Impact Investing*

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Abstract

We show that investors derive utility from non-pecuniary characteristics of investments by studying impact funds, defined as venture or growth equity funds with dual objectives of generating financial returns and positive externalities. Impact funds earn internal rates of return that are 4.7% less than traditional VC funds in reduced form regressions. Based on estimates of a willingness to pay (WTP) model derived from a utility framework, investors accept 3-4% lower returns for impact funds. Development organizations, banks, and public pension funds have the greatest WTP; endowments and private pensions have negligible WTP. Europeans and UNPRI signatories have larger WTPs. Mapping WTP to investor preferences for and hindrances against impact investing, we find that mission-oriented objectives and political pressure to invest locally increase the WTP for impact and legal restrictions (e.g. ERISA) decrease it.

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I. Introduction

Classic asset pricing models generally define an investor's objective function using utility over wealth or consumption. While there have been innovations in the form of these utility functions, such as the introduction of preferences over time and risk (Epstein and Zin 1989; Laibson 1997), wealth generation is the common goal of investors. Economists are now taking seriously the possibility that investors might value positive societal externalities in utility in addition to wealth. Recent theoretical models consider the implications of these nonpecuniary preferences in a variety of settings (e.g., Fama and French 2007; Hart and Zingales 2017; Niehaus 2014), and seminal work by Andreoni (1989, 1990) considers *warm glow* altruism in his model of charitable giving. These theoretical models assume nonpecuniary motives in the allocation of capital and naturally raise the question of whether nonpecuniary motives affect investors' decisions.

Alongside these theoretical developments, there is accumulating evidence that investors are interested in the broader implications of capital allocations. As of April 2016, 1500 organizations representing $62 trillion in asset under management are signatories to the United Nations Principles of Responsible Investment (UNPRI). Virtually all major consulting groups have implemented a social impact practice, and all major investment banks have an impact division, to meet corporate, institutional, and private wealth demands for impact considerations in investment.

These trends and the renewed theoretical interest in nonpecuniary motives to investment raise the following questions in our context: Do investors care about the externalities associated with the investments they make? If so, what is the price they are willing to pay for the generation of positive externalities? And does the willingness to pay depend on who controls the capital (e.g., pension fund, bank, or development organization) or the legal or regulatory framework governing the allocation of capital?

We take up these questions by analyzing impact investments. Impact investments are a unique and emerging sector of private equity (typically, venture capital and growth equity), which explicitly promotes generation of a positive externality (e.g., the alleviation of poverty or the reduction of greenhouse gas emissions) and financial returns. When capital is allocated solely to maximize financial return, some investments will generate positive externalities (e.g., investments in alternative energies might reduce pollution). However, the generation of these positive externalities is not the objective of the investment. In contrast, we define impact funds as funds that explicitly have a dual objective of generating both a positive externality and financial returns. This narrow definition of impact investments allow us to identify investors' utility over impact and financial returns.[1,2]

We manually construct a sample of 159 impact funds launched over the period 1995-2014 using a strict criterion that the fund must state dual objectives in its motivation. We hand code the type of impact each fund aims to achieve. The impact objectives are quite broad, including funds that seek to reduce greenhouse gas emissions, encourage the development of women and minority-owned firms, alleviate poverty in developing countries, or develop local business communities. We merge these data with a Preqin dataset containing more than 25,000 investments by more than 3,500 investors (which we call limited partners or LPs) to more than 5,000 traditional VC and impact funds. LPs are not all alike in their portfolio choice decisions; thus we manually look up the ultimate source of capital for each of the 3,500 LPs, coding them into ten LP types.

Our primary analysis estimates the willingness to pay (WTP) for impact across investor types and characteristics. To set the stage for this analysis, we document impact funds underperform traditional VC funds. Specifically, the annualized internal rate of return (IRR) on impact funds is 4.7 percentage points lower than traditional VC funds after we control for industry, vintage year, fund sequence, and geography. If impact funds survive in the VC market, these reduced-form results suggest investors are willing to sacrifice returns in exchange for impact in equilibrium.

To investigate whether investors willingly forego expected return at the time of their investment decision, our primary empirics employ a discrete choice methodology using investors' observed choices of investments (yes/no decisions) among a large set of VC funds fundraising in a year as the dependent variable. This approach builds on a large literature on hedonic pricing techniques, which provide tools for estimating implicit prices of attributes that a

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[1] Some VC funds use the term impact fund because they invest in a green (e.g, energy, agriculture) or good (e.g., education, health) sectors. However, given that they only seek to maximize financial returns rather than dual financial and impact returns, they are not impact investments in the more narrow sense of the term. Also, some venture philanthropy funds invest in social enterprises that may earn financial returns, but since their primary agenda is in addressing a social and/or environmental concern, they are also not strictly impact investments.

