identify the geographic focus of fund investments. Most funds invest only in one of the eight global regions (84% of VC and 73% of buyout). The remaining funds invest in multiple regions or lack geography data. We use these data to construct a series of geography dummy variables that take a value of one if the fund invests in the region. In table 2, we present the means across funds. (Note that the percentages sum to a number greater than one because the same fund can invest in multiple regions.) As was the case for investors (LPs), investments (funds) are also concentrated in North America and Europe.

We use Preqin codes to identify the industry focus of fund investments, where we collapse the industry codes into 11 different industries (business services, energy, consumer, industrials, information technology, health care, infrastructure, food and agriculture, real estate, and telecom/media/communications). Many funds invest in multiple industries; we categorize these funds as diversified funds. In table 2, we present the means of these dummy variables across funds; as was the case with the fund geography dummies, the fund industry dummies sum to a number greater than one because some funds invest in multiple industries. Buyout funds tend to be diversified across different industry categories. Relative to buyout, VC funds are more likely to be specialized in IT, health care, or telecom.

C. Impact Funds

Our second dataset is a hand-collected dataset of 146 impact funds, which we define as a fund with a stated objective of generating a positive externality (e.g., addressing climate change, generating jobs, reducing poverty, or reducing world hunger). We start with the universe of funds in Preqin's

Performance Analyst database. From these funds, we identify potential impact funds from a combination of keyword searches of articles about funds and managers and third-party lists of funds and managers. After compiling a set of potential impact funds, we manually read articles about funds and their managers to verify the impact orientation of the fund, which leaves us with a final sample of 170 impact funds. This step ensures that our sample of impact funds is clean. However, we recognize that there are likely some impact funds that do not make our sample because we simply lack information on the funds. Additional data requirements (e.g., requiring information on LPs invested in the fund) reduce the sample to 146 impact funds.

Impact funds have diverse goals, so it's useful to consider specific examples of impact funds in our final sample. Bridges Ventures is a London-based GP "…dedicated to sustainable and impact investment…" that uses an "…impact-driven approach to create returns for both investors and society at-large…"[13] that has several funds in our sample including the CarePlaces Fund, which builds care homes for the elderly, and Social Entrepreneurs Fund, which raised funds "…for investment in scalable social enterprises and charities delivering high social impacts and operating sustainable business models." NGEN Partners is a Manhattan-based GP that "…invests in companies that positively improve the environment and human wellness" and manages three funds in our impact dataset (NGEN Partners I and II, and NextGen Enabling Technologies Fund). The North Texas Opportunity Fund is a Dallas-based GP that Bloomberg describes as a GP that "…seeks to invest in companies located in or willing to expand operations to underserved North Texas region markets, with a special emphasis on the southern sector of Dallas. The firm invests in minority or women owned or managed companies located anywhere in North Texas."[14] Leapfrog is a GP that "…invests capital, people and knowledge in purpose-driven businesses, helping them to grow, to be profitable and to have real social impact."[15] Leapfrog is identified by ImpactAssets 50 as an experienced impact investment firm, which specializes in providing financial services to emerging markets (primarily Africa and India).

Returning to table 1, we present descriptive statistics on the 146 impact funds (75 VC and 71 buyout). For both VC and buyout, the average impact fund is much smaller than the mean size of other funds. Impact funds are less likely to invest in North America or Europe and have considerable investment in Africa relative to other funds. The VC and buyout funds tilt toward energy investments. Buyout impact funds appear in infrastructure and real estate, while VC impact funds tend to be diversified.

[13] Company website, November 17, 2015 (http://bridgesventures.com/about-us/).
[14] http://www.bloomberg.com/research/stocks/private/snapshot.asp?privcapId=156715
[15] Company website, November 17, 2015 (http://www.leapfroginvest.com/about-leapfrog/).

In figure 7, we present the distribution of LP types for impact vs. other funds. Public pensions and development organizations represent more than 60% of LPs that invest in the 146 impact funds. While these LP types are important in other funds, they are more important for impact funds. This is evident when we plot the change in share in a bar chart depicted at the bottom of figure 7. Of course, these are univariate comparisons of LP types across impact vs. other funds. In the next section, we investigate whether this variation in the demand for impact funds survives and is similar to these patterns when we control for other LP, fund, and fund-LP characteristics.

D. UN PRI Signatories

Our final dataset is a list of UN PRI signatories, which we download from the UN PRI website (http://www.unpri.org/signatories/signatories/). As of November 16, 2015, there were 1422 signatories (297 asset owners, 931 investment managers, and 194 professional service managers) who collectively manage $59 trillion. The UN PRI website (http://www.unpri.org/news/pri-fact-sheet/) indicates "…94% of signatories now have a responsible investment policy in place, covering a range of asset classes." We match UN PRI signatories to our LP dataset using investor names. LPs that are subsidiaries of a UN PRI signatory are also coded as a signatory.

Relative to other LPs, the UN PRI signatories tend to be more experienced and larger PE investors. On average, UN PRI signatories invest in about 3 VC and 2.8 buyout funds over a three-year horizon, roughly twice the number of capital commitments we observe in other LPs (see table 2). The average years of experience for UN PRI signatories is 7 years in VC and 8.5 in buyout, more than 50% more experience than other LPs (see table 2).

The percent of LPs that sign the UN PRI varies by LP type and region. In figure 8, we graph the percent of LPs that sign by LP type, with separate bars for VC and buyout. Across all LP types (far right of graph), 9.2% of all VC and 9.2% of buyout LPs are UN PRI signatories. By far, the LP type with the greatest percent of signatories is pooled assets (about 22%), followed by insurance and public pensions (about 12.5%). In general, the signatory patterns across LP types are similar for VC and buyout.

In figure 9, we graph the percent of LPs that sign the UN PRI by region. Recall that most LPs reside in developed Europe and North America, but the percent of LPs in developed Europe that sign the UN PRI is more than four times that of LPs in North America. LPs based in the developing regions of Africa, South America, and developed Asia also sign at relatively high rates, particularly LPs in the VC arena.

III. METHODS

We analyze the factors that explain the decision of an LP investor to choose one private equity fund over others. We begin by modeling this choice problem generally. Consider a market where there are $i=1,\ldots,N$ private equity funds raising capital and $j=1,\ldots, M$ LPs prepared to invest in private equity. This market generates NM possible fund-LP matches. [16] For each possible match, define INV_{ij} as a dummy variable that takes a value of one if LP_j invests in fund i and zero otherwise. We model this general choice problem along three main dimensions:

(1) Fund (or GP) characteristics (e.g., the targeted size of the fund or the GP's prior fund performance),

(2) LP characteristics (e.g., a large LP will invest in more funds), and

(3) Fund-LP match characteristics (e.g., whether LP i invested with the GP for fund j previously).

Specifically, we estimate the following logit model separately for each of the 11 LP types:

$$Logit(\pi_{ij}) = X_i\alpha + Y_j\beta + Z_{ij}\gamma + \varepsilon_{ij}$$

where π_{ij} is the probability that LP j invests in fund i, X_i is a matrix of fund (or GP) characteristics, Y_j is a matrix of LP characteristics, and Z_{ij} is a matrix of match characteristics for fund i and LP j. The associated vectors of coefficient estimates α, β, and δ (respectively).

To estimate this baseline model, we construct an unbalanced panel dataset. We begin by identifying all funds in the market during year t, N_t, and all LPs that invested in at least one of the funds in the market, Mt. For expositional ease, we suppress the time subscript (t) in equation X.

Our goal with this baseline model is to provide a reduced form control for the variables that affect the LP demand for a particular fund. Controlling for the baseline determinants of LP demand will allow us to more precisely estimate whether PE funds with the stated purpose of generating positive externalities generate LP demand and whether this demand varies as a function of fund, LP, and/or fund-LP match characteristics. In theory, there could also be a supply response if LPs have heightened demand for a particular type of fund (e.g., infrastructure funds). In practice, the supply response is likely slow so we believe it is reasonable to interpret estimated relations as reflecting LP demand.

In Table 3, we summarize the fund, LP, and match characteristics that we consider. Fund characteristics (Panel A) include the size of the fund, the performance of prior funds in the series, and the first-time fund dummy variable. For each LP type, we also include fixed effects for 12 sectors and 5

[16] See Ljungqvist et al. (2006) and Bottazzi et al. (2015) for studies using similar empirical models to examine underwriter-issuer matches and VC-portfolio company matches, respectively.

geographic regions. These fixed effects will allow us to test the null hypothesis that different LP types have similar sector and geographic demand for funds.

LP characteristics (Panel B) include measures of the LP's recent fund commitments to private equity, length of experience with private equity, and the LP type. We expect greater LP demand from LPs with large allocations to PE and a track record of PE investments.

Fund-LP match characteristics (Panel C) include fund-lp geography and fund-lp relationship. Hochberg and Rauh (2012) document that U.S. institutional investors (and particularly U.S. public pension funds) exhibit a substantial home bias in their PE portfolios, so we anticipate LP demand will be stronger for geographically proximate funds. We also anticipate that LPs will have greater demand for funds where the LP has an established relationship with the GP offering the fund.

This baseline model allows us to identify the economically important determinants of the demand for PE funds. In addition, the model provides a baseline control for the factors that affect the demand for impact investing. To explore the factors that affect the demand for impact investing, we augment our baseline model as follows:

$$Logit(\pi_{ij}) = X_i\alpha + Y_j\beta + Z_{ij}\gamma + S\rho + \varepsilon_{ij}$$

where S is a matrix of variables that we conjecture might affect the demand for impact investments and ρ is the associated vector of coefficient estimates.

The key variable underlying ρ coefficient estimates is IMPACT_i, which is a dummy variable that takes a value of one for funds with a stated objective of generating a positive externality. The direct effect of impact investing on the demand for a fund is captured by the standalone dummy variable, where we conjecture that impact investments have low demand relative to other PE funds because of the potential tradeoff between financial returns and the generation of positive externalities.

We are also interested in the variation in this demand for impact investments across LP types. For example, we conjecture that development organizations will have relatively strong demand for impact funds because they clearly interested in generating positive externalities. At the other extreme, LPs subject to strong fiduciary standards and those that manage intermediated or pooled capital will generally spurn impact investments because of the potential tension between financial returns and impact. Our empirical strategy will allow us to explore this variation by analyzing the variation in the coefficient estimate on the key dummy variation, IMPACT_i, across LP Type.

To assess whether UN PRI signatories are more likely to invest in impact funds, we interact the IMPACT_i with the UN PRI dummy variable. If the UN PRI principles are materially affecting the investment decisions of its signatories, we would expect the coefficient on this interaction variable to be positive.

We interact the key $IMPACT_i$ dummy variable with sector and geography fixed effects. These interaction allows us to assess whether there is stronger demand for impact funds with a particular sector or geography focus. For example, clean tech impact funds may generate stronger demand than funds targeting the alleviation of poverty. Similarly, impact funds with a China focus may generate stronger demand than funds with a U.S. focus.

Hochberg and Rauh (2013) document that U.S. LPs tilt their PE portfolios toward local funds, particularly U.S. public pension funds. There is a large literature exploring the reasons for local tilts in investor portfolios. Scholars hypothesize that informational advantages (Coval and Shumway (2001), Ivkovich and Weisbenner (2005)) and/or familiarity (Massa and Siminov (2006)) might drive the preference for local investments. In the context of PE, Hochberg and Rauh (2013) conjecture that U.S. state pension funds prefer local funds because these funds can be justified as spurring state economic development. To investigate whether some LPs favor impact funds *because* of their local tilt, we interact $GEOMATCH_{ij}$ with $IMPACT_i$.

Finally, to assess whether LPs are more likely to invest in impact funds launched by a GP with whom they have prior experience, we include the interaction of IMPACTi and RELATIONSHIPij.

IV. RESULTS

A. Baseline Model of Fund-LP Matches

We present the results of our baseline logit model in Table 4 for VC funds and Table 5 for buyout funds. For ease of presentation we also employ figures to summarize the main points that emerge from the analysis. To set the stage, we present the baseline investment rates by LP type in Figure 10. Recall that each LP investor can in principle invest in any fund in the market when they seek to invest. Thus, the baseline rates indicate the rate at which different LPs participate in the VC or buyout market. The overall investment rates for venture and buyout (far right bars) are roughly 0.9%. For both venture and buyout, the baseline investment rates vary by LP type. We currently do not seek to explain these differing rates, but rather take them as given and ask what characteristics affect cross-sectional variation in this baseline investment rate across LPs within a particular type. We do so in two ways. First, we measure what sets of explanatory variables are most important in explaining investments rates using partial R-Squareds. Second, we measure the economic significance of specific variables by scaling the marginal effects associated with a variable by the baseline investment rates of figure 10.

We present the partial R-Squared (coefficient of partial determination) for various sets of explanatory variables in the baseline linear probability model specification. (In subsequent drafts, we plan to adapt this to a logit specification.) Coefficients of partial determination are calculated by (i) estimating the full model and a constrained model where a set of variables of interest is omitted from the right hand side (reduced model), and (ii) taking the difference in sum of squared errors between the two models, and dividing it by the sum of squared errors from the reduced model:

$$\frac{SSE(reduced) - SSE(full)}{SSE(reduced)}$$

Figure 11 presents results for the full set of variables; figure 12 presents the same results rescaled after excluding the GP-LP relationship variable, which is the most important variable to explain LP choice of a particular fund. In both graphs, panel A presents results for VC while Panel B is buyout.

In Figure 11, the relationship variable between LPs and GPs has by far the largest partial R-squared of all explanatory variables in the baseline model. For venture (Panel A), the magnitudes vary from 0.05 for Banks to 0.20 for foundations, but in every one of the 11 LP types this variable dominates all others as the most important explanatory variable. This suggests that prior relationships matter the most in determining LP-fund matches in the VC fundraising market. In panel B, we see similarly singular importance of relationships in explaining the LP-fund matches in the buyout fundraising market. Magnitudes are somewhat muted, however, ranging from 0.04 for banks to about 0.11 for public pensions.

In Figure 12, we exclude the relationship variable from the figure and rescale the x-axis so that variation across other variables and across LP types is more easily viewed. For VC (panel A), geography match between GPs and LPs is the second most important variable (after prior GP-LP relationship) in explaining the matches between GPs and LPs. Magnitudes vary considerably across LP types, and is the most important for pooled assets, insurance, high net worth, development organizations, corporations, and banks. It is not very important for endowments.[17] The importance of geography match is less universally for buyout investments, as shown in Panel B: It is the second most important explanatory variable (after relationships) for only 3 LP types—development organizations, corporations, and Banks.

Note that a large partial R-squared for geo-match variables can stem from (i) a higher propensity of domestic investors to invest in local areas, (ii) aversion by foreign investors, or a mix of (i) and (ii). To unpack the partial R-squared result, we compute the average marginal effect (scaled by baseline likelihood for each group) of being a domestic vs. a foreign investor in each of the following 5 regions:

[17] The geography-match variable is constructed using (i) the fund's geographic focus and (ii) LP location for most LP types with the exception of development organizations. For development organizations, we used the LP's mission geographic focus rather than the HQ physical location. For example, a development bank headquartered in Washington, D.C., and targets developing countries in the Americas would be a geographic match to a fund focused on Latin America. We intend to construct a similar mission-based geography match variable for foundations and funds, but this is still a work in progress, so the current estimates for foundations reflect their HQ locations rather than the mission geographic focus. Thus, the reported partial R-squared of the geographic match for foundations is imprecisely estimated.

North America, developed Europe, developed Asia, Rest of the World (which consists of South America, Emerging Europe, and Africa), and developing Asia (which also includes the Middle East). The results are reported in Figure 13. Panel A shows that VC investors' tilts away from investments in certain foreign regions is as important as their tilts towards their own regions. For example, bank and development organization (many of which are development banks) LPs located outside of North America or Europe exhibit strong aversion to investing in VC funds located in those well-developed regions. In contrast, banks domestically located in North America or Europe are neutral with respect to their likelihood of investing in domestic funds (all relative to baseline probabilities). Note that these marginal effects are always scaled by appropriate baseline probabilities of a given LP type to invest in a fund, which are shown in Figure 9.

For other LP types, domestic investors in certain regions exhibit strong local bias. For example, endowments and foundations located in Africa, South America, Eastern Europe, and developing Asia/Middle East overwhelming prefer to invest in those regions of their own. A magnitude of 6 indicates that there is a 6-fold increase in the choice probability due to a geographic match, relative to the baseline unconditional probability of investing. Panel B for BO investments show qualitative similar results, though the magnitudes are somewhat smaller, as before.

B. Impact Fund Effect

To examine the investors' propensity to invest in impact funds and how this effect varies across different LP types, we estimate the logit model with an impact fund indicator variable and present the results in Table 6 (VC funds) and Table 7 (buyout funds). Again, we summarize the main takeaways from this analysis in a series of figures. (We also use linear probability models where practical because logit models significantly more time-consuming to run.)

Figure 14 presents the coefficients for the impact fund variable in various model specifications (using linear probability models for ease of estimation) scaled by the baseline investment propensity for each LP type. Five scaled coefficients (corresponding to the most spare to the fullest set of controlled included in the model, from top to bottom) are plotted in different bar colors for each LP type, according to the legend. "Impact w LPChar" is a model run with only LP characteristics and time dummy variables. "Plus Fund" is a model run with the previous set of controls plus fund characteristics. "Plus Relation" is a model run with the cumulative set of controls plus the relationship variable between LPs and fund's GPs. "plus Geography" further adds the fund geography focus and fund-LP geography-match variable. "Plus Industry" adds the fund industry focus as the set of controls to all the others.