[2] Impact funds also stand in contrast to SRI *public equity* portfolios, whereby investors either negatively screen out companies that engage in objectionable practices (e.g., divesting fossil fuel or tobacco) or positively screen for sectors, geographies or companies.

good possesses (e.g., Court 1939, Griliches 1961, Rosen 1974, McFadden 1974, 1986). Cameron and James (1987) introduced the idea that willingness to pay can be estimated in discrete choices over alternatives. In discrete choice models, the selected choices made by agents over alternatives can be used to infer the sensitivity of the choice probability to price and to the attributes (McFadden 1974). Cameron and James (1987) noted that if one re-parameterizes the sensitivity of choice to an attribute by scaling it relative to the sensitivity of choice to price, the result is an estimate of the individual's willingness to pay for that attribute.

Our empirical analysis relies on two key independent variables: an impact dummy variable and an ex-ante estimate of expected return for each fund, which we model using historic data on a fund's characteristics that investors would observe at the time of fundraising. From investors' choices, we observe whether impact is a desirable fund characteristic (i.e., positively affects the probability of investing in a fund—the fund's investment rate—conditional on the fund's expected return). How sensitive these investment rates are to a fund's expected return allow us then to convert the desirability of impact into a willingness to pay for impact. We do not assume that impact funds deliver lower returns than other funds, but allow our estimations to reveal whether investors are willing to pay for impact.

A relevant example of the method is Huber and Train (2001), who study households who choose among a set of electricity providers. They are interested in the tradeoffs in price households make when choosing characteristics of the provider (e.g., local utility vs. conglomerate), making inference as to people's willingness to pay to do business with a more expensive local provider. Analogously, we study the choice of alternatives of funds and ask whether different types of private capital investors exhibit differential levels of willingness to pay for the impact characteristic of a fund.

We estimate a conditional (investor fixed effects) logit model over the choice of funds and include a rich array of fund (e.g., manager quality) and investor characteristics as control variables. Importantly, the model reveals fund investment rates are positively related to ex-ante estimates of a fund's expected return, and impact funds have higher investment rates than traditional VC funds. Using these estimates, we find that the average investor exhibits a willingness to pay of about 3-4% in IRR for impact funds.[3] This result reinforces the realized

[3] Our primary model is based on a fund's percentile rank relative to vintage year cohort funds. We document that investors are willing to pay about 17 percentile ranks for impact funds, which translates into 3-4% in IRR.

performance difference result and suggests that investors knowingly make a tradeoff between financial returns and the generation of positive externalities when investing in impact.

Having established the baseline measure of WTP, we next document that the taste for impact varies across investor types. Four main investor types exhibit a positive and significant WTP for impact: (i) Development organizations, with their mission as such, have a high WTP for impact. (ii) Financial institutions (banks and insurance companies) have a high WTP for impact, presumably reflecting their community investments to comply with the Community Reinvestment Act (CRA) and to garner goodwill. (We later confirm that investments with these pressures are only evident in local community impact funds.) (iii) Finally, public pension funds have a high WTP for impact, in line with the tendency for state pensions in the U.S. to prefer investments within their home state as documented by Hochberg and Rauh (2013).

We also document that the WTP for impact comes almost entirely from European investors and investors in Latin America and Africa. Our geography analysis supports the existing circumstantial evidence that preference for impact should be higher for investors active in more recent periods and from Europe. This analysis also alleviates concerns that investors simply are naïve to the investment criteria when capital managers invest in impact funds.

To better understand the observed variation by investor type and geography, we explore the investor attributes that might capture differential utility from investing in impact across investors. To gain more confidence on the causal nature of the correlation between investors and impact WTP, we use variation in some attributes across geography as well as LP type. The six investor attributes that we examine include whether the capital is (1) held by households (as opposed to an organization), (2) intermediated by an asset manager, (3) held by an organization with a mission objective, (4) held by an organization with pressure to invest in impact, (5) held by an organization subject to laws restricting investments in impact, or (6) held by an organization (e.g., corporation) with charters that restrict investments in impact.

We find that mission-focused investors, and organizations that face political or regulatory pressure to invest in impact exhibit higher impact investment rates, ceteris paribus. Legal restrictions against investments for non-financial motives (e.g., ERISA and UPMIFA) materially decrease the investment rates in impact funds. In contrast, we find no evidence that organizational charters that require a focus on financial returns (e.g., corporate charters that require shareholder wealth maximization) hinder the demand for impact.

We also provide evidence on whether investors' WTP varies across the different types of impact, though we characterize this evidence as preliminary given the small sample sizes within each impact category. Impact funds focused on environmental impact, poverty alleviation, women and minorities, and social concerns generate the highest WTP estimates. In contrast, impact funds focused on small and medium-sized enterprises (SMEs), social infrastructure (e.g. health, education, and mainstream infrastructure), and other geographic-focused funds do not generate investment rates that reliably differ from those of traditional VC funds. These preliminary findings, which we hope provides fodder for future research, suggest that the internalization of utility from public good investing depends on how much the good is viewed as a public good versus an endeavor that could be profitable.

To summarize, we analyze investors' willingness to pay for the generation of positive externalities by examining the performance of impact funds and investor's willingness to pay for impact. We begin by documenting impact funds underperform traditional VC funds by 4.7% per annum. We then estimate an investor choice model with two key parameters, expected returns and the impact orientation of a fund, which allows us to extract an investor's WTP for impact. These choice models indicate investors willingly sacrifice 3-4% in annual IRR when choosing an impact fund, estimates that dovetail nicely with the realized underperformance of impact funds. We then document that the WTP varies across investor type and geography. When we delve into the investor attributes that are a function of investor types and location, we find mission objectives and political/regulatory pressure increase the WTP for impact, while legal impediments to impact (e.g., ERISA) reduce it.

There is little prior academic work on impact investing directly. Kovner and Lerner (2015) study 28 community development venture capital funds in the U.S., finding that these funds tend to invest in companies at an earlier stage, in industries outside the VC mainstream, and with fewer successful exits. Chowdry, Davies, and Waters (2016) develop a theoretical model of how social impact bonds (SIBs) can solve under or over-investment in social goods for heterogeneous pools of investors.

Our work relates to the broader literature on socially responsible investing (SRI) that dates back as far as Milton Friedman's 1970 doctrine on responsible investing.[4] A survey by

[4] "The Social Responsibility of Business is to Increase Its Profits," The New York Times Magazine, September 13, 1970. Also see Geczy et al. (2003).

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 expected 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), Renneboog, Ter Horst, and Zhang (2011) and Bialkowski and Starks (2016) show that SRI fund flows are less sensitive to performance than non-SRI flows while Bollen (2007) documents SRI funds have less volatile flows. For example, Bialkowski and Starks (2016) document that demand for SRI mutual funds has grown faster than traditional mutual funds in recent years, fueled by investors' nonfinancial considerations. Riedl and Smeets (2017) find that social preferences and social signaling affect retail investors' choice of mutual funds. Similarly, One strand of the SRI literature argues the non-pecuniary interests of investors affect the expected returns of investors; stocks preferred for nonfinancial reasons earn lower returns than spurned stocks. Building on this idea, Hong and Kacpercyzk (2009) find that stocks subject to widespread negative investment screens earn strong returns (also see Chava 2014). The above studies highlight the potential importance of non-pecuniary motives when investing, which dovetails with our analysis of the performance of impact funds and investors' willingness to pay for impact.[5]

Our paper also relates to a strand of the private equity literature that focuses on understanding demand. For example, Lerner, Schoar and Wongsunwai (2007) and Sensoy, Wang and Weisbach (2014) compare returns earned by different types of LPs. Our findings complement those of Lerner, Schoar and Wongsunwai (2007), Hochberg, Ljungqvist, and Vissing-Jørgensen (2014), and Hochberg and Rauh (2013) in finding the importance of relationship and geography in understanding investment patterns in private equity.

II. Data and Statistics

II.a. Data and Impact Funds Designation

Our data on funds, LP investors, and performance come from Preqin's Investor Intelligence and Performance Analyst datasets. Because the majority of impact funds are venture or growth oriented, we restrict our analysis to venture and growth funds. Our first task is to

[5] Dimson et al. (2015) provides contrary evidence that investor engagement with the management of publicly traded firms on a collection of environmental, social, and governance issues is associated with positive abnormal returns.

designate funds as being impact or traditional VC, using the criterion of an impact fund having the stated objective of generating a positive externality in addition to pursuing financial returns.[6] 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, third-party lists of funds and managers, and a screen based on funds that invest primarily in companies located in poverty-stricken countries. We then manually read descriptions and online resources about funds and fund families, strictly requiring that a fund explicitly state an externality objective to be deemed an impact fund in our dataset. We likely fail to designate some funds as impact (false negatives) due to a lack of detailed information, but our approach yields a clean sample of impact funds (i.e., false positives are unlikely).

Impact funds have diverse goals, so it is useful to consider specific examples of impact funds in our final sample. Bridges Ventures is a London-based family of funds "…dedicated to sustainable and impact investment…" that uses an "…impact-driven approach to create returns for both investors and society at-large." Bridges has several funds in our sample including, for example, the CarePlaces Fund, which builds care homes for the elderly. Its limited partners include university endowments, banks, pension funds, and high-net-worth investors. NGEN Partners is a Manhattan-based family of funds 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 "…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."

To parsimoniously summarize these diverse impact goals, we construct seven, non-mutually exclusive impact categories: environmental impact, minority and women funding, poverty alleviation, social concerns, social infrastructure development, small and medium-sized enterprise (SME) funding, and geography-focused impact excluding poverty regions. Two categories require further explanation. Social concern funds invest in firms that address social welfare concerns not captured in other categories or explicitly measures the social impact of its investments. Geography-focused impact funds are funds that have a clear objective of creating

[6] We summarize the steps used to identify impact status here and provide further details in Appendix B.

jobs or economic development in a specific region, but we exclude funds that focus on poverty alleviation to avoid a large overlap between geography-focused and poverty alleviation categories (geo and poverty). For each impact fund, we read fund descriptions in three databases (Preqin, Capital IQ, and ThomsonOne) as well as in the fund's own marketing materials on their websites and code the impact objectives of the fund using these seven categories, allowing funds to have multiple objectives.