According to the linear probability specifications, the impact fund coefficients are positive, large and significant for banks, corporations, development organizations, and public pensions for VCs; they are positive, large and significant for banks, development organizations, high net worth, and public pensions for BOs. Across the two asset classes the 3 LP types consistently tilt positively towards impact funds—Banks, development organizations, and public pensions. The results are consistent with the univariate results shown earlier in the paper.

Figure 15 presents the scaled marginal effects from the logit model using the full set of control variables (thus corresponding to the bottom bar for each LP type in Figure 14). Panel A presents the results for VC; Panel B presents results for BO. Stars *, **, and *** indicate statistical significance at 10, 5, and 1%, respectively. The qualitative results are similar to those in Figure 14, though the magnitudes of the scaled coefficients are more modest in the logit model. For example, a magnitude of + 0.4 (e.g., banks in the VC sample) indicates that being an impact fund increases bank LPs' propensity to invest by 40% of the baseline probability. For statistically significant result, magnitudes range from about 15% (for development organizations) to nearly 50% (for corporations). Notably, there are no measurable tilts for endowments and for private pension funds.

Panel B shows the results for the BO sample. Note that no coefficient is estimated for corporations because corporations never invest in impact BO funds in the sample. We find that, again, banks, development organizations, and public pensions exhibit significantly positive tilts towards impact funds, with economic magnitude of about 0.3 (relative to the baseline propensity). High net worth investors also exhibit strong tilts towards impact funds. The reason why they tilt towards BO but not towards VC may be because high net worth investors often invest in fund-of-fund vehicles, and impact fund-of-fund vehicles are mostly found in the BO sample. As before, endowments and private pensions exhibit no significant tilts towards impact funds. Surprisingly, foundations exhibit significant negative tilts away from BO impact funds.

To summarize, banks and development organizations tilt towards impact funds, as conjectured. Public pensions, despite their being subject to strong fiduciary duty (at least in the U.S.), also tilt towards impact funds, which suggests that the political pressure they face is perhaps stronger than the fiduciary duty constraint. In contrast, private pensions do not tilt towards impact funds, which is consistent with the ERISA being a major friction. Finally, foundations exhibit positive tilts towards VC impact funds but negative tilts away from BO impact funds. The dichotomy is intriguing in light of the conjectured tension between the mission-based nature of foundations and the IRS restrictions on PRIs that may dis-incentivize them from making PE-type impact investments. Clearly more work is needed to unpack the last result.

C. UNPRI Signatories vs. Non-Signatories

To examine whether UNPRI signatories and non-signatories invest in impact funds at differential rates, we interact our impact fund variable with the UNPRI indicator variable for LPs. Since UNPRI signatories tend to be large investors, it is important to scale the estimated marginal effects by differential baseline investment rates for signers and non-signers. The results are presented in Figure 16. As in the previous subsection, the full set of control variables (time dummy variables, LP characteristics, fund characteristics, the relationship variable between LPs and fund's GPs, fund geography focus variables, fund-LP geography-match variable, and the fund industry focus variables) are included in the estimation. These interacted coefficients are estimable for only 6 out of 11 LP types because for other LP types there were no impact fund investments by UNPRI signers and thus no variation in the data to exploit.

We find that being an UNPRI signer does not significantly increase an investor's chance of investing in an impact fund for the 3 LP types we identified as the main providers of capital to impact funds in the previous subsection – namely banks, development organizations, and public pensions. For these LPs, there appears to be no meaningful correlation between being an UNPRI signer and being an active impact fund investor.

We find meaningful variation between signers and non-signers in pooled assets (which mainly cater to retail investors) and private pension categories. For pooled assets, the overall positive effect found in the previous subsection is entirely driven by UNPRI signers; pooled asset managers who have not signed UNPRI do not exhibit any meaningful tilts towards impact funds. We interpret this result as suggestive evidence that some asset managers specialize in meeting the demands of end investors (primarily retail investors) to invest in funds that aim to generate positive externality as well as financial returns, and those asset managers sign UNPRI and invest in impact funds at higher rates, since they face less tensions between UNPRI pledges, impact investments and their fiduciary duty.

For private pensions, we find no meaningful tilts overall and among non-signers, whereas we find significant and positive tilts towards impact among the UNPRI signers, for both VC and BO samples. One possibility is that private pension funds located in non-U.S. countries are not subject to the ERISA-type strong form of fiduciary duty. In some of these cases, pensions' parent companies may face stronger societal pressure to be good citizens and responsible businesses, and such pressure may lead their pensions to sign UNPRI and to invest in impact funds, e.g., those that focus on local regions where the headquarters of the parent company is located. These are conjectures at this point, and we plan to examine the results further to test these conjectures.

In summary, we find no meaningful variation between UNPRI signers and non-signers among LPs who provide the bulk of capital to impact funds—banks, development organizations, and public pensions—but we do find meaningful positive correlation between UNPRI signatories and active impact investors and thus variation between signers and non-signers in their propensity to invest in impact funds among pooled asset managers and private pension funds.

V. CONCLUSION

We study the determinants of limited partner (LP) investments in private equity funds in general and impact funds in particular using LP and fund data for over 10,000 funds and over 6,000 investors. Based on our conjecture that PE investors are heterogenous in their latent demand for impact investments as well as the type of their constraints that potentially limit their exposure, we sort LPs into 11 types – public pensions, foundations, endowments, and the like – and examine the questions separately for each type.

We show that prior relationships and geographic proximity matter the most in explaining LP-fund matches. Other fund attributes – e.g., GPs' prior performance and industry focus – and LP attributes – e.g., prior experience in PE investments – explain relatively little. Importance of local bias suggests that investors' interests in impact funds may interact with their overall regional tilts.

We find that being an impact fund generally has a positive effect on the choice probability that an investor invests in a given fund relative to (LP type-specific) baseline probabilities; the magnitude of this effect is significant and consistently large for development organizations, public pension funds, and banks. Foundations (high-net-worth investors) tilt their investments towards VC (BO) impact funds but not towards BO (VC) impact funds. In contrast, endowments show no meaningful tilts towards impact funds.

We further examine whether UNPRI signatories, potentially a proxy for investors that desire impact, are more likely to invest in impact funds than non-signatories of the same LP type. We find that with the exception of pooled assets (catering generally to retail investors) and private pensions, UNPRI signatories' investment rates are not meaningfully higher than those of non-signers.

Our findings suggest that: (1) despite the fiduciary duty being a potential impediment, public pensions and banks have been the main providers of capital to impact funds, especially for locally-focused GPs; (2) endowments and private pensions do not exhibit any meaningful tilts towards impact investments; and (3) when they are UNPRI signers, private pensions and pooled asset managers (but not other LP types) appear to tilt more heavily towards impact investments than otherwise. Our anlayses shed light on the rich heterogeneity across LP types in their initial propensity towards impact investments in the industry's early years and identify several potential growth areas for increased capital supply in the future.

Appendix: Construction of Impact Fund Sample

We construct our dataset of impact funds as follows.

We create a dataset of articles that mention the Preqin funds in the article text using Factiva (and particularly Private Equity Analyst, a leading trade publication with extensive reporting on PE fundraising). From the article dataset, we identify *potential* impact fund by performing a keyword search (see Table A1 for a list of keywords). We review these articles and delete illegitimate word hits (e.g., keywords referred not to the fund but to another entity discussed in the article). From this process, we identify 56 managers of impact funds (e.g., a keyword "mission investing" appears in the article and describes one of the funds managed by the manager). We consider all PE funds managed by these 56 managers as potential impact funds ("text56" sample).

We also identify potential impact funds using data from the organizations that compile lists of impact funds (ImpactBase and Preqin) or GPs with impact investments (ImpactAssets and Cambridge) or:

(1) ImpactBase (www.impactbase.org) is an online directory of impact investment vehicles. Fund managers can register their impact funds and investors can search the database to identify funds they may be interested in. We downloaded funds listed in ImpactBase as potential impact funds ("ibase" sample) as of 2014.
(2) ImpactAssets (www.impactassets.org) is a 501(c)3 organization affiliated with Calvert Foundation. ImpactAssets annually selects a list of 50 firms that engage in impact investments "to demonstrate a wide range of impact investing activities". We downloaded the ImpactAssets manager lists for all years that are available from their website as of 2014 ("i50" sample).
(3) Preqin (www.preqin.com) is a leading provider of data and intelligence for the alternative assets industry. Its fund database has a field called "fund ethos", and GPs of funds have the option to report their fund as falling into one or more of the following 6 categories – "Economic Development", "Environmentally Responsible", "Microfinance", "Sharia Compliant", and "Socially Responsible". We exclude "Sharia Compliant" but downloaded all funds that check at least one of the other five "fund ethos" categories as of 2014 ("ethos" sample).
(4) Cambridge Associates (www.cambridgeassociates.com) is a leading investment advisor to foundations, endowments, private wealth, and corporate and government entities. As part of their advisory service to their investor clients Cambridge compiles a list of mission-related investing managers (MRI Manager Database). We obtained the list of managers as of May 2013 ("Cambridge" sample). This list includes many very large GPs that do not specialize in impact investments (e.g., Blackstone).

At this stage, we cast our net broadly and consider all GPs with at least one impact investment. Specifically, we identify all funds managed by GPs that (a) manage an ibase fund, Preqin ethos fund, or text56 fund or (b) are listed as a GP with impact investments by ImpactAssets or Cambridge Associates. This results in 777 funds – far more than our final sample because we include *all* funds managed by GPs with impact funds, which includes some GPs with many funds but only a few are impact funds (e.g., Blackstone and Hamilton Lane).

For these 777 funds, we read detailed fund and/or GP descriptions from vendors (Capital IQ, Thomson One), PE firm websites, and the original source articles from Private Equity Analyst. This process yields 170 impact funds. Finally, we require that there is data about at least one LP per fund in Preqin, which leaves us with our final sample of 146 impact funds.

Table A1: Impact Investment Search phrases

base of the pyramid	greenhouse	social objectives
bottom of the pyramid	impact investing	social responsible
clean air	impoverished	socially conscious
clean water	indigenous	socially motivated
community invest	invest ethical	socially responsible
disadvantaged	investing ethical	socially-motivated
double bottom line	low carbon	SRI
dual bottom-line	low-carbon	sustainable agriculture
environmental impact	lower-carbon	sustainable development
environmental objective	minority community	sustainable economic development
environmentally clean	minority-owned	sustainable farming
environmentally conscious	missing middle	sustainable forestry
environmentally motivated	mission driven	sustainable investment
environmentally sustainable	mission investing	sustainable property
ethical invest	mission related	sustainable water
ethical objectives	mission-driven	tribe
ethically conscious	mission-related	triple bottom line
ethically motivated	poverty	triple bottom-line
ethically-conscious	S.R.I.	women owned
ethically-motivated	social finance	women-owned
green energy	social good	
green focused	social impact	

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Table 1: LP Summary Statistics by LP Type

For each of the LP types and all LPs, we present descriptive statistics by first averaging all observations for a unique LP and then calculating the mean (standard deviation) for each variable across N LPs. No. of Funds per LP (NUM_FUND) is the number of funds to which an LP commits per year (averaged over the last three years). LP Years of Experience (EXPER) is the number of years since the LPs first capital commitment, and % LPs > 10 years Experience (EXPERDUM) is a dummy variable that is equal to one if the LP has invested in Venture (or Buyout) for more than 10 years.

	Venture				Buyout			
LP Type	N (No. of LPs)	No. of Funds per LP	LP Years of Experience	% LPs > 10 years Experience	N (No. of LPs)	No. of Funds per LP	LP Years of Experience	% LPs > 10 years Experience
Bank	220	0.65	3.23	0.11	233	0.76	3.65	0.12
		(0.76)	(4.18)			(0.80)	(4.24)	
Corporation	332	0.35	1.49	0.04	140	0.49	2.35	0.07
		(0.54)	(2.94)			(0.68)	(3.55)	
Dev. Org.	244	0.95	3.43	0.14	151	1.52	6.04	0.29
		(1.40)	(4.34)			(1.79)	(5.71)	
Endowment	168	1.55	5.08	0.20	258	1.28	4.87	0.20
		(2.08)	(5.80)			(1.88)	(5.74)	
Foundation	442	1.38	4.98	0.20	584	1.33	5.29	0.21
		(1.96)	(5.49)			(1.71)	(5.41)	
Gov't Port.	36	2.17	5.28	0.18	45	1.86	5.12	0.19
		(3.80)	(6.13)			(3.85)	(6.83)	
HNW	139	0.72	2.73	0.09	188	0.75	3.23	0.11
		(1.23)	(4.05)			(1.23)	(4.49)	
Insurance	276	1.77	5.39	0.22	384	1.61	5.86	0.26
		(2.67)	(5.90)			(2.44)	(6.32)	
Pooled Assets	511	1.57	4.33	0.17	600	1.54	5.07	0.21
		(2.78)	(5.48)			(2.53)	(5.87)	
Private Pens.	384	2.34	7.00	0.33	640	1.74	6.27	0.28
		(3.02)	(6.52)			(2.46)	(6.30)	
Public Pens.	362	3.31	8.68	0.38	483	2.80	8.80	0.39
		(4.48)	(7.39)			(3.98)	(7.98)	
ALL LPs	3114	1.58	4.88	0.20	3706	1.57	5.62	0.24
		(2.70)	(5.87)			(2.50)	(6.22)	

Table 2: Fund Summary Statistics

This table presents the summary statistics for VC and buyout funds in the LP-fund sample. The first column indicates the number of funds in the all sample; the second column indicates the mean values for the all sample; and the third column indicates the mean values for the impact fund sample.

	VENTURE				Buyout			
	All Funds N=4546		Impact Funds N=71		All Funds N=5933		Impact Funds N=75	
Variable	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Vintage Year	2003.23	6.92	2004.32	5.26	2005.15	6.30	2007.17	3.98
Fund Size ($M)	148.65	218.17	61.42	58.87	706.23	1399.49	238.10	205.75
First-time Fund	0.36	0.48	0.35	0.48	0.25	0.43	0.30	0.46
Top Tercile GP	0.32	0.47	0.36	0.48	0.50	0.50	0.39	0.49
Medium Tercile GP	0.31	0.46	0.28	0.45	0.25	0.43	0.27	0.45
Fund Geography Focus:								
North America	0.54		0.44		0.52		0.45	
Developed Europe	0.24		0.17		0.29		0.24	
Emerging Europe	0.06		0.08		0.08		0.13	
Africa	0.02		0.11		0.02		0.18	
Central and South America	0.02		0.16		0.02		0.06	
Developed Asia	0.07		0.01		0.07		0.00	
Emerging Asia	0.12		0.07		0.09		0.10	
Middle East	0.03		0.00		0.01		0.00	
All Regions	1.11		1.04		1.10		1.15	
Fund Industry Focus:								
Business Services	0.02		0.04		0.06		0.03	
Energy	0.06		0.24		0.06		0.21	
Consumer Discretionary	0.04		0.07		0.11		0.03	
Diversified	0.28		0.48		0.58		0.41	
Industrials	0.03		0.01		0.13		0.11	
Information Technology	0.47		0.12		0.08		0.00	
Health Care	0.23		0.09		0.04		0.00	
Infrastructure	0.01		0.01		0.01		0.10	
Food and Agriculture	0.01		0.04		0.01		0.01	
Materials	0.01		0.01		0.04		0.07	
Real Estate	0.00		0.00		0.01		0.10	
Media and Communications	0.13		0.05		0.05		0.01	
All Industries	1.28		1.17		1.18		1.08	

Table 3: Summary of Key Independent Variables

This table presents the definitions of key independent variables use in the model estimation. Panel A defines the fund characteristics; Panel B defines the LP characteristics; Panel C defines the Fund-LP match variables; and Panel D defines the impact investment variables.