Figure 1 depicts the percentage of the 159 impact funds that have a stated impact goal, with the counts of funds displayed at the top of each bar. The smallest impact categories are minority and women funding (11% of funds) and social infrastructure development, which includes health and education as well as other social or physical infrastructure (16%). The remaining impact categories are more common and relatively uniformly distributed with the most prevalent being poverty alleviation (43%) and SME funding (42%), followed by geography focus excluding poverty (33%), environmental impact (28%) and social concerns (27%).

We augment our Preqin data with the list of UNPRI signatories, which we downloaded from the UNPRI website. As of November 16, 2015, there were 1,422 signatories (297 asset owners, 931 investment managers, and 194 professional service managers) who collectively manage $59 trillion. We match UNPRI signatories to our LP dataset using investor names. LPs that are subsidiaries of a UNPRI signatory are also coded as signatories, but not LPs who are parents of UNPRI signatory subsidiaries.

II.b. Fund Statistics

Our main analysis focuses on 4,659 funds with vintage years from 1995 to 2014. In Table 1, we present descriptive statistics on the 4,500 traditional VC funds on the left and the 159 impact funds on the right.

Because our empirics are at the investment level rather than the capital commitment levels, it is important for inference that the capital commitments per investment for impact and traditional funds are similar. Traditional VC funds are somewhat larger than impact funds ($204.6 million v. $129.6 million when comparing the average fund size and $102 million versus $83 million when comparing the median fund size). This could be because impact funds are more likely than traditional funds to be smaller VC-oriented rather than larger growth capital funds in our sample. Thus, we examine the individual commitment amounts. Though we observe

23,986 investments, commitment amounts are available for only 7,867 (32.8%). For this sample, the mean and median capital commitment (first taking the average across investors in a fund and calculating statistics across funds) for traditional VC funds is $22.2 million and $14.6 million. Impact funds have larger capital commitments, with the mean and median being $27.1 and $15.0 million.[7] One might wonder if the difference arises because we are more likely to observe investment size for traditional funds and thus are more likely to observe smaller capital commitments. This does not appear to be the case as we observe proportionately more investment amounts for impact investments (38.0%) than for traditional funds (32.6%).

Simple univariate statistics suggest that impact funds have lower mean and median performance. Traditional funds have a mean (median) IRR of 11.59% (7.4%), while impact funds have mean (median) IRR of 3.7% (6.4%). The same patterns emerge for value multiples and the percentile ranks. However, these univariate comparisons of un-adjusted returns ignore a large time variation in VC performance during the sample period. VC funds historically had the highest IRRs during the mid- to late-1990's but impact funds became more common in the 2000's – a decade which saw VC returns decrease substantially. Looking at the percentile rank helps us correct for this bias. The percentile rank is based on a fund's performance ranking (either IRR or VM) relative to cohort funds (where we define a cohort by vintage year and geography using five geographic regions). We use the average of a fund's VM percentile rank and IRR percentile rank because some funds have IRR data, but not VM and vice versa. Using this measure, traditional funds have a mean (median) percentile rank of 0.49 (0.5), while impact fund have mean (median) rank of 0.34 (0.28). The difference of 0.15[8] (0.22) in percentile rank translates to about 2.9% (4.2%) difference in excess IRR centered at the median in historical returns (see Table A1 of the appendix).

In our analysis, we focus on percentile rank, rather than IRR or VM; we do this for three reasons. First, percentile ranks are less prone to extreme value problems that plague IRR and VM, particularly in VC funds. Second, investors routinely reference percentile ranks relative to a vintage-year cohort (e.g., top quartile funds) when evaluating fund performance. By employing percentile ranks in our empirical analysis, we are mapping into the decision process commonly employed by investors when selecting fund investments. Finally, percentile ranks have the added

[7] The statistics are similar if we average across investors. The mean (and median) capital commitment is $20.9 million ($11 million) for traditional VC funds and $25.6 million ($13.4 million) for impact funds.
[8] 0.49-0.34 = 0.15.

dividend that we have more observations on performance since percentile ranks can be calculated with either IRR or VM.