Variable	Description
	PANEL A: Fund Characteristics
LOGSIZEi	Log of fund size for fund *i*
TOPi	=1 if the past fund performance of the GP managing fund *i* raised in vintage year *t* is ranked in the top tercile among all GPs in the market in year *t*, and 0 otherwise.
MEDIUMi	=1 if the past fund performance of the GP managing fund *i* raised in vintage year *t* is ranked in the middle tercile among all GPs in the market in year *t*, and 0 otherwise. (omitted category = BOTTOM)
FIRSTi	=1 if fund *i* is its GP's debut fund, and 0 otherwise.
μ_{sec}	Fund industry sector fixed effect (see Table 2).
μ_{geo}	Fund geography fixed effects (see Table 2).
	PANEL B: LP Characteristics
NUM_FUNDjt	Average number of funds committed per year by LP *j* in the last 3 years; a proxy for LP *j*'s PE portfolio size.
EXPERIENCEDj,t	= 1 if LP *j* has invested in PE funds for 10 years or longer as of time *t* (when it is in the market to invest in a new fund)
UNPRIj	=1 if LP j is an UN PRI signatory institution.
	PANEL C: Fund-LP Match Characteristics
GEO_MATCHij	=1 if fund i's fund geography focus is in the same region as LP j's HQ location (8 regions are as defined in Table 2)
RELATION_Dij	=1 if LP j has invested in funds previously raised by fund i's GP
	PANEL D: Impact Investment Variables
IMPACTi	=1 if fund i is an impact fund
*IMPACTi*UNPRIj*	=1 if fund *i* is an impact fund and LP *j* is an UNPRI signatory
*IMPACTi*NON-SIGNERj*	=1 if fund *i* is an impact fund and LP *j* is not an UNPRI signatory

Table 4: Logit Estimates of Demand for VC Funds

The dependent variable is an indicator for an LP investing in a VC fund. Presented are marginal effects from a fixed effects logit estimation. Each column is an estimation for a different sample of LPs and continues onto a second page. The dataset sets up a matrix of all LPs active in the VC market this year, making yes/no choice decisions among all VC funds of the vintage. Investment per year fixed effects are fixed effects from pooling LPs with the same number of average investments per year. We control for LP charactertistics that are dynamic -- the number of fund an LP has invested in the past three years and the experience level overall with PE investing. Fund-level variables of demand include the size of the VC fund, whether the fund is the first fund for the GP, whether the fund in the past was a top or middle tertile performer, industry, and georgraphy. The match explanatory variables include whether the LP has previously invested in the fund series and whether the LP and the fund investment focus are in the same region as denoted. *,**, and *** indicate 1%, 5%, and 10% significance levels.

	Sample of LP Choices:	Bank	Corporation	Development Org.	Endowment	Foundation	Government Portfolio	HNW	Insurance	Pooled Assets	Private Pension	Public Pension
LP Characteristics	Investment/Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Number of funds	-0.0000568	-0.000306**	-0.0000371	-7.78e-05***	-0.000209***	-0.0000192	-0.000178***	-4.87e-05***	-7.13e-05***	-0.000129***	-7.45e-05***
		[6.27e-05]	[0.000126]	[2.40e-05]	[2.53e-05]	[2.26e-05]	[4.96e-05]	[6.77e-05]	[1.70e-05]	[1.18e-05]	[1.29e-05]	[8.09e-06]
	Experience	-1.11E-04	-0.000205	-0.0000635	-0.000477**	-0.000727***	-0.000454	-0.000515	-2.09E-04	-0.000385**	-0.000506***	-0.000681***
		[0.000198]	[0.000338]	[0.000162]	[0.000225]	[0.000177]	[0.000720]	[0.000409]	[0.000178]	[0.000153]	[0.000144]	[0.000124]
Fund Characteristics	Log (Size)	0.000204***	0.000267***	-0.000245***	0.00117***	0.00145***	0.000321	0.000851***	0.00102***	0.00165***	0.00189***	0.00157***
		[6.83e-05]	[0.000103]	[5.99e-05]	[1.00e-04]	[7.45e-05]	[0.000197]	[0.000145]	[8.02e-05]	[7.01e-05]	[7.11e-05]	[6.14e-05]
	Size Missing	-0.000369	-0.0000634	0.000121	-0.00137***	-0.00163***	-0.00140*	-0.00137**	-0.000384	-0.00167***	-0.00147***	-0.00129***
		[0.000254]	[0.000334]	[0.000225]	[0.000457]	[0.000330]	[0.000809]	[0.000626]	[0.000274]	[0.000315]	[0.000280]	[0.000210]
	First Fund of GP	0.00102*	0.00133	0.000863*	-0.00144**	-0.000714	-0.000524	0.00349*	0.00220*	0.000815	0.0000872	0.00430***
		[0.000599]	[0.000887]	[0.000479]	[0.000732]	[0.000681]	[0.00165]	[0.00200]	[0.00127]	[0.000714]	[0.000788]	[0.00108]
	Missing Performance	0.000580**	0.00123***	0.000299	-0.000771**	0.000897***	0.00249***	-0.000278	-0.000358	-0.000934***	-0.000644***	-0.00303***
		[0.000293]	[0.000428]	[0.000245]	[0.000353]	[0.000272]	[0.000928]	[0.000567]	[0.000253]	[0.000235]	[0.000230]	[0.000225]
	Top Performer	0.000253	0.000806	-0.0000467	-0.00222***	-0.000367	0.00169	0.00251	0.00112	-0.000554	-0.000126	0.00162
		[0.000666]	[0.000986]	[0.000535]	[0.000741]	[0.000696]	[0.00187]	[0.00206]	[0.00128]	[0.000731]	[0.000785]	[0.00109]
	Medium Performer	0.000596	0.00119	0.000315	-0.00212***	-0.000731	-0.000549	0.00211	0.00207	0.000235	-0.0000135	0.00215**
		[0.000596]	[0.000885]	[0.000479]	[0.000717]	[0.000673]	[0.00165]	[0.00201]	[0.00126]	[0.000710]	[0.000779]	[0.00108]
LP - Fund Match Variables	Prior Relation	0.00610***	0.0135***	0.00879***	0.00914***	0.0137***	0.0121***	0.0116***	0.00966***	0.0121***	0.0107***	0.0113***
		[0.000625]	[0.000809]	[0.000494]	[0.000605]	[0.000499]	[0.00131]	[0.00103]	[0.000520]	[0.000400]	[0.000384]	[0.000356]
	LP&Fund N.America	0.00297***	0.00227***	0.00585***	0.00577***	0.00511***	0.00895***	0.00307***	0.00444***	0.00269***	0.00224***	0.00403***
		[0.000288]	[0.000331]	[0.000266]	[0.000867]	[0.000516]	[0.000936]	[0.000434]	[0.000290]	[0.000184]	[0.000239]	[0.000218]
	LP&Fund Europe	0.00451***	0.00464***	0.00567***	0.00665***	0.00642***	0.00879***	0.00753***	0.00692***	0.00479***	0.00498***	0.00668***
		[0.000449]	[0.000439]	[0.000363]	[0.000503]	[0.000370]	[0.00131]	[0.000729]	[0.000353]	[0.000268]	[0.000308]	[0.000250]
	LP&Fund Dev Asia	0.00683***	0.00815***	0.00812***		0.0110***	0.0185***	0.0105***	0.00963***	0.0108***	0.00885***	0.0114***
		[0.000735]	[0.000722]	[0.000584]		[0.00140]	[0.00465]	[0.00222]	[0.000774]	[0.000511]	[0.00135]	[0.000824]
	LP&Fund ROW	0.00532***	0.00893***	0.00364***	0.00979***	0.0138***	0.0153***	0.00642***	0.0133***	0.0126***	0.0143***	0.0152***
		[0.000583]	[0.00112]	[0.000310]	[0.00194]	[0.00168]	[0.00190]	[0.00190]	[0.000919]	[0.000857]	[0.000911]	[0.000890]
	LP&Fund Emrg Asia	0.00441***	0.00496***	0.00421***	0.00461***	0.0125***	0.0118***	0.00514***	0.00888***	0.00810***	0.00996***	0.0109***
		[0.000443]	[0.000456]	[0.000317]	[0.00126]	[0.00129]	[0.00141]	[0.000949]	[0.000527]	[0.000423]	[0.000883]	[0.000896]

Fund Characteristics Continued: Industry and Geography

Sample of LP Choices:	Bank	Corporation	Development Org.	Endowment	Foundation	Government Portfolio	HNW	Insurance	Pooled Assets	Private Pension	Public Pension
Each column estimation continued from prior page…											
Business Services	0.000223		0.000529	-0.00324**	0.000428	-0.00197	0.0000725	0.00265***	0.000605	0.000840**	-0.000425
	[0.000427]		[0.000353]	[0.00135]	[0.000519]	[0.00166]	[0.000974]	[0.000368]	[0.000433]	[0.000407]	[0.000429]
Energy	0.0000443	0.00203***	0.000830***	-0.00235***	0.000679**	-0.000697	0.00103*	-0.000238	0.000722**	-0.00018	0.0000575
	[0.000282]	[0.000354]	[0.000245]	[0.000604]	[0.000322]	[0.000872]	[0.000548]	[0.000370]	[0.000303]	[0.000313]	[0.000266]
Consumer	0.000298	-0.00146**	-0.000630*	0.000782**	0.000686**	-0.000921	-0.000798	-0.0000938	0.0000233	-0.0000595	0.000700***
	[0.000348]	[0.000728]	[0.000339]	[0.000389]	[0.000331]	[0.00122]	[0.000857]	[0.000378]	[0.000351]	[0.000289]	[0.000232]
Diversified	0.0000896	-0.00184***	-0.000592***	-0.000979***	0.000895***	-0.00225***	-0.000468	0.0000919	-0.000998***	-0.000409*	0.000292
	[0.000227]	[0.000377]	[0.000222]	[0.000338]	[0.000243]	[0.000765]	[0.000503]	[0.000252]	[0.000238]	[0.000211]	[0.000178]
Industrials	0.000295	-0.00154**	0.000179	-0.00108	-0.000295	0.000111	-0.000267	0.000431	-0.00138***	-0.0000183	0.000297
	[0.000319]	[0.000722]	[0.000315]	[0.000729]	[0.000473]	[0.00118]	[0.000919]	[0.000405]	[0.000473]	[0.000381]	[0.000317]
IT	0.0000868	-0.000212	-0.000285	0.000393	0.0000241	0.000456	0.000144	0.00012	0.0000908	-0.0000666	-0.000121
	[0.000194]	[0.000275]	[0.000185]	[0.000246]	[0.000191]	[0.000582]	[0.000380]	[0.000186]	[0.000174]	[0.000148]	[0.000133]
Health Care	0.000107	0.000685**	0.000275	-0.0000538	0.000354*	0.0000629	-0.000196	0.000634***	0.000266	0.000712***	0.0000705
	[0.000201]	[0.000287]	[0.000196]	[0.000229]	[0.000186]	[0.000610]	[0.000390]	[0.000187]	[0.000173]	[0.000142]	[0.000130]
Infrastructure	0.00107**	-0.00043	0.000859*	0.00138*	0.00174***	0.00142	0.00188	-0.00107	0.00027	-0.000185	0.00120**
	[0.000503]	[0.00106]	[0.000513]	[0.000718]	[0.000586]	[0.00190]	[0.00118]	[0.000970]	[0.000670]	[0.000637]	[0.000545]
Food & Agriculture	0.00114**	-0.00031	0.000692*		0.00319***	0.00282*	-0.00182	0.000808	-0.000353	-0.00352*	-0.00528**
	[0.000462]	[0.000918]	[0.000410]		[0.000644]	[0.00157]	[0.00253]	[0.000869]	[0.000895]	[0.00200]	[0.00213]
Materials	0.00104	0.00146	0.00104*	0.000221	-0.00105	0.000766			-0.000123	-0.00131	0.000206
	[0.000743]	[0.000963]	[0.000593]	[0.00168]	[0.00144]	[0.00289]			[0.00113]	[0.00165]	[0.000999]
Telecom	-0.000814***	-0.000595*	-0.000383*	-0.000830***	-0.000508**	0.000182	-0.000589	0.0000102	-0.000327*	-0.000119	0.000115
	[0.000266]	[0.000333]	[0.000232]	[0.000249]	[0.000210]	[0.000622]	[0.000426]	[0.000201]	[0.000182]	[0.000155]	[0.000138]
North America	-0.00145***	-0.00139***	-0.00474***	-0.00394***	-0.00277***	-0.00478***	-0.00101**	-0.00152***	-0.00195***	-0.000518*	-0.00159***
	[0.000269]	[0.000326]	[0.000280]	[0.000897]	[0.000542]	[0.000789]	[0.000499]	[0.000315]	[0.000204]	[0.000276]	[0.000241]
Europe	-0.00185***	-0.00207***	-0.00380***	-0.00134***	-0.00110***	-0.00216*	-0.00336***	-0.00126***	-0.00122***	-0.000864***	-0.000998***
	[0.000421]	[0.000434]	[0.000317]	[0.000336]	[0.000244]	[0.00119]	[0.000737]	[0.000298]	[0.000258]	[0.000199]	[0.000182]
Developed Asia	-0.00219***	-0.00226***	-0.00307***	-0.00130**	-0.000972**	-0.00436***	-0.00195**	-0.000522	-0.00174***	-0.000192	-0.00105***
	[0.000582]	[0.000613]	[0.000409]	[0.000522]	[0.000387]	[0.00156]	[0.000938]	[0.000449]	[0.000431]	[0.000333]	[0.000366]
ROW	-0.0000467	-0.000457	0.00102***	-0.000133	0.0000508	0.00111*	-0.000305	-0.00100***	-0.000649***	-0.00175***	-0.00191***
	[0.000221]	[0.000393]	[0.000216]	[0.000476]	[0.000333]	[0.000573]	[0.000572]	[0.000343]	[0.000249]	[0.000364]	[0.000290]
Emerging Asia	-0.000839***	-0.0000206	-0.000572**	0.00035	0.000374	-0.00416***	0.000608	-0.000413	-0.000582**	-0.000127	-0.00110***
	[0.000307]	[0.000339]	[0.000232]	[0.000312]	[0.000254]	[0.00117]	[0.000512]	[0.000328]	[0.000230]	[0.000226]	[0.000230]
Observations	103,097	134,937	204,343	131,110	300,046	31,720	67,672	198,261	373,170	352,062	432,821

Table 5: Logit Estimates of Demand for BO Funds

The dependent variable is an indicator for an LP investing in a buyout fund. Presented are marginal effects from a fixed effects logit estimation. Each column is an estimation for a different sample of LPs and continues onto a second page. The dataset sets up a matrix of all LPs active in the buyout market this year, making yes/no choice decisions among all buyout funds of the vintage. Investment per year fixed effects are fixed effects from pooling LPs with the same number of average investments per year. We control for LP charactertistics that are dynamic -- the number of fund an LP has invested in the past three years and the experience level overall with PE investing. Fund-level variables of demand include the size of the buyout fund, whether the fund is the first fund for the GP, whether the fund in the past was a top or middle tertile performer, industry, and georgraphy. The match explanatory variables include whether the LP has previously invested in the fund series and whether the LP and the fund investment focus are in the same region as denoted. *,**, and *** indicate 1%, 5%, and 10% significance levels.

	Sample of LP Choices:	Bank	Corporation	Development Org.	Endowment	Foundation	Government Portfolio	HNW	Insurance	Pooled Assets	Private Pension	Public Pension
	Investment/Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
LP Characteristics	Number of funds	-0.000110***	-0.000106	-0.0000237	-0.000111***	-0.000123***	-0.0000447	-0.000166***	-9.12e-05***	-6.39e-05***	-8.59e-05***	-6.31e-05***
		[3.53e-05]	[9.71e-05]	[1.73e-05]	[1.61e-05]	[1.20e-05]	[3.11e-05]	[3.64e-05]	[1.12e-05]	[7.92e-06]	[7.74e-06]	[6.07e-06]
	Experience	-7.42E-05	-0.0000234	0.0000134	-0.000368***	-0.000422***	-0.000189	-0.0000883	-0.000406***	-0.000331***	-0.000445***	-0.000790***
		[0.000110]	[0.000294]	[0.000131]	[0.000119]	[7.94e-05]	[0.000332]	[0.000181]	[0.000106]	[8.50e-05]	[7.33e-05]	[8.12e-05]
Fund Characteristics	Log (Size)	0.000377***	0.0000362	-0.0000292	0.00133***	0.00115***	0.000824***	0.000901***	0.00144***	0.00148***	0.00173***	0.00219***
		[4.03e-05]	[7.91e-05]	[4.45e-05]	[5.47e-05]	[3.22e-05]	[0.000105]	[6.63e-05]	[4.45e-05]	[3.74e-05]	[3.41e-05]	[3.90e-05]
	Size Missing	-0.000628***	-0.000319	-0.000151	-0.00170***	-0.00184***	-0.00124***	-0.00103***	-0.00179***	-0.00243***	-0.00113***	-0.00188***
		[0.000195]	[0.000321]	[0.000161]	[0.000289]	[0.000181]	[0.000389]	[0.000369]	[0.000212]	[0.000225]	[0.000151]	[0.000151]
	First Fund of GP	0.00073	0.000599	0.0000389	0.00342	0.00114	0.000489	0.00142	0.000337	0.0000154	0.00122**	0.00179***
		[0.000505]	[0.000777]	[0.000408]	[0.00217]	[0.000734]	[0.000885]	[0.00122]	[0.000572]	[0.000518]	[0.000591]	[0.000524]
	Missing Performance	0.000447***	-6.18E-06	0.000583***	0.000630**	0.00128***	0.00138***	0.000469*	0.000517***	0.000362**	-0.000824***	-0.00284***
		[0.000157]	[0.000368]	[0.000177]	[0.000257]	[0.000144]	[0.000382]	[0.000282]	[0.000190]	[0.000159]	[0.000166]	[0.000200]
	Top Performer	0.000501	-0.000319	0.000099	0.00536**	0.00253***	0.00105	0.00145	0.000274	0.000198	0.000748	-0.00109**
		[0.000517]	[0.000837]	[0.000435]	[0.00215]	[0.000734]	[0.000927]	[0.00123]	[0.000580]	[0.000526]	[0.000591]	[0.000522]
	Medium Performer	0.000745	-0.000306	0.000137	0.00445**	0.00230***	0.000592	0.00155	0.00014	0.000125	0.000621	-0.00114**
		[0.000504]	[0.000787]	[0.000408]	[0.00216]	[0.000730]	[0.000879]	[0.00122]	[0.000572]	[0.000518]	[0.000589]	[0.000520]
LP - Fund Match Variables	Prior Relation	0.00409***	0.00668***	0.00497***	0.00810***	0.00891***	0.00564***	0.00710***	0.00915***	0.00824***	0.00846***	0.0104***
		[0.000320]	[0.000783]	[0.000366]	[0.000311]	[0.000199]	[0.000622]	[0.000449]	[0.000244]	[0.000192]	[0.000167]	[0.000182]
	LP&Fund N.America	0.00276***	0.00172***	0.00381***	0.00411***	0.00289***	0.00460***	0.00244***	0.00590***	0.00261***	0.00321***	0.00393***
		[0.000194]	[0.000332]	[0.000226]	[0.000687]	[0.000289]	[0.000496]	[0.000233]	[0.000207]	[0.000119]	[0.000163]	[0.000139]
	LP&Fund Europe	0.00174***	0.00194***	0.00274***	0.00324***	0.00310***	0.00274***	0.00160***	0.00485***	0.00228***	0.00327***	0.00399***
		[0.000168]	[0.000324]	[0.000262]	[0.000378]	[0.000192]	[0.000419]	[0.000215]	[0.000164]	[0.000113]	[0.000128]	[0.000125]
	LP&Fund Dev Asia	0.00464***	0.00417***	0.00556***	0.00730***	0.00523**	0.00598***	0.00555***	0.00842***	0.00713***	0.00384	0.0106***
		[0.000440]	[0.000679]	[0.000493]	[0.00160]	[0.00220]	[0.00109]	[0.00102]	[0.000672]	[0.000271]	[0.00260]	[0.000622]
	LP&Fund ROW	0.00345***	0.00444***	0.00156***		0.00861***	0.00777***	0.00275	0.0125***	0.0101***	0.0102***	0.0140***
		[0.000388]	[0.000801]	[0.000208]		[0.00104]	[0.000937]	[0.00184]	[0.000849]	[0.000511]	[0.000516]	[0.000835]
	LP&Fund Emrg Asia	0.00376***	0.00275***	0.00207***	0.00625***	0.00688***	0.00472***	0.00207	0.00956***	0.00820***	0.0134***	0.0101***
		[0.000337]	[0.000464]	[0.000249]	[0.00135]	[0.000974]	[0.000674]	[0.00142]	[0.000495]	[0.000354]	[0.000934]	[0.000787]