Collapsing Preqin codes of the geographic focus of fund investments to eight regions, we designate a fund to have a geographic focus if more than a third of all geographic descriptors are concentrated in a given region. Most funds (84%) focus on only one of the eight global regions. Panel B of Table 1 reports that impact funds tilt more toward developing countries including Africa, Latin America, and Emerging Europe than traditional funds. We do the same exercise for industry foci, collapsing the Preqin codes to 11 different industries (business services, energy, consumer, diversified, industrials, information technology, health care, infrastructure, food and agriculture, real estate, and media/communications) and coding a fund as having an industry focus if more than a third of industry sector descriptors are concentrated in a given industry. Both self-described diversified funds and funds that lack any focus on particular industries (according to our coding method) are categorized as "diversified." Panel C of Table 1 reports that impact funds are more likely to be energy or diversified funds, and less likely to be IT, health care, or media and communication funds than traditional VC funds.

II.c. Investor (LP) Statistics

We categorize each LP to reflect one of ten LP Types: *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). *Corporation & Government Portfolios* include corporations who invest in VC (e.g., Cisco and Siemens), state-owned corporations (e.g., China Steel and China Oceanwide Holdings), and sovereign wealth funds that are not development-oriented (e.g., Abu Dhabi Investment Authority).[9] *Wealth Managers* include family offices (e.g., Merrion Family Trust) and advisers who serve retail or high net worth clients (e.g., BNY Mellon Wealth Management). *Private Pensions* are primarily corporate pensions, but also include multiemployer retirement funds (e.g., Carpenters' Pension Fund of Illinois).[10] *Foundations*, *Banks*, *Insurance*, *Endowments*, and *Public Pensions* are self-explanatory. Finally, *Institutional*

[9] We sort sovereign wealth funds into development organization and government portfolios following Dyck and Morse (2010).
[10] There are 81 multiemployer pension funds and the majority are union-backed. Our results by LP type and LP attributes are qualitatively similar if we group these multiemployer pension funds with public pensions.

Asset Managers, a residual category, include LPs who manage money for a diverse institutional client base (e.g., Adams Street Partners), where the capital appears to be primarily institutional capital, and its constituents are mixed. We accomplish this with manual web searches for each LP in our sample. The goal is to attribute the capital to the constituent (rather than the intermediary). Thus, for asset managers, we search each manager to uncover whether the asset manager specializes in servicing a particular constituent (e.g., public pensions).

In Table 2, Panel A, we provide descriptive statistics on LPs. The smallest categories in terms of LP counts are endowments and wealth managers, but even these have over 200 distinct LPs participating in the market. The total number of investments by LP type generally mirrors the patterns of LP numbers, though both pension categories have more investments per LP while Banks and Corporations/Government Portfolios have fewer. The most active investors are Public Pensions (15.3 funds per investor), Private Pensions (8.9 funds) and Development Organizations (8.1 funds), relative to 6.9 fund investments the average LP. The average LP has 4.3 years of experience as an LP, though this number is positively skewed. Public Pensions, Private Pensions, and Endowments are the most experienced LPs. Overall, 9% of LPs are UNPRI signatories. Institutional Asset Managers are the most likely to sign the UNPRI (19.6%), followed by Insurance (13.8%) and Public Pensions (13.6%). Foundations, Corporations, and Endowment are extremely unlikely to be UNPRI signatories.

The last two rows of panel A present statistics across the 23,986 investments made by the 3,460 LPs. The penultimate row of Panel A reports that for 1/3rd of investments, there is a prior investment relationship between the LP and fund family. Likewise, the home bias rate is strikingly large with 3/4ths of investments made into funds focusing on the home region of the LP headquarters.[11]

In Table 2, Panel B, we present the regional distribution of LP headquarters.[12] Focusing on all LPs (last column of Table 2), nearly half of all LPs are in North America, while another 29% are in Developed Europe. However, the regional distribution of LPs varies by LP type. For example, 82% of Endowment LPs are in North America, while only 15% of Bank LPs are in

[11] In our later regression analysis, we analyze five regions (rather than eight) by combining Emerging Europe, Africa, and Central and South America into "Rest of the World", and Emerging Asia-Pacific and Middle East into "Emerging Asia-Pacific." However, to establish an LP-fund geography match we continue to employ the eight-region code first and then combine the eight home-bias dummies into five.

[12] For development organizations, we manually coded geographic foci of their missions and used them instead of the actual headquarters location. For example, Inter-American Development Bank is headquartered in the U.S., but its mission is focused on South and Central America.

North America. Relative to other LPs, Development Organization LPs have greater presence in Emerging Europe, Africa, Central and South America, and Emerging Asia-Pacific.

III. Realized Performance Results

Our starting point, and the topic of this section, is reduced form regressions of performance. One conjecture is that impact funds will earn below average returns because they impose a constraint (the generation of positive externalities) on the investment opportunity set, which should yield lower performance. Another conjecture is that the market fails to fully price macro and micro factors (natural resources, human capital) in a long-run perspective, thus resulting in above-market opportunities for impact funds, although this argument requires a friction in pricing. We consider both conjectures plausible and test for performance differences between impact and traditional VC funds.