Fund Characteristics Continued: Industry and Geography

Sample of LP Choices:	Bank	Corporation	Development Org.	Endowment	Foundation	Government Portfolio	HNW	Insurance	Pooled Assets	Private Pension	Public Pension
Each column estimation continued from prior page…											
Business Services	0.000242	-0.000371	0.000353*	0.000596***	0.0000654	-0.0000569	0.000729***	0.000645***	0.000456***	0.000132	0.000161
	[0.000176]	[0.000401]	[0.000214]	[0.000203]	[0.000152]	[0.000460]	[0.000270]	[0.000165]	[0.000151]	[0.000131]	[0.000140]
Energy	0.000159	0.000504	0.0000185	0.000956***	0.000712***	-0.000064	0.000845***	-0.000552**	-0.000520**	-0.000399**	-0.000469***
	[0.000224]	[0.000340]	[0.000223]	[0.000211]	[0.000145]	[0.000456]	[0.000322]	[0.000216]	[0.000208]	[0.000156]	[0.000162]
Consumer	0.000117	-0.0000458	-0.000156	-0.000482**	-0.000572***	0.0000151	0.000301	0.000352**	-0.0000775	0.000249**	0.000356***
	[0.000143]	[0.000289]	[0.000188]	[0.000203]	[0.000146]	[0.000385]	[0.000245]	[0.000143]	[0.000129]	[0.000112]	[0.000119]
Diversified	-0.000122	-0.000895***	-0.000158	-0.000449**	-0.000224*	-0.0000183	-0.000196	-0.000780***	-0.000945***	-0.000343***	-0.000372***
	[0.000149]	[0.000309]	[0.000174]	[0.000180]	[0.000128]	[0.000356]	[0.000245]	[0.000150]	[0.000131]	[0.000110]	[0.000117]
Industrials	0.000368***	-0.0000365	0.000357**	-0.000455**	-0.000293**	0.000211	0.000458**	0.000451***	0.000369***	0.000181*	0.000431***
	[0.000134]	[0.000278]	[0.000175]	[0.000185]	[0.000129]	[0.000353]	[0.000226]	[0.000135]	[0.000119]	[0.000105]	[0.000112]
IT	0.000182	0.000164	-0.0000991	-0.000226	-0.000413***	0.00107***	0.000445	-0.000146	0.0000936	0.0000167	0.000440***
	[0.000167]	[0.000299]	[0.000212]	[0.000202]	[0.000149]	[0.000399]	[0.000275]	[0.000171]	[0.000146]	[0.000125]	[0.000130]
Health Care	-0.000397	-0.00103*	0.000206	0.000785***	0.000290*	-0.000521	0.000111	0.000516***	0.000674***	0.000614***	0.000663***
	[0.000244]	[0.000531]	[0.000245]	[0.000222]	[0.000174]	[0.000564]	[0.000347]	[0.000194]	[0.000165]	[0.000146]	[0.000156]
Infrastructure	0.000734**	-0.00146	0.00102***	-0.00428***	-0.000665	0.000778	-0.00181	-0.000515	-0.000391	-0.000462	-0.000729
	[0.000337]	[0.00124]	[0.000312]	[0.00115]	[0.000446]	[0.000820]	[0.00125]	[0.000599]	[0.000500]	[0.000434]	[0.000458]
Food & Agriculture	0.0001	-0.0000359	0.000770***	-0.00200***	-0.00103**	-0.00175	-0.00175	0.000249	-0.00106**	0.000948***	-0.000357
	[0.000369]	[0.000613]	[0.000270]	[0.000764]	[0.000454]	[0.00118]	[0.00122]	[0.000374]	[0.000443]	[0.000293]	[0.000356]
Materials	-0.00218***	0.000262	-0.000658**	0.000574**	0.000868***	-0.00054	-0.000944	-0.00116***	-0.00144***	0.000249	-0.000429*
	[0.000758]	[0.000419]	[0.000320]	[0.000257]	[0.000175]	[0.000728]	[0.000612]	[0.000326]	[0.000348]	[0.000209]	[0.000233]
Diversified	-0.00186*	-0.000238	-0.00176**	-0.000673	0.000383	-0.00108	-0.00114	-0.00220***	-0.00351***	0.0000685	-0.000355
	[0.00110]	[0.000965]	[0.000894]	[0.000489]	[0.000280]	[0.00145]	[0.000950]	[0.000571]	[0.000695]	[0.000288]	[0.000328]
Telecom	-0.0000994	0.000455	0.00027	0.000331*	0.000324**	0.000524	-0.000133	-0.000359**	-0.000087	-0.0000702	0.000491***
	[0.000186]	[0.000320]	[0.000231]	[0.000187]	[0.000134]	[0.000443]	[0.000288]	[0.000172]	[0.000143]	[0.000118]	[0.000124]
North America	-0.00180***	-0.00160***	-0.00338***	-0.00347***	-0.00244***	-0.00343***	-0.00171***	-0.00372***	-0.00239***	-0.00226***	-0.00217***
	[0.000155]	[0.000309]	[0.000208]	[0.000688]	[0.000289]	[0.000373]	[0.000210]	[0.000208]	[0.000105]	[0.000164]	[0.000137]
Europe	0.0000169	-0.0000334	-0.00199***	-0.000364***	-0.000489***	0.0000468	0.000490**	-0.000592***	0.000348***	-0.000318***	-0.000258***
	[0.000141]	[0.000281]	[0.000198]	[0.000115]	[7.93e-05]	[0.000292]	[0.000200]	[0.000110]	[0.000105]	[7.14e-05]	[7.92e-05]
Developed Asia	-0.00169***	-0.00126**	-0.00229***	-0.00154***	-0.00103***	-0.00254***	-0.00102**	-0.00135***	-0.000934***	-0.00117***	-0.00132***
	[0.000370]	[0.000515]	[0.000312]	[0.000352]	[0.000198]	[0.000647]	[0.000404]	[0.000282]	[0.000215]	[0.000205]	[0.000213]
ROW	0.0000944	-0.000278	0.00183***	-0.000418**	-0.00109***	0.000564**	0.0000402	-0.000384***	-0.0000308	-0.000326***	-0.000879***
	[0.000105]	[0.000281]	[0.000168]	[0.000194]	[0.000139]	[0.000245]	[0.000196]	[0.000148]	[0.000105]	[0.000108]	[0.000118]
Emerging Asia	-0.000919***	0.000353	0.000542***	-0.000237	-6.61E-06	-0.00139***	0.000490*	-0.000915***	-0.000576***	-0.000615***	-0.00104***
	[0.000215]	[0.000333]	[0.000158]	[0.000271]	[0.000157]	[0.000498]	[0.000288]	[0.000235]	[0.000163]	[0.000168]	[0.000173]
Observations	207,089	69,004	184,592	350,833	909,128	58,216	168,055	605,741	827,906	1,093,481	1,132,174

Table 6: Logit Estimates of Role of Impact in Demand for VC Funds

The dependent variable is an indicator for an LP investing in a VC fund. Presented are marginal effects from a fixed effects logit estimation. Each column is an estimation for a different sample of LPs and continues onto a second page. The dataset sets up a matrix of all LPs active in the VC market this year, making yes/no choice decisions among all VC funds of the vintage. Investment per year fixed effects are fixed effects from pooling LPs with the same number of average investments per year. We control for LP charactertistics that are dynamic -- the number of fund an LP has invested in the past three years and the experience level overall with PE investing. Fund-level variables of demand include the size of the VC fund, whether the fund is the first fund for the GP, whether the fund in the past was a top or middle tertile performer, industry, and georgraphy. The match explanatory variables include whether the LP has previously invested in the fund series and whether the LP and the fund investment focus are in the same region as denoted. *,**, and *** indicate 1%, 5%, and 10% significance levels.

	Sample of LP Choices:	Bank	Corporation	Development Org.	Endowment	Foundation	Government Portfolio	HNW	Insurance	Pooled Assets	Private Pension	Public Pension
LP Char.	Investment/Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Other LP Characteristics Included: Number of Funds by LP in last 3 years, LP Experience with PE investing											
Fund Char	Fund Charactersitics Included: Log(Fund Size), Indicator for size missing, First Fund of GP, Fund GP is missing prior performance, Top Performer, Medium Performer											
LP - Fund Match Variables	Prior Relation	0.00587***	0.0132***	0.00865***	0.00904***	0.0134***	0.0120***	0.0113***	0.00950***	0.0118***	0.0105***	0.0110***
		[0.000608]	[0.000795]	[0.000487]	[0.000600]	[0.000491]	[0.00129]	[0.00101]	[0.000512]	[0.000390]	[0.000377]	[0.000348]
	LP&Fund ROW	0.00538***	0.00922***	0.00359***	0.0104***	0.0145***	0.0155***	0.00648***	0.0135***	0.0130***	0.0152***	0.0155***
		[0.000580]	[0.00111]	[0.000308]	[0.00196]	[0.00173]	[0.00190]	[0.00192]	[0.000915]	[0.000857]	[0.000925]	[0.000891]
	LP&Fund Emrg Asia	0.00437***	0.00502***	0.00421***	0.00499***	0.0136***	0.0119***	0.00538***	0.00908***	0.00852***	0.0107***	0.0112***
		[0.000437]	[0.000454]	[0.000316]	[0.00127]	[0.00132]	[0.00139]	[0.000952]	[0.000527]	[0.000423]	[0.000896]	[0.000898]
	Other LP - Fund Match Variables Included: LP & Fund North America, LP & Fund Europe, LP & Fund Developed Asia											
LP Industry & Geography Characteristics	Energy	-0.000174	0.00187***	0.000749***	-0.00239***	0.000660**	-0.000431	0.00112**	-0.000366	0.000611**	-0.000186	-0.000224
		[0.000287]	[0.000356]	[0.000246]	[0.000611]	[0.000333]	[0.000864]	[0.000555]	[0.000373]	[0.000310]	[0.000321]	[0.000270]
	Health Care	0.000153	0.000722**	0.000283	-0.0000607	0.000412**	0.0000535	-0.000215	0.000650***	0.000274	0.000726***	0.000109
		[0.000199]	[0.000285]	[0.000195]	[0.000231]	[0.000191]	[0.000604]	[0.000394]	[0.000186]	[0.000174]	[0.000145]	[0.000129]
	Infrastructure	0.000751	-0.000652	0.000832	0.00140*	0.00174***	0.00162	0.00194	-0.0011	0.000229	-0.000123	0.00111**
		[0.000508]	[0.00106]	[0.000511]	[0.000722]	[0.000603]	[0.00188]	[0.00119]	[0.000958]	[0.000670]	[0.000642]	[0.000542]
	Food & Agriculture	0.00105**	-0.000418	0.000566		0.00327***	0.00294*	-0.00183	0.000773	-0.000329	-0.00360*	-0.00529**
		[0.000453]	[0.000915]	[0.000411]		[0.000664]	[0.00156]	[0.00256]	[0.000869]	[0.000897]	[0.00204]	[0.00212]
	ROW	-0.0001	-0.000492	0.000978***	-0.000153	0.0000164	0.00111**	-0.000305	-0.00105***	-0.000679***	-0.00178***	-0.00202***
		[0.000219]	[0.000392]	[0.000216]	[0.000480]	[0.000342]	[0.000566]	[0.000577]	[0.000342]	[0.000250]	[0.000370]	[0.000289]
	Emerging Asia	-0.000794***	0.0000237	-0.000557**	0.000372	0.000386	-0.00420***	0.000603	-0.00042	-0.000617***	-0.000166	-0.00110***
		[0.000301]	[0.000338]	[0.000231]	[0.000313]	[0.000261]	[0.00116]	[0.000516]	[0.000327]	[0.000230]	[0.000230]	[0.000230]
	Other LP Industry & Geography Variables Included: Business Services, Consumer Products, Diversified, Industrials, IT, Materials, Telecommunications											
Impact Fund		0.00193***	0.00248***	0.00105***	0.000509	0.00148***	-0.00414*	-0.00135	0.00173***	0.00146***	0.0000269	0.00296***
		[0.000363]	[0.000608]	[0.000323]	[0.000873]	[0.000519]	[0.00226]	[0.00151]	[0.000511]	[0.000520]	[0.000657]	[0.000335]
Observations		103,097	134,937	204,343	131,110	300,046	31,720	67,672	198,261	373,170	352,062	432,821

Table 7: Logit Estimates of Role of Impact in Demand for Buyout Funds

The dependent variable is an indicator for an LP investing in a buyout fund. Presented are marginal effects from a fixed effects logit estimation. Each column is an estimation for a different sample of LPs and continues onto a second page. The dataset sets up a matrix of all LPs active in the buyout market this year, making yes/no choice decisions among all buyout funds of the vintage. Investment per year fixed effects are fixed effects from pooling LPs with the same number of average investments per year. We control for LP charactertistics that are dynamic -- the number of fund an LP has invested in the past three years and the experience level overall with PE investing. Fund-level variables of demand include the size of the buyout fund, whether the fund is the first fund for the GP, whether the fund in the past was a top or middle tertile performer, industry, and georgraphy. The match explanatory variables include whether the LP has previously invested in the fund series and whether the LP and the fund investment focus are in the same region as denoted. *,**, and *** indicate 1%, 5%, and 10% significance levels.