We analyze the realized (or last reported) performance of funds in our sample: internal rate of return (IRR), value multiple (VM), and the average percentile rank of a fund relative to its vintage year and region cohort (Rank). We include funds with vintage years 1995 through 2012 in this analysis and use last reported performance for funds with later vintage years that are not yet completely liquidated. We regress a fund's IRR on a key impact dummy variable (IMP_j) that equals one for impact funds and step in control variables (denoted by the matrix X) in estimating three variations of the following regression:

$$IRR_j = \alpha + \beta IMP_j + X\Gamma + \varepsilon_j. \tag{1}$$

In our first regression specification, we estimate a univariate regression with only the key impact dummy, which recovers the average difference in IRR between traditional VC funds and impact funds from Table 1. In a second variation, we add controls for fund size, fund sequence number, and vintage year. In a third variation, we add controls for fund industry and fund geography. In each regression, we estimate robust standard errors clustered by vintage year. The three regressions are also estimated using either a fund's VM as the dependent variable or a fund's percentile rank as the dependent variable.

Table 3 reports the coefficient estimates on the key impact dummy variable. We find that impact funds reliably underperform traditional VC funds. Focusing first on IRR results in columns (1) to (3), the univariate regression of column (1) reveals that impact funds underperform traditional VC funds by 7.89 PPTs (p<.05).[13] When we add controls for fund size, sequence number, and vintage year in column (2), the performance spread grows to 9.94 PPTs (p<.01). Finally, in column (3) we add controls for fund geography and industry. While fund geography and industry explain some of the performance variation, the performance spread of 4.73 PPTs remains reliably negative. This third specification is a particularly stringent test of performance differences because traditional VC funds and impact funds vary in their industry and geography focus (see Table 1). While we work hard to code only funds with a dual objective as impact funds, we may misclassify some traditional VC funds, which are actually impact funds. To the extent that this misclassification varies by industry focus or geography of a fund, which seems likely given the industry and geography tilts of impact funds, models with industry and geography fixed effects will understate the true performance spread.

The analysis of value multiples and percentile ranks are qualitatively similar to the analysis of IRRs. Value multiples for impact funds are reliably less than those of traditional VC funds, ranging from 0.346 to 0.464 depending on model specification. Percentile ranks for impact fund are also reliably less than those of traditional VC funds, ranging from 7.8 PPTs to 15.5 PPTs depending on model specification.

These performance results represent one contribution of our analysis as we clearly establish impact funds have reliably lower performance than traditional VC funds. However, this fund level analysis of realized returns does not allow us to explore how different investors view the tradeoff between financial returns and the generation of positive externalities at the time of an investment decision. To explore this tradeoff, we now turn to our models that allow us to estimate a willingness to pay (WTP) for different investors.

IV. Willingness to Pay Methodology

In this section we present the empirical model for estimating investors' willingness to pay (WTP) for impact funds, i.e., how much (if any) in expected financial return the investor is willing to give up when investing in impact funds relative to traditional VC funds. Our primary model is a conditional logit model; we also verify robustness of our findings using a linear probability model (reported alongside the conditional logit model results) and a random

[13] Since in theory impact funds should earn equal or worse returns than traditional VC funds, the null hypothesis for statistical tests is impact fund performance is equal to or greater than traditional VC funds and we report one-sided p-values.

coefficients logit model (the overview of the model is reported in the online Appendix; results are available upon request) with analogous specifications.

IV.a. Logit Model of Willingness to Pay

Logit models are theoretically founded in random utility functions applied to discrete choice data. Consider investor *i* facing a binary choice of whether to invest in fund *j*. A random utility function of investor *i* investing in fund *j* is given by:

$$U^*_{ij} = \mu_i + \beta\mathbb{E}[\mathrm{r}_j] + \delta_i \mathrm{IMP}_j + \Gamma' X_{ij} + \varepsilon_{ij} \tag{2}$$

where U^*_{ij} is the utility that investor *i* derives from investing in fund *j* and $\mathbb{E}[\mathrm{r}_J]$ is the expected return for fund *j*. In Section IV.c, we develop a model of expected returns based on observable fund characteristics at the time of investment. IMP_j is a dummy variable equal to one if fund *j* is an impact fund (and 0 otherwise). X_{ij} is a matrix of control variables (such as the attributes of the funds and investors, including attributes of the match between funds and investors) with the associated vector of coefficients Γ. Investor fixed effects, denoted μ_i, allow the baseline investment probability to vary across investors *i*; thus, our model generates within-LP estimators for their willingness to pay for impact.