	Sample of LP Choices:	Bank	Corporation	Development Org.	Endowment	Foundation	Government Portfolio	HNW	Insurance	Pooled Assets	Private Pension	Public Pension
LP Char.	Investment/Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
LP Char.	Other LP Characteristics Included: Number of Funds by LP in last 3 years, LP Experience with PE investing											
Fund Char	Fund Charactersitics Included: Log(Fund Size), Indicator for size missing, First Fund of GP, Fund GP is missing prior performance, Top Performer, Medium Performer											
LP - Fund Match Variables	Prior Relation	0.00399***	0.00672***	0.00494***	0.00805***	0.00887***	0.00560***	0.00692***	0.00901***	0.00811***	0.00840***	0.0103***
		[0.000313]	[0.000786]	[0.000363]	[0.000309]	[0.000199]	[0.000618]	[0.000439]	[0.000241]	[0.000189]	[0.000166]	[0.000181]
	LP&Fund ROW	0.00353***	0.00462***	0.00155***		0.00903***	0.00783***	0.00266	0.0127***	0.0102***	0.0106***	0.0141***
		[0.000390]	[0.000817]	[0.000206]		[0.00106]	[0.000941]	[0.00191]	[0.000851]	[0.000515]	[0.000522]	[0.000846]
	LP&Fund Emrg Asia	0.00374***	0.00283***	0.00208***	0.00693***	0.00728***	0.00492***	0.0023	0.00977***	0.00848***	0.0136***	0.0102***
		[0.000336]	[0.000471]	[0.000248]	[0.00137]	[0.000992]	[0.000672]	[0.00142]	[0.000496]	[0.000356]	[0.000938]	[0.000791]
	Other LP - Fund Match Variables Included: LP & Fund North America, LP & Fund Europe, LP & Fund Developed Asia											
LP Industry & Geography Characteristics	Energy	0.0000399	0.000547	-0.000116	0.000976***	0.000729***	-0.0000496	0.000787**	-0.000556**	-0.000545***	-0.000403**	-0.000479***
		[0.000228]	[0.000346]	[0.000224]	[0.000215]	[0.000149]	[0.000457]	[0.000326]	[0.000217]	[0.000210]	[0.000159]	[0.000163]
	Health Care	-0.000366	-0.00107**	0.000277	0.000804***	0.000278	-0.000541	0.000142	0.000518***	0.000682***	0.000619***	0.000699***
		[0.000244]	[0.000540]	[0.000244]	[0.000226]	[0.000179]	[0.000565]	[0.000349]	[0.000195]	[0.000167]	[0.000148]	[0.000157]
	Infrastructure	0.000499	-0.00125	0.000801***	-0.00439***	-0.00056	0.000866	-0.00218*	-0.000569	-0.000484	-0.000397	-0.00117**
		[0.000345]	[0.00125]	[0.000310]	[0.00117]	[0.000454]	[0.000839]	[0.00126]	[0.000600]	[0.000507]	[0.000441]	[0.000463]
	Food & Agriculture	0.000141	-0.0000695	0.000823***	-0.00204***	-0.00104**	-0.00175	-0.00174	0.000252	-0.00107**	0.000958***	-0.000302
		[0.000369]	[0.000623]	[0.000270]	[0.000777]	[0.000463]	[0.00118]	[0.00123]	[0.000375]	[0.000446]	[0.000298]	[0.000359]
	ROW	0.0000548	-0.000236	0.00171***	-0.000439**	-0.00112***	0.000563**	-0.0000154	-0.000413***	-0.0000448	-0.000335***	-0.000957***
		[0.000106]	[0.000286]	[0.000164]	[0.000198]	[0.000141]	[0.000246]	[0.000198]	[0.000149]	[0.000106]	[0.000109]	[0.000119]
	Emerging Asia	-0.000933***	0.000374	0.000467***	-0.000255	-0.0000163	-0.00143***	0.000495*	-0.000932***	-0.000589***	-0.000628***	-0.00106***
		[0.000216]	[0.000338]	[0.000156]	[0.000276]	[0.000160]	[0.000498]	[0.000290]	[0.000236]	[0.000164]	[0.000170]	[0.000174]
	Other LP Industry & Geography Variables Included: Business Services, Consumer Products, Diversified, Industrials, IT, Materials, Telecommunications											
Impact Fund		0.00118***	--	0.00151***	-0.000319	-0.00113**	-0.00041	0.00149***	0.000784*	0.000727*	-0.000626	0.00303***
		[0.000279]		[0.000249]	[0.000765]	[0.000546]	[0.000931]	[0.000550]	[0.000438]	[0.000411]	[0.000435]	[0.000295]
Observations		207,089	68,087	184,592	350,833	909,128	58,216	168,055	605,741	827,906	1,093,481	1,132,174

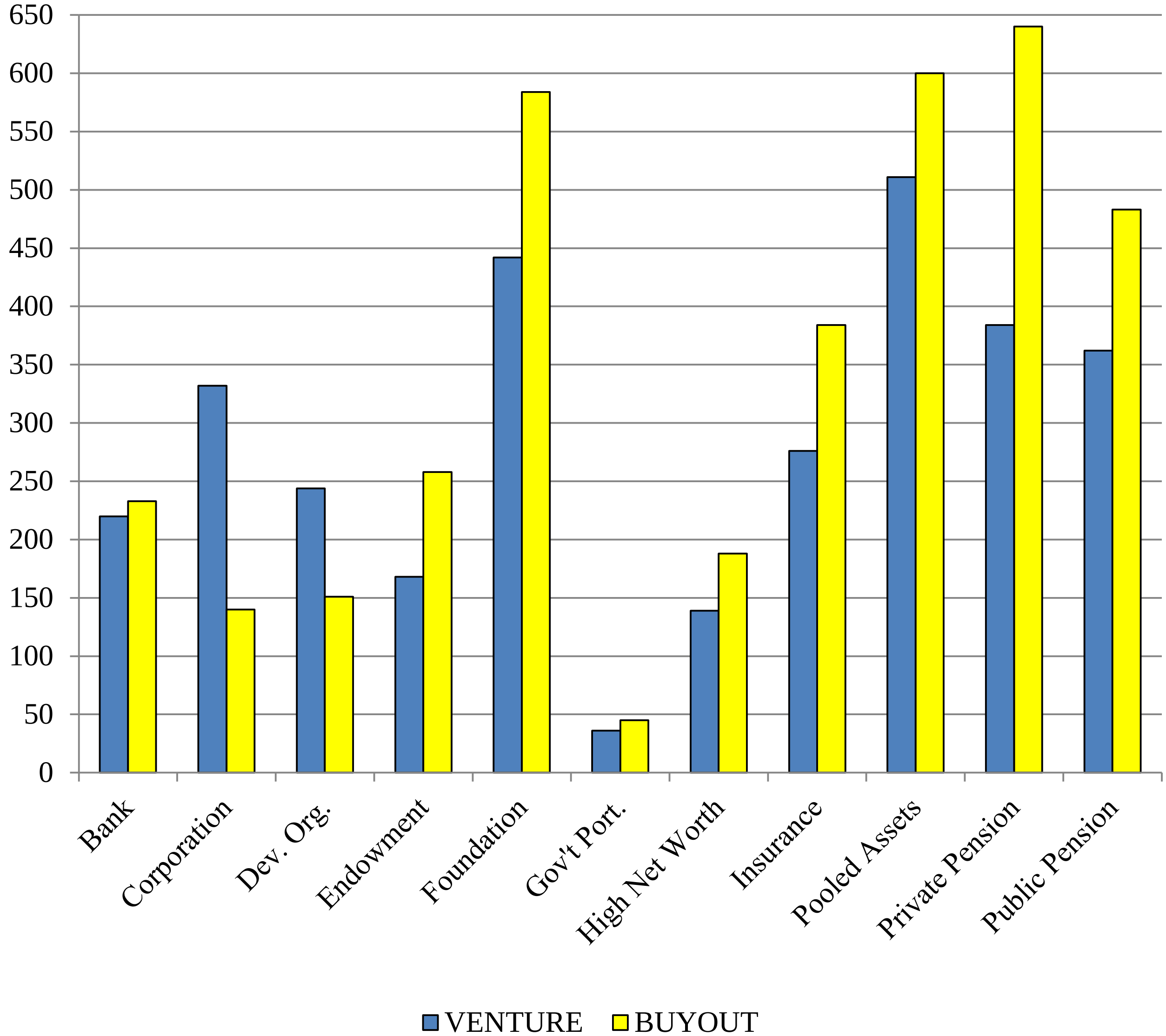


Figure 1: Number of LPs by LP Type
Types of LPs are labelled along the x-axis. The y-axis is a raw count of LPs in Preqin which have at least one fund investment in the period, calculated separately for LPs investing in buyout versus venture funds.

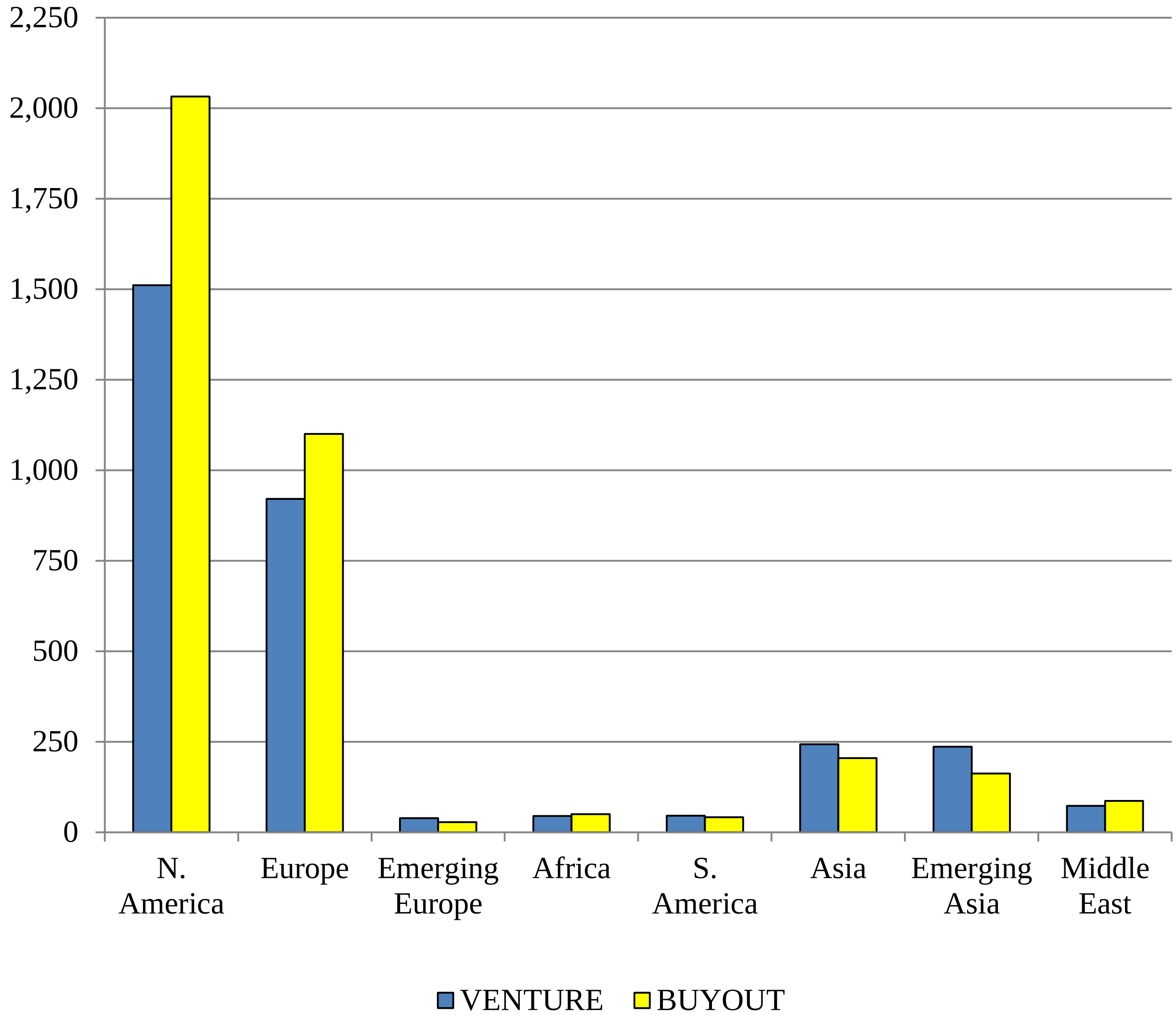
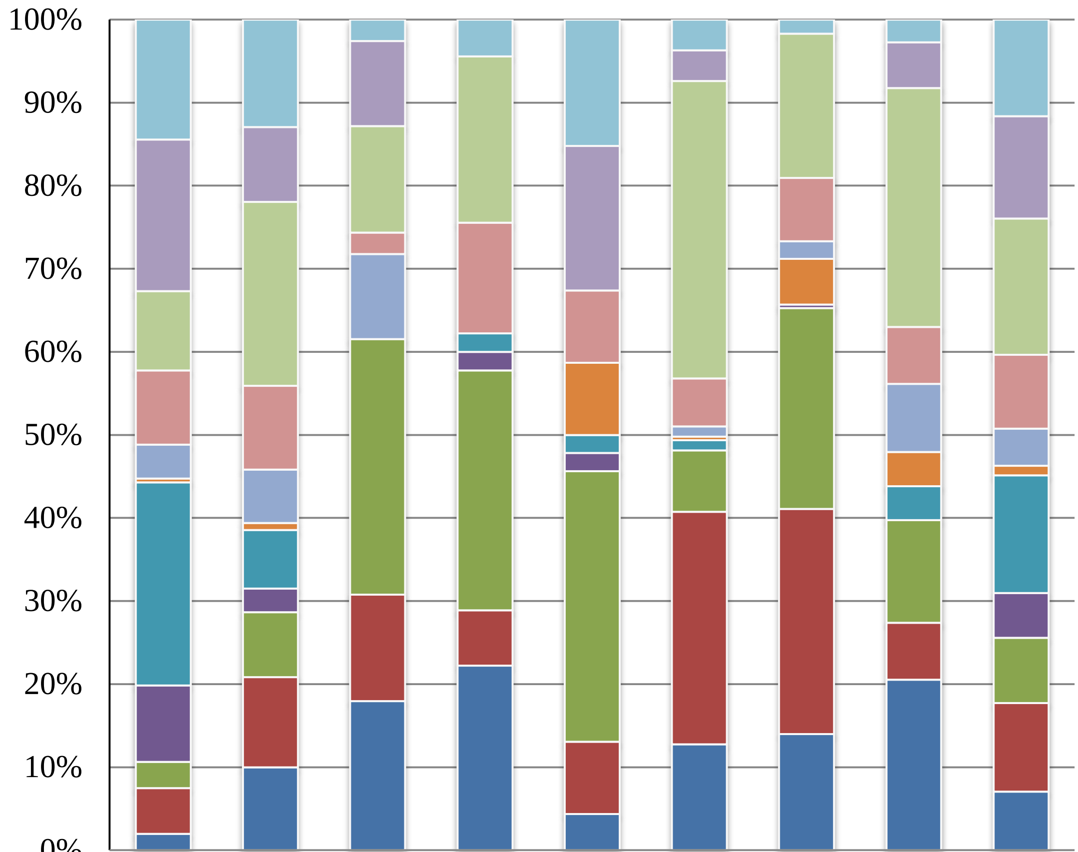
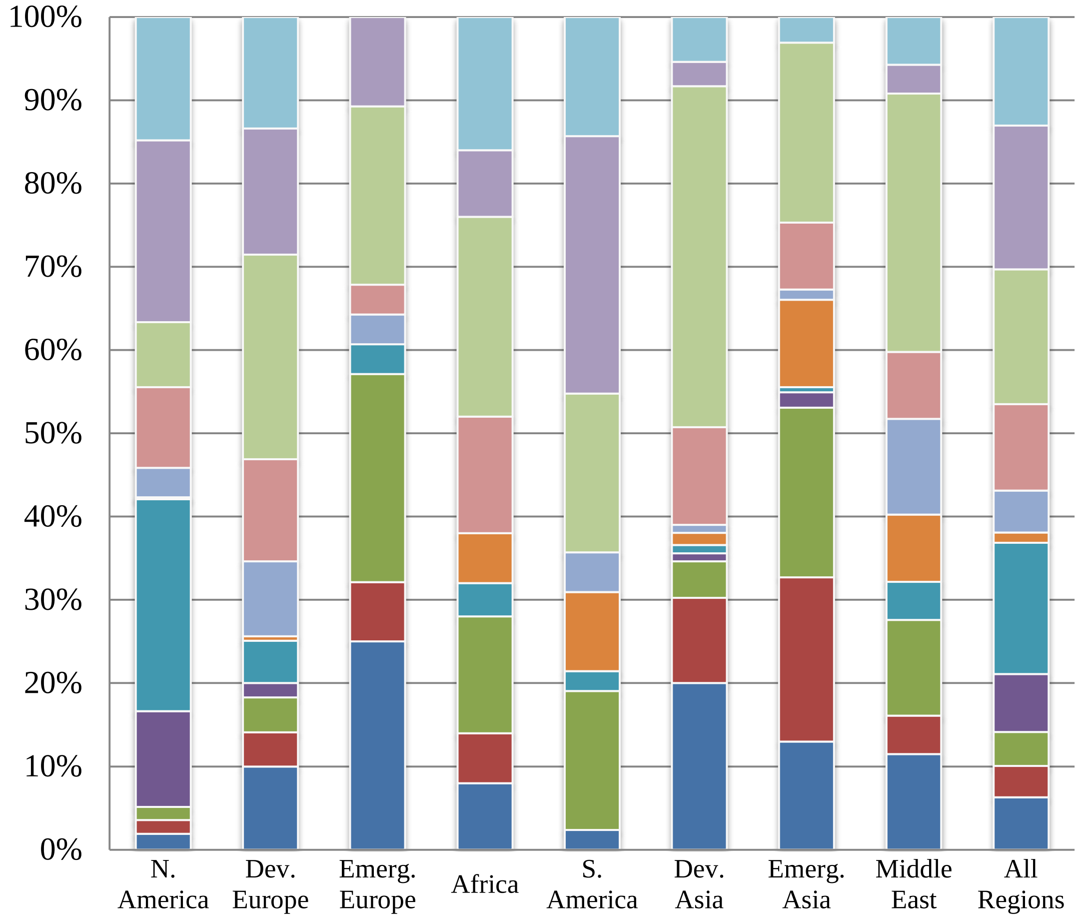


Figure 2: Number of LPs by LP Region
Regions are labelled along the x-axis. The y-axis is a raw count of Preqin LPs whose home region is the region listed. The set of LPs are those which have at least one fund investment in the period, calculated separately for LPs investing in buyout versus venture funds.