Random utility U^*_{ij} is not directly observable to the econometrician, who instead only observes the investor's choice to invest or not. The observable, discretized response U_{ij} (investment decision) corresponds to the latent utility U^*_{ij} as follows:

$$U_{ij}=1 \text{ iff } U^*_{ij}>0, \text{ and } U_{ij}=0 \text{ iff } U^*_{ij} \leq 0. \tag{3}$$

Under the assumption that the error term ε_{ij} is distributed *iid* extreme value, a logit estimation can uncover the parameters of equation (2).[14]

For this baseline model, we define the willingness to pay for impact (*wtp_imp*) for investor *i* as follows:

$$wtp\_imp_i = \frac{\left(\partial u / \partial \mathrm{IMP_j}\right)_i}{\partial u / \partial \mathbb{E}[\mathrm{r}_j]} = \frac{\delta_i}{\beta}.^{15} \tag{4}$$

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[14] The assumption of iid extreme value distribution for the error term allows this form of random utility to map to a logistic distribution with a mean 0 and variance π^2/3.

[15] In practice, Impact is a discrete choice variable; thus the correct form is:

$$wtp\_imp_i = \frac{U_i\left(.\,|IMP_j = 1\right) - U_i\left(.\,|IMP_j = 0\right)}{\partial u / \partial \mathbb{E}[\mathrm{r}_j]}$$

Suppose that δ_i>0 for investor *i* (impact is a desirable fund attribute for investor *i*). Assuming that β>0 (investors prefer funds with higher expected returns), such estimation results indicate investor *i* is willing to accept a lower financial expected return from impact funds than from (otherwise similar) traditional VC funds because the investor internalizes utility from impact for either social, institutional or regulatory reasons. In our empirical model, expected return, $\mathbb{E}[r_J]$, is expressed as the percentile rank among cohort funds (ranging between 0 and 1 with 0 = worst performing fund and 1 = best performing fund) and IMP_j is a dummy variable, so $\frac{\delta_i}{\beta}$ = 0.5 implies that investor *i* (or investors in cluster *i*) is indifferent between investing in an impact fund that is expected to perform at 25th percentile of cohort VC funds and investing in a traditional VC fund at 75th percentile.

We make one modification to the above logit model. The default assumption is that μ_i captures investor *i*'s base investment rate and that this remains constant for given investor *i* for all of his/her investment decisions over time. While this may be appropriate in the contexts for consumer demand, in our particular setting it raises a concern because LPs may increase or decrease their VC investment program over the sample period, and thus their baseline investment probability may fluctuate. Thus, we replace the time-constant fixed LP effects with dynamic grouped LP fixed-effects. We pool LP investors into 363 groups, combining investors in the same LP type (e.g., development organization, bank, foundation, pension, etc.) with the same average number of investments per year made in the prior three years. This grouping is dynamic since an investor can move into different groups as its VC portfolio grows or shrinks over time. We continue to use LP fixed effects in the linear probability model.

IV.b. Implementation of WTP Model

Having specified our baseline WTP model, we then use it to analyze the variation in the taste for impact by various investor characteristics. We begin our analysis by allowing δ_i, the coefficient on IMP_j, to vary across five geographic regions and 10 investor types. This implies that investors belonging to a particular investor type (e.g., banks) are assumed to have the same taste for impact δ_i. This is a natural way to introduce investor heterogeneity in taste for impact, as these investor types may signify differences across types in underlying constituents' preferences for externality generation, or legal or regulatory constraints faced by investors that induce tilts towards or away from impact investing. Similarly, we explore investor heterogeneity across five geographic regions (e.g., North America). Next we analyze whether investor's INPRI designation is a meaningful marker of their taste for impact—i.e., whether UNPRI signatories have greater WTP for impact than non-signatories—and whether this differential taste for impact by UNRPI signatories has grown over the sample period. We then analyze the variation in the taste for impact by investor attributes. Finally, we examine the variation in the taste for impact by funds' impact category.

IV.c. Expected Returns Formation

To estimate an investor's willingness to pay for impact, we must model an investor's expected return prediction. To do so, we construct an expected return that is based on a fund's observable characteristics at the time of investment. The fund characteristics we choose are motivated by the literature on the determinants of fund performance (Kaplan and Schoar, 2005; Sorenson 2007).

Consider an investor who is making decisions about VC investments offered in the market in vintage year 1995. The investor forms return expectations based on performance of prior funds in that VC fund family (the manager) and other fund characteristics (e.g., it's impact status). This 1995 investor would have a good indication regarding the performance of funds from vintage 1983 to 1990 and could see how the key independent variables (i.e., past manager performance) relate to performance. Then, using the parameter estimates, the investor can obtain out-of-sample forecasts of expected return for 1995 funds. The estimation model we describe is given by:

$$R_j = aR_j^{-1} + bMiss_j^{-1} + cFirst_j \ + \\ dIMP_j + eIMP_j * Miss_j^{-1} + fIMP_j * First_j \ + \varepsilon_j, \quad (5)$$

where R_j is performance of the fund j, R_j^{-1} is the performance of the prior fund managed by the same general partnership, $Miss_j^{-1}$ and $First_j^{-1}$ are dummy variables that equal one if the prior performance is missing or the current fund is a first-time fund (respectively), and IMP_j is a dummy variable that equals one if the fund is an impact fund. We also interact a fund's impact status with the missing and first-time fund indicator variables.