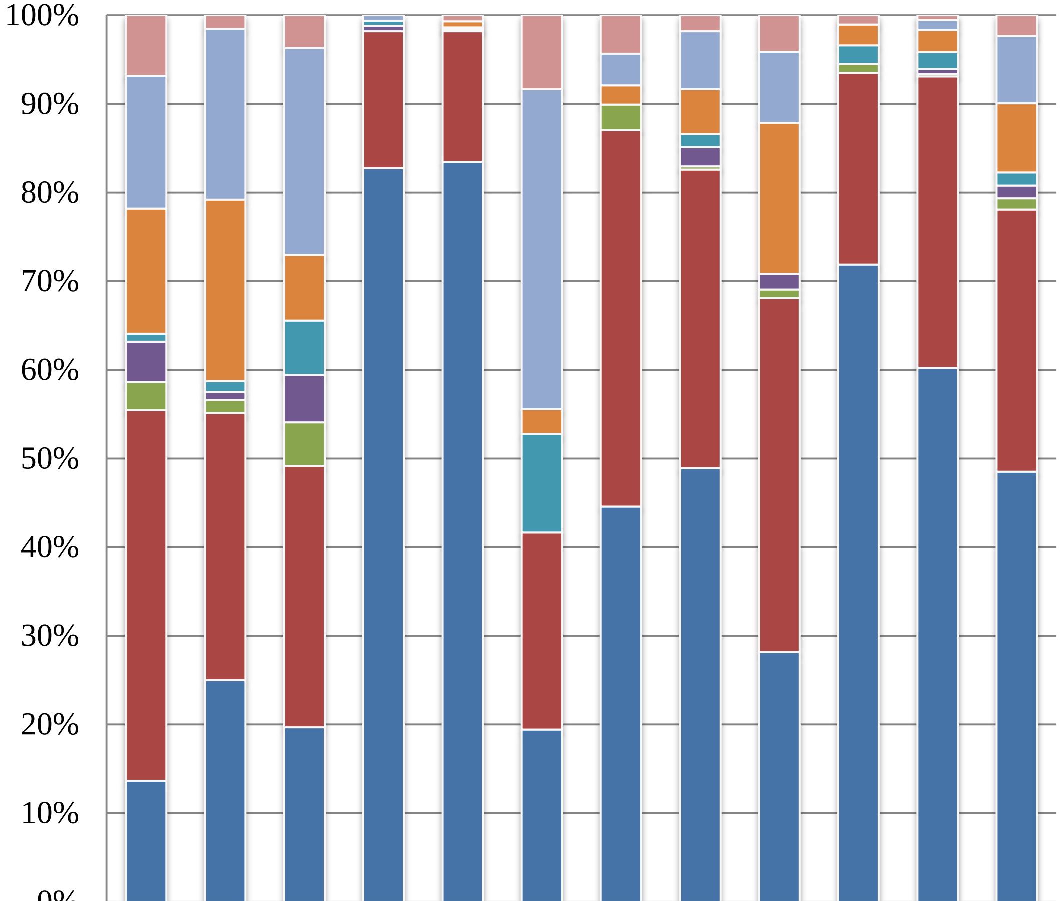
	N. America	Dev. Europe	Emerg. Europe	Africa	S. America	Dev. Asia	Emerg. Asia	Middle East	All Regions
Public Pension	14.4%	12.9%	2.6%	4.4%	15.2%	3.7%	1.7%	2.7%	11.6%
Private Pension	18.3%	9.0%	10.3%	0.0%	17.4%	3.7%	0.0%	5.5%	12.3%
Pooled Assets	9.5%	22.1%	12.8%	20.0%	0.0%	35.8%	17.4%	28.8%	16.4%
Insurance	8.9%	10.1%	2.6%	13.3%	8.7%	5.8%	7.6%	6.8%	8.9%
High Net Worth	4.1%	6.4%	10.3%	0.0%	0.0%	1.2%	2.1%	8.2%	4.5%
Gov't Port.	0.5%	0.9%	0.0%	0.0%	8.7%	0.4%	5.5%	4.1%	1.2%
Foundation	24.4%	7.1%	0.0%	2.2%	2.2%	1.2%	0.0%	4.1%	14.2%
Endowment	9.2%	2.8%	0.0%	2.2%	2.2%	0.0%	0.4%	0.0%	5.4%
Dev. Org.	3.2%	7.8%	30.8%	28.9%	32.6%	7.4%	24.2%	12.3%	7.8%
Corporation	5.5%	10.9%	12.8%	6.7%	8.7%	28.0%	27.1%	6.8%	10.7%
Bank	2.0%	10.0%	17.9%	22.2%	4.3%	12.8%	14.0%	20.5%	7.1%

Figure 3: Distribution of LP Type across Regions for VC LPs
Regions are labeled along the x-axis. The y-axis is the relative a stacked column depiction of the percent of total LPs in an x-axis region.



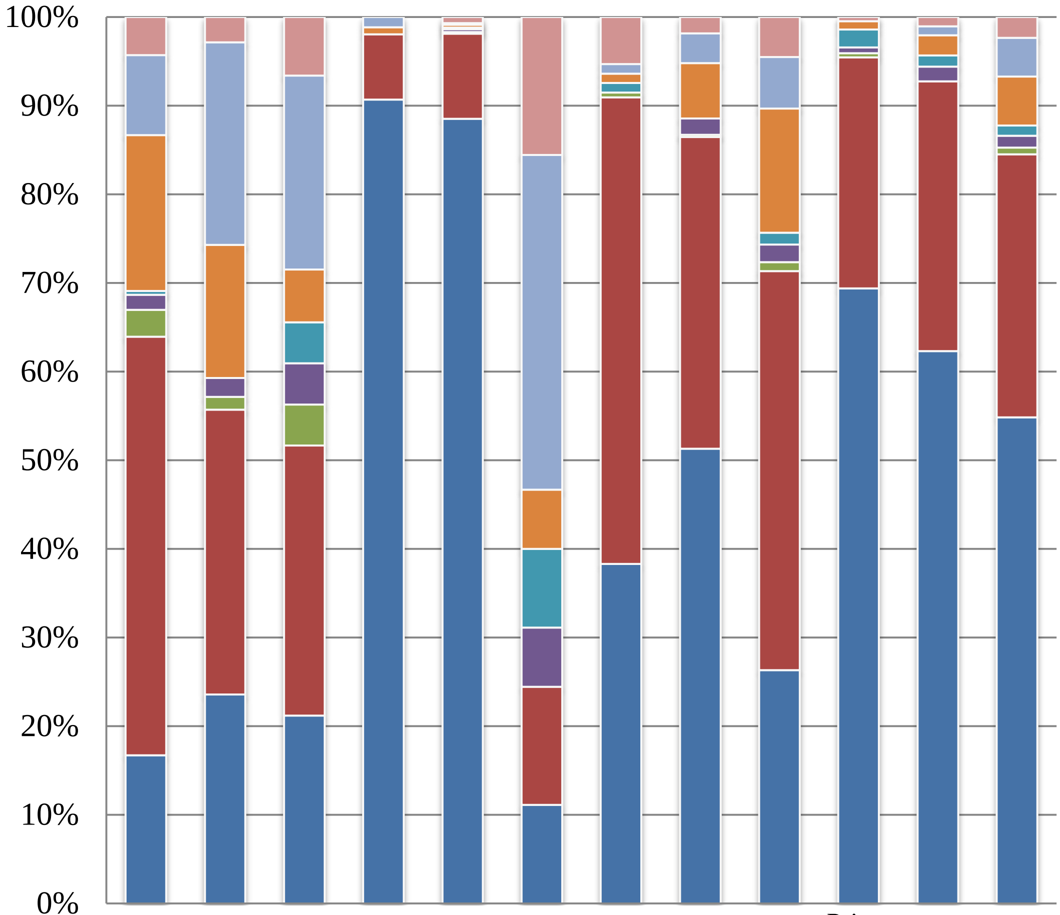
	N. America	Dev. Europe	Emerg. Europe	Africa	S. America	Dev. Asia	Emerg. Asia	Middle East	All Regions
Public Pension	14.8%	13.4%	0.0%	16.0%	14.3%	5.4%	3.1%	5.7%	13.0%
Private Pension	21.9%	15.2%	10.7%	8.0%	31.0%	2.9%	0.0%	3.4%	17.3%
Pooled Assets	7.8%	24.5%	21.4%	24.0%	19.0%	41.0%	21.6%	31.0%	16.2%
Insurance	9.7%	12.3%	3.6%	14.0%	0.0%	11.7%	8.0%	8.0%	10.4%
High Net Worth	3.5%	9.0%	3.6%	0.0%	4.8%	1.0%	1.2%	11.5%	5.1%
Gov't Port.	0.2%	0.5%	0.0%	6.0%	9.5%	1.5%	10.5%	8.0%	1.2%
Foundation	25.4%	5.1%	3.6%	4.0%	2.4%	1.0%	0.6%	4.6%	15.8%
Endowment	11.5%	1.7%	0.0%	0.0%	0.0%	1.0%	1.9%	0.0%	7.0%
Dev. Org.	1.6%	4.2%	25.0%	14.0%	16.7%	4.4%	20.4%	11.5%	4.1%
Corporation	1.6%	4.1%	7.1%	6.0%	0.0%	10.2%	19.8%	4.6%	3.8%
Bank	1.9%	10.0%	25.0%	8.0%	2.4%	20.0%	13.0%	11.5%	6.3%

Figure 4: Distribution of LP Type across Regions for BO LPs
Regions are labeled along the x-axis. The y-axis is the relative a stacked column depiction of the percent of total LPs in an x-axis region.



	Bank	Corporation	Dev. Org.	Endowment	Foundation	Gov't Port.	High Net Worth	Insurance	Pooled Assets	Private Pension	Public Pension	ALL LPs
Middle East	6.8%	1.5%	3.7%	0.0%	0.7%	8.3%	4.3%	1.8%	4.1%	1.0%	0.6%	2.3%
Emerging Asia	15.0%	19.3%	23.4%	0.6%	0.0%	36.1%	3.6%	6.5%	8.0%	0.0%	1.1%	7.6%
Asia	14.1%	20.5%	7.4%	0.0%	0.7%	2.8%	2.2%	5.1%	17.0%	2.3%	2.5%	7.8%
S. America	0.9%	1.2%	6.1%	0.6%	0.2%	11.1%	0.0%	1.4%	0.0%	2.1%	1.9%	1.5%
Africa	4.5%	0.9%	5.3%	0.6%	0.2%	0.0%	0.0%	2.2%	1.8%	0.0%	0.6%	1.4%
Emerging Europe	3.2%	1.5%	4.9%	0.0%	0.0%	0.0%	2.9%	0.4%	1.0%	1.0%	0.3%	1.3%
Europe	41.8%	30.1%	29.5%	15.5%	14.7%	22.2%	42.4%	33.7%	39.9%	21.6%	32.9%	29.6%
N. America	13.6%	25.0%	19.7%	82.7%	83.5%	19.4%	44.6%	48.9%	28.2%	71.9%	60.2%	48.5%

Figure 5: Distribution of LP Regions across LP Types for VC LPs
LP Types are labelled along the x-axis. The y-axis is the relative a stacked column depiction of the percent of total LPs by type in an x-axis region.



	Bank	Corporation	Dev. Org.	Endowment	Foundation	Gov't Port.	High Net Worth	Insurance	Pooled Assets	Private Pension	Public Pension	ALL LPs
Middle East	4.3%	2.9%	6.6%	0.0%	0.7%	15.6%	5.3%	1.8%	4.5%	0.5%	1.0%	2.3%
Emerging Asia	9.0%	22.9%	21.9%	1.2%	0.2%	37.8%	1.1%	3.4%	5.8%	0.0%	1.0%	4.4%
Asia	17.6%	15.0%	6.0%	0.8%	0.3%	6.7%	1.1%	6.3%	14.0%	0.9%	2.3%	5.5%
S. America	0.4%	0.0%	4.6%	0.0%	0.2%	8.9%	1.1%	0.0%	1.3%	2.0%	1.2%	1.1%
Africa	1.7%	2.1%	4.6%	0.0%	0.3%	6.7%	0.0%	1.8%	2.0%	0.6%	1.7%	1.3%
Emerging Europe	3.0%	1.4%	4.6%	0.0%	0.2%	0.0%	0.5%	0.3%	1.0%	0.5%	0.0%	0.8%
Europe	47.2%	32.1%	30.5%	7.4%	9.6%	13.3%	52.7%	35.2%	45.0%	26.1%	30.4%	29.7%
N. America	16.7%	23.6%	21.2%	90.7%	88.5%	11.1%	38.3%	51.3%	26.3%	69.4%	62.3%	54.8%

Figure 6: Distribution of LP Regions across LP Types for BO LPs
Regions are labelled along the x-axis. The y-axis is the relative a stacked column depiction of the percent of total LPs by type in an x-axis region.

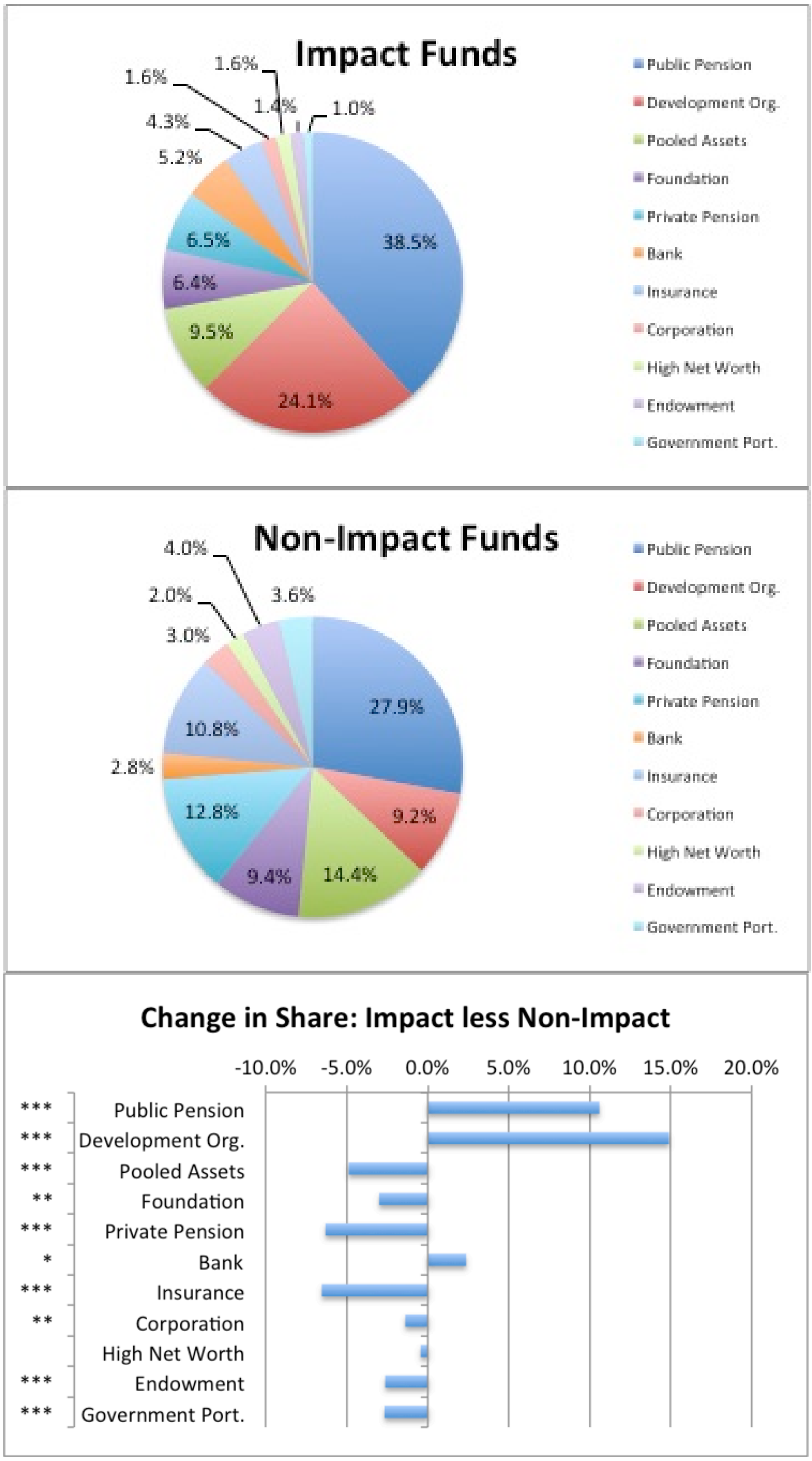


Figure 7: LP Type Market Share in Impact v. Non-Impact Funds

We calculate the percentage of LP Types that invest in impact funds (top pie chart) and non-impact funds (bottom pie chart). The difference in the percentage for impact v. non-impact for each LP type is presented in the bar chart (***, **, * - significant at the 1, 5, and 10% level).

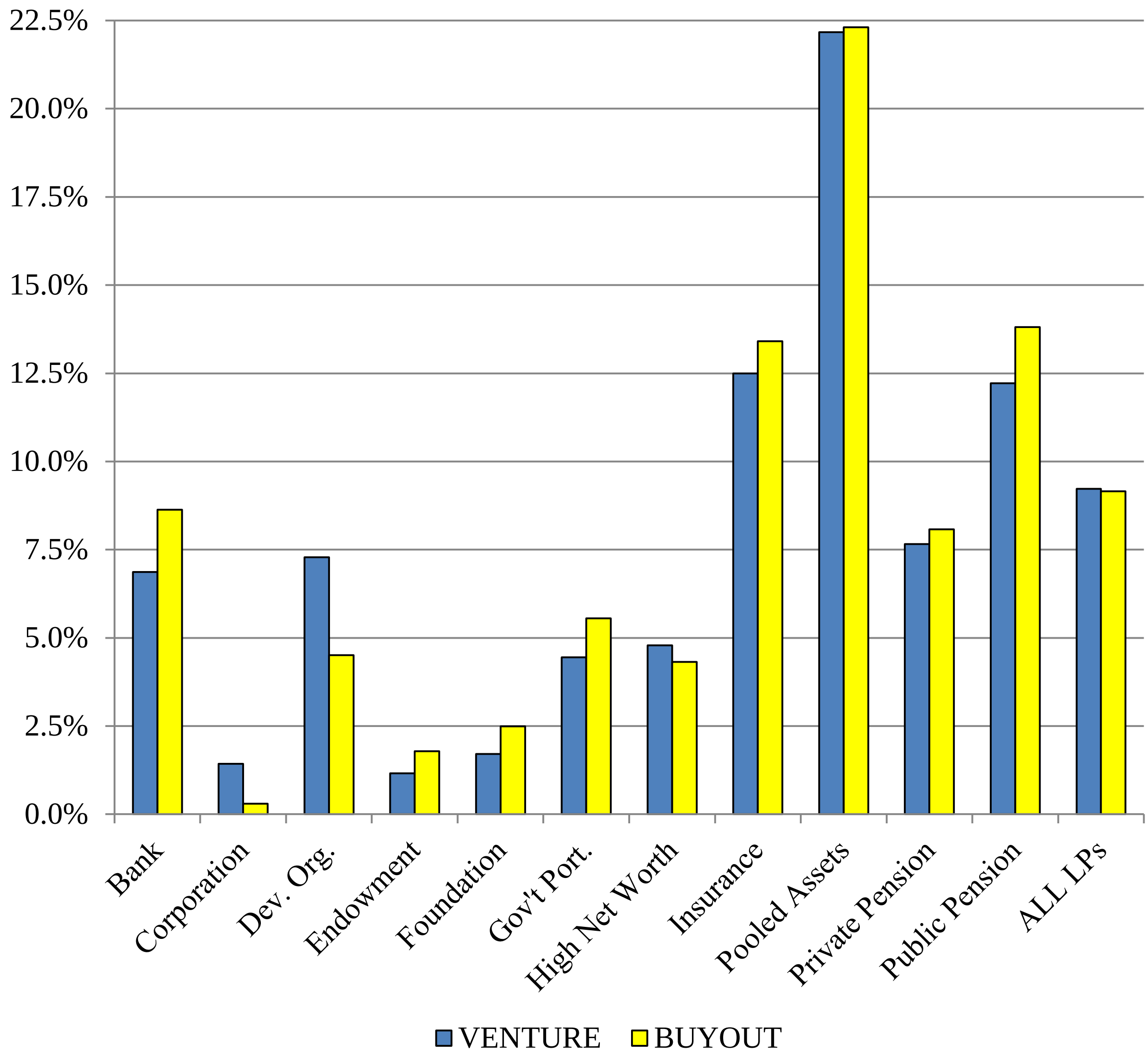


Figure 8: Percent of Each LP Type that are UN-PRI Signatories
LP Types are labelled along the x-axis. The y-axis is a percent of all Preqin LPs with the LP Type of the x-axis which sign the United Nations Principles of Responsible Investing (UN-PRI). The set of LPs are those which have at least one fund investment in the period, calculated separately for LPs investing in buyout versus venture funds.

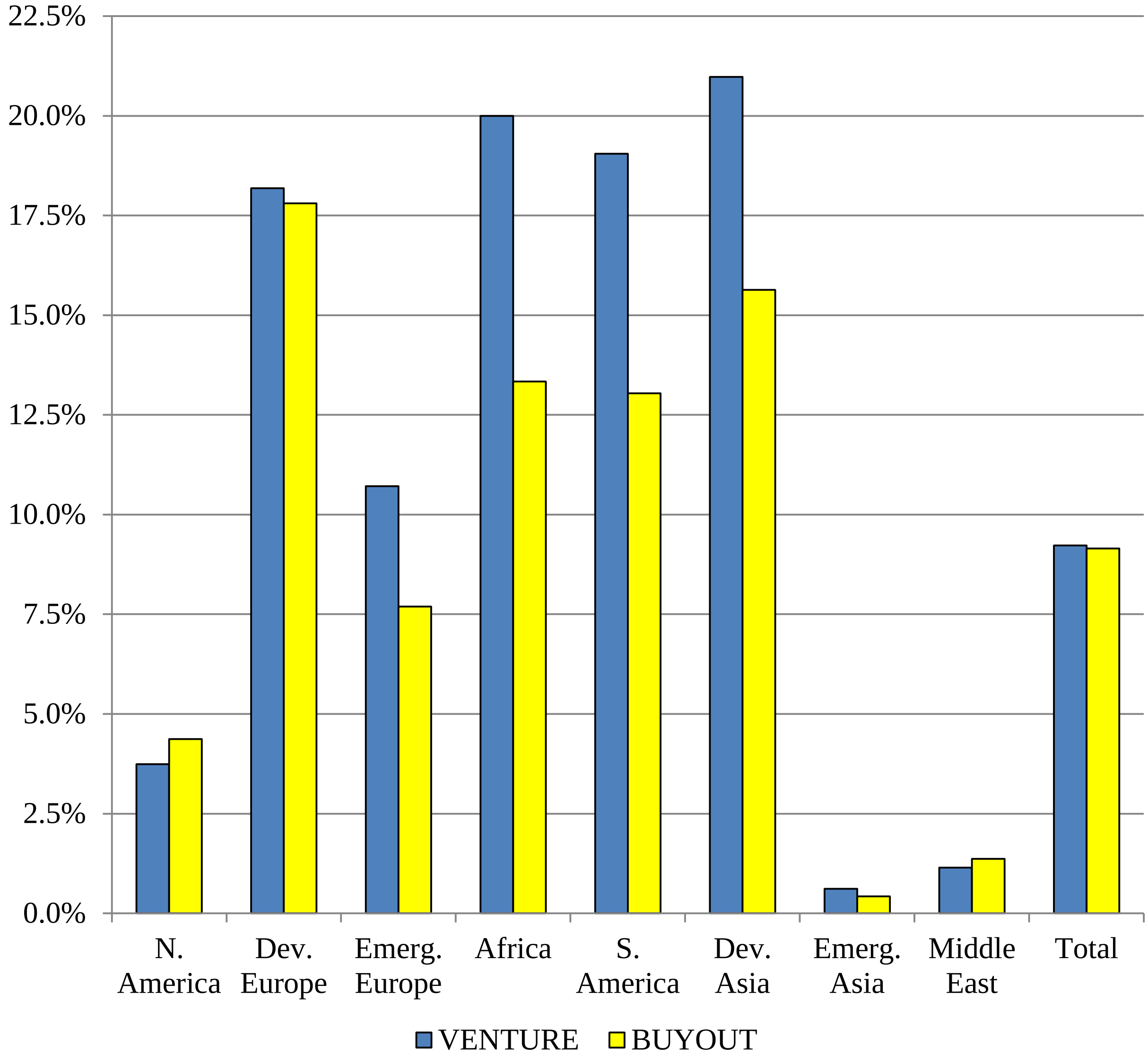


Figure 9: Percent of Each Region LPs that are UN-PRI Signatories
Regions are labelled along the x-axis. The y-axis is a percent of all Preqin LPs within the Region of the x-axis which sign the United Nations Principles of Responsible Investing (UN-PRI). The set of LPs are those which have at least one fund investment in the period, calculated separately for LPs investing in buyout versus venture funds.

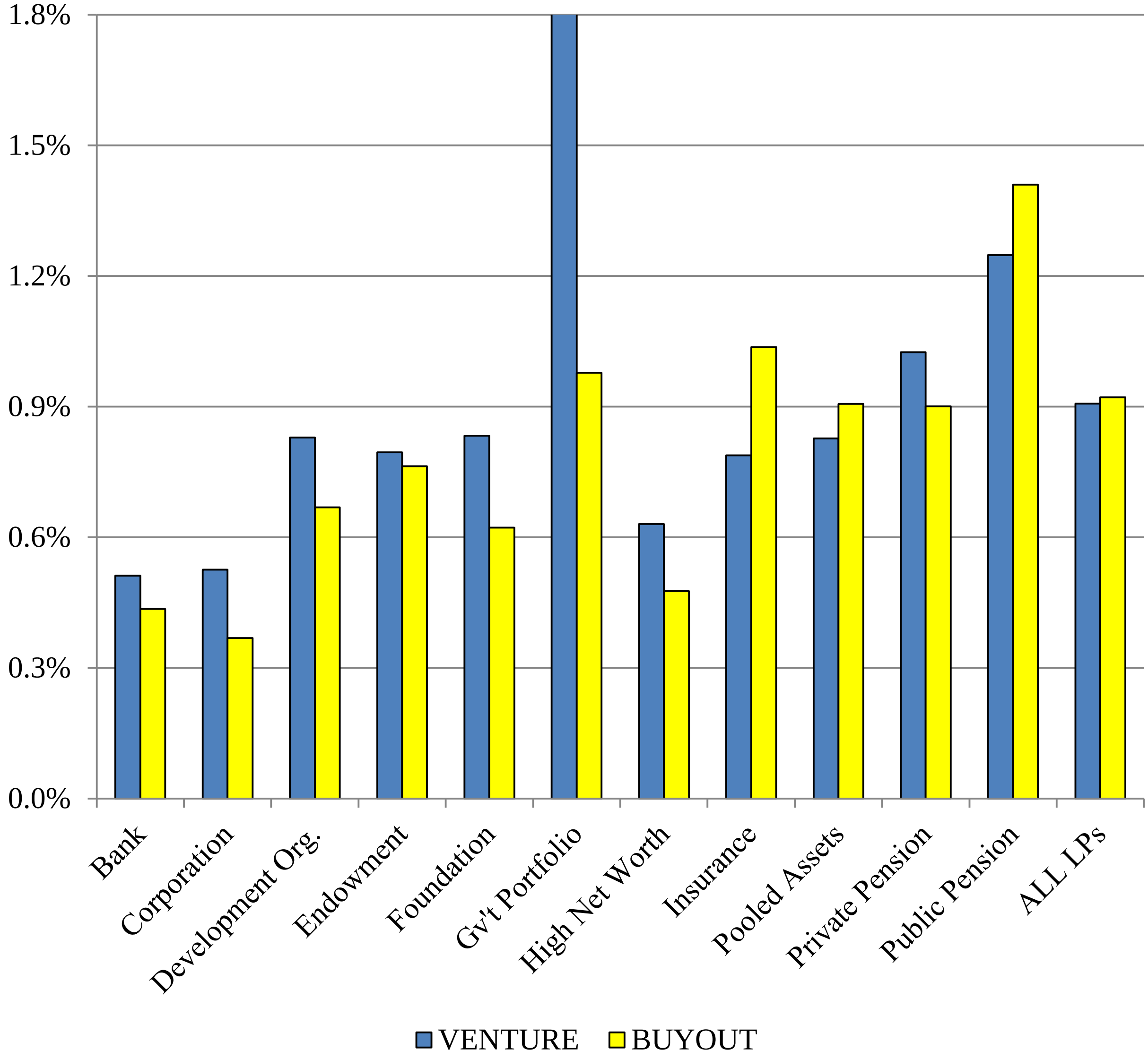


Figure 10: Baseline Investment Propensity in the Choice Set of Funds
Each LP investor faces a choice set of VC or Buyout Funds which that operate at a given vintage in which the LP investor is active. The Baseline Investment Propensity is the observed number of investments per LP divided by the number of Fund choices the LP faces. The Baseline Investment Propensity is simple the unconditional likelihood of investing in any Fund. The set of LPs are those which have at least one fund investment in the year, calculated separately for LPs investing in buyout versus venture funds.

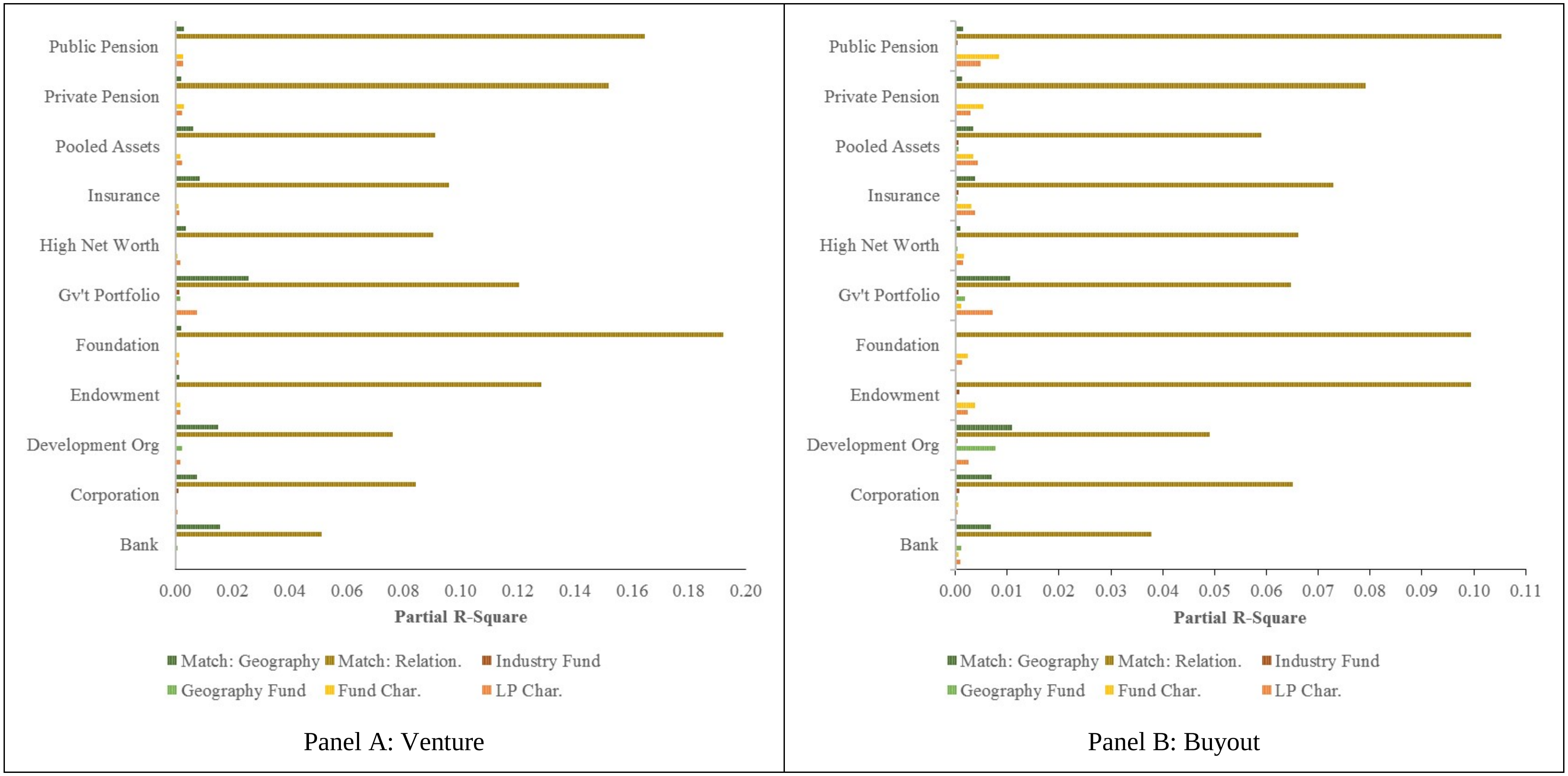


Figure 11: The Importance of Prior GP-LP Relationship
Each bar represents the partial R^2 for Sets of Variables from Linear Probability Choice Model of LP Demand for PE Funds (Panel A for VC and Panel B for buyout). The sets of variables include (1) Prior GP-LP relation, (2) GP-LP geography match, (2) Fund Industry fixed effects, (2) Fund Geography fixed effects, (5) Fund characteristics, and (6) LP characteristics.

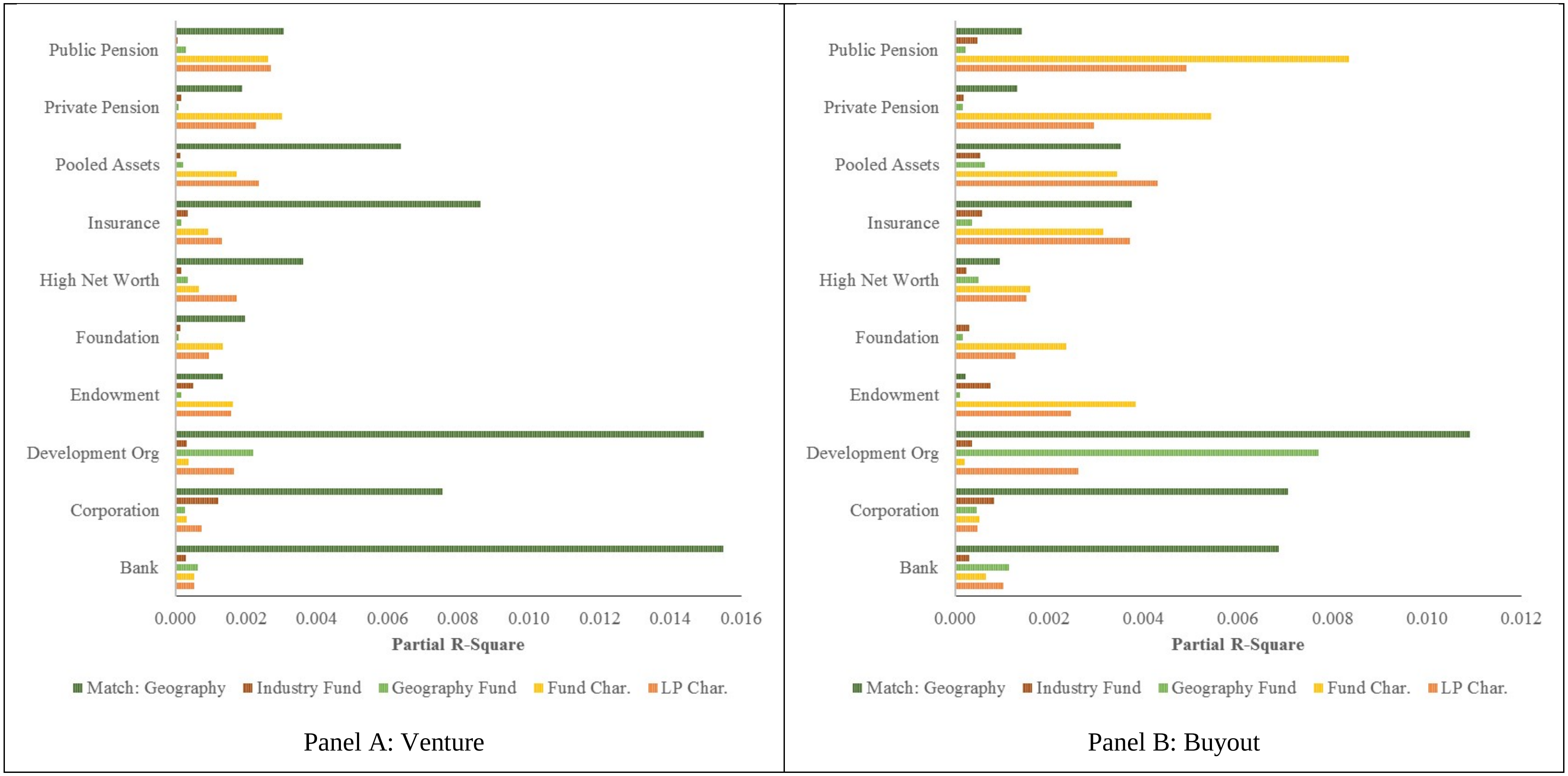
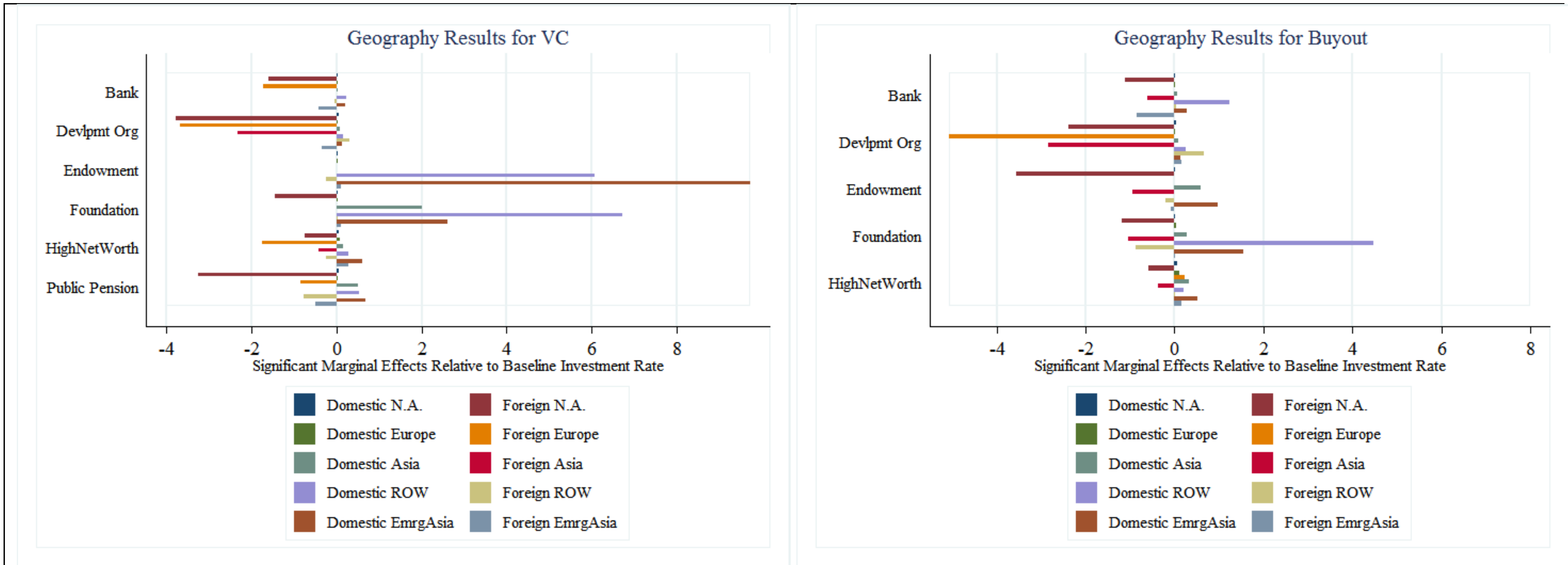


Figure 12: The Importance of GP-LP Geographic Proximity
The graphs are identical to those in figure 11, but the bar associated with prior GP-LP relationship is omitted to allow rescaling of the graph.



Panel A: Venture | Panel B: Buyout

Figure 13: The Importance of Geography by Global Region and select LP Types

We plot the average marginal effect (scaled by baseline likelihood for each group) of being a domestic vs. a foreign investor in each of the following 5 regions: North America, developed Europe, developed Asia, Rest of the World (which consists of South America, Emerging Europe, and Africa), and developing Asia (which also includes the Middle East).

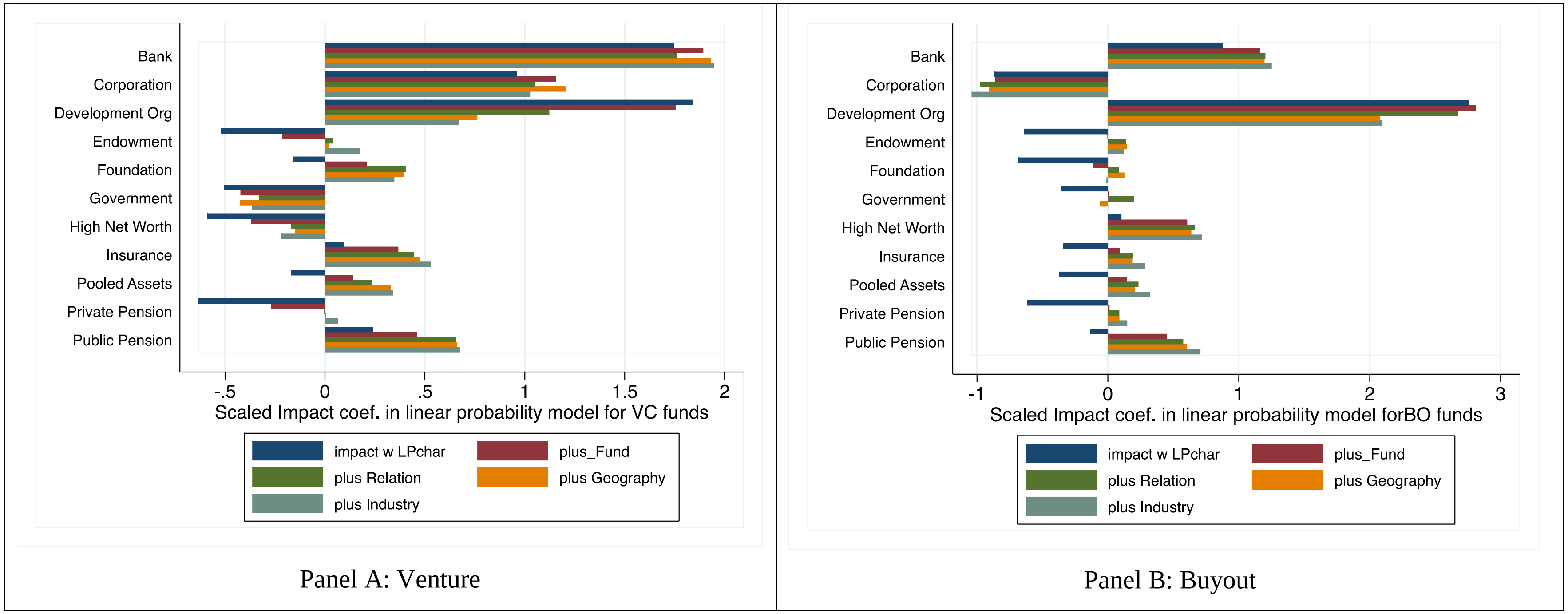
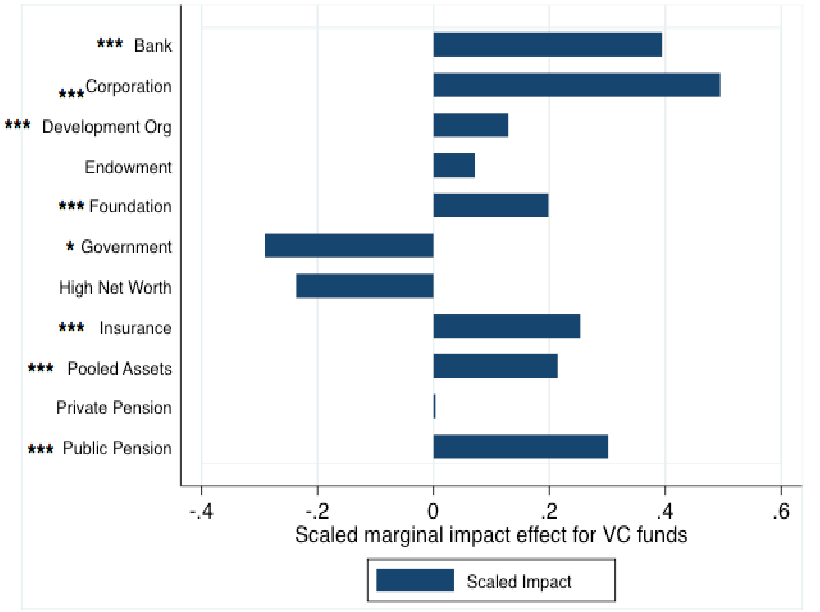
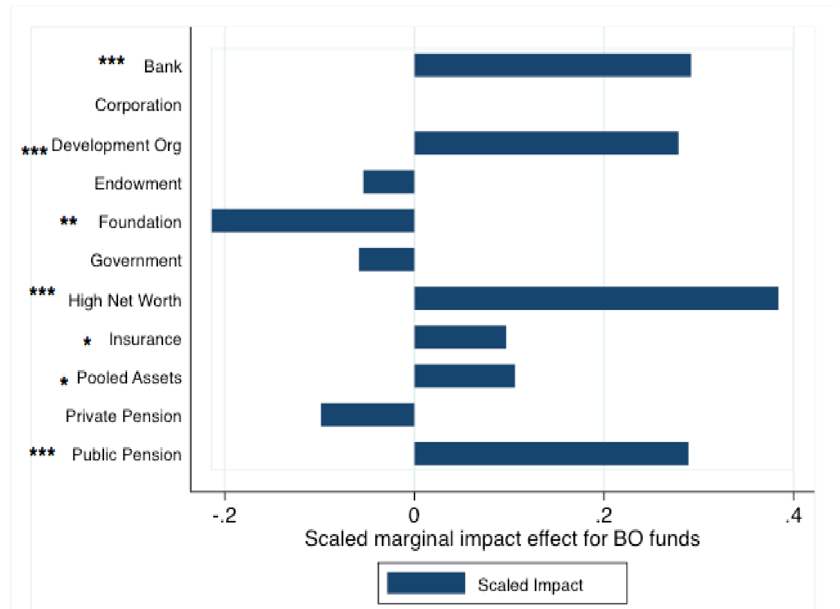


Figure 14: Economic Significance of Impact Fund Dummy relative to Baseline Investment Rates (Linear Probability Model)
We plot the coefficients for the impact fund variable scaled by baseline investment propensity in the estimations of a LP demand for BO funds. Different colors correspond to different models, starting with the most parsimonious model (top blue bar, “impact w LPChar” that includes just LP characteristics as controls). To this model, we sequentially add controls for fund characteristics (“plus_Fund,” red), GP-LP relationship (“plus Relation,” green), fund geography and fund-LP geography-match variable (“plus Geography,” orange), and industry fixed effects (“plus Industry,” light blue).

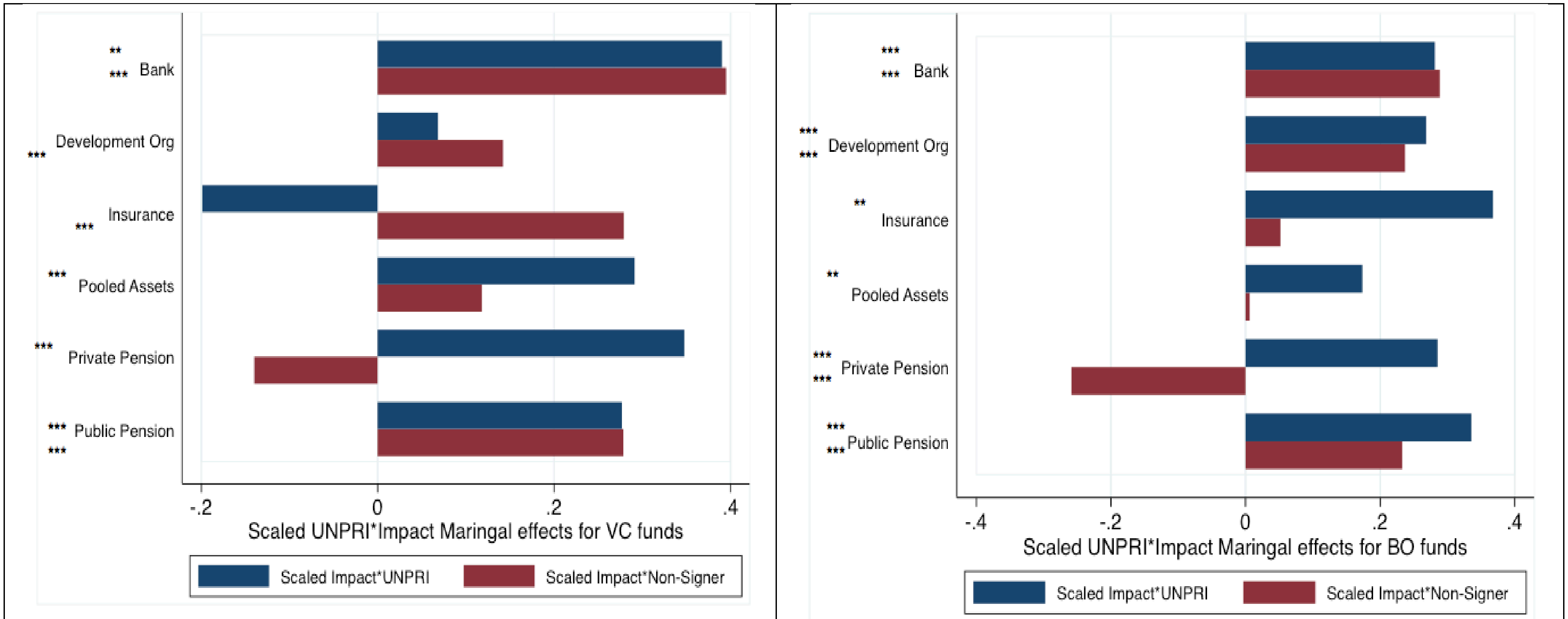


Panel A: Venture



Panel B: Buyout

Figure 15: Economic Significance of Impact Fund Dummy relative to Baseline Investment Rates (Logit Model)
We plot the marginal effects for the impact fund dummy variable from the logit estimation scaled by baseline investment propensity. The model includes the full set of control variables (time dummy variables, LP characteristics, fund characteristics, the relationship variable between LPs and fund's GPs, fund geography focus variables, fund-LP geography-match variable, and the fund industry focus variables).



Panel A: Venture

Panel B: Buyout

Figure 16: Economic Significance of Impact Fund/UN PRI Interaction relative to Baseline Investment Rates (Logit Model)
We plot the marginal effects for the interaction of the UNPRI signatory variable and the impact fund variable scaled by respective baseline investment propensities (different for signers and non-signers) in the logit estimations of a LP demand for VC funds. The model includes the full set of control variables (time dummy variables, LP characteristics, fund characteristics, the relationship variable between LPs and fund's GPs, fund geography focus variables, fund-LP geography-match variable, and the fund industry focus variables).