We model returns in terms of percentile rank in a vintage-region, rather than IRRs or VM for three reasons. First, because of the volatility in VC fund returns, investors often reference percentile ranks when choosing funds (e.g., "top quartile fund"). Second, modeling expected return predictions in ranks avoids outlier issues that crop up with the other performance measures. Finally, using ranks allows us to utilize all of our data, where we might have IRR or VM but not both.

After obtaining the out-of-sample expected return estimates for 1995 funds, we roll forward to the remaining vintage years in our sample, until we have estimates for expected returns for each fund 1995-2014. A time series summary of the results of these 20 first stage regressions for forecast years 1995 to 2014 are presented as Appendix Table A2.

Because predictions of future returns are notoriously noisy, these out-of-sample forecasts of expected returns from a fitted model generate more dispersion in expected returns than investors would rationally expect ex-ante. Thus, investors would rationally shrink the extreme forecasts toward a global mean expected return.[16] To calibrate a simple rule of thumb regarding the level of shrinkage that investors might use, we regress our realized fund returns on the forecast of returns. This regression yields an intercept coefficient of 0.25 and a slope coefficient of 0.50 (*p<.01)*. Thus, the return forecasts indeed contain information about future returns but the dispersion in forecast returns is too large. Note that these parameters indicate a fund with a forecast percentile rank of 1.0 should be expected to have realized performance at the 75th percentile while a fund with a forecast percentile rank of 0.01 would have performance at about the 25th percentile. This shrinkage adjustment to expected returns is a crucial step in appropriately assessing investor's willingness to pay for impact since the unadjusted forecasts would generate too much dispersion in expected returns and thus dramatically overestimate the willingness to pay.

V. Willingness to Pay Results

V.a. WTP by Investors

Table 4 reports our first set of WTP results. An observation in Table 4 is a potential investment by an LP in a fund, estimated over 3 million observations, which reflect the crossing

[16] Fama and French (1997) similarly shrink factor exposures when estimating industry expected returns. Jorion (1986) introduces shrinkage estimators in portfolio selection problems.

of all funds of a vintage year with all LPs that make at least one fund investment in that vintage year. Note that we construct this variable with observations not just for the LP investments that are made, but also for the investment possibilities that were not made, thus making a "long" choice dataset akin to Ljungqvist et al. (2006) and Bottazzi et al. (2015). As standard controls in this and later models, we include other determinants of VC investment – expected fund size, LPs' experience in VC investments, fund industry, fund geography, fund vintage year, prior relationship between the LP and fund family, and whether the fund region is home to the investor.[17] We also include the LP fixed effects in the linear probability model, and dynamic LP grouped fixed effects in the logit model, as defined in Section IV.b.

In the baseline model of Table 4, the coefficient on impact is 0.593 and the coefficient on expected returns is 3.521 (p<.01 for both coefficients). For the impact coefficient, the transformed marginal effect is 0.00383; an impact fund has an increased investment rate of 0.00383. The base investment rate into traditional VC funds is 0.0082; an LP chooses to invest in 0.82 out of every 100 (or 1 out of 122) traditional VC funds offered of a vintage. Impact funds experience investment rates of 1.2 out of every 100 (or 1 out of 83), which is an economically much larger (46% larger) investment rate.

In Panel B, we translate the impact coefficient into a WTP estimate using the estimated coefficient on expected returns. Our baseline result implies that when investors invest in impact funds, they are doing so with a willingness to pay of 17 percentile rank points (0.17 = 0.593/3.521). For the limited probability model, the analogous baseline model WTP for impact is 0.13. Centering at the median rank performance, the logit estimate of WTP implies that the average investor is indifferent (obtains identical utility) between investing in an impact fund at the 42nd percentile rank of its vintage-geography cohort and investing in a traditional VC fund at the 59th percentile rank. In term of the excess IRR of the fund, this suggests that investors who

[17] Of these variables, the prior relationship between the LP and fund family and the home bias are the most important economically, in line with the literature (Lerner, Schoar and Wongsunwai 2007; Hochberg, Ljungqvist, and Vissing-Jørgensen 2014; and Hochberg and Rauh 2013). To prevent the impact coefficient from picking up LPs' portfolio choice demand for particular investment characteristics, we include fixed effects for fund vintage, geography and industry. We also include two match characteristics, variables capturing paired characteristics between the investor and the particular fund considered for investment. First, following Hochberg and Rauh (2013), we include a home bias variable, defined as whether fund j focuses its investments on the home region of investor i, where we consider eight major regions globally. Second, because the prior relationship between an investor and a particular VC fund manager matters (Hochberg, Ljungqvist, and Vissing-Jørgensen 2014), we include an indicator variable for a prior investment relationship between investor i and any prior fund managed by fund j's fund manager. We measure expected fund size as the 3-year prior average of the median fund size in the vintage and market (U.S. or non-U.S.).

invest in impact funds are willing to give up between 2.9 and 4.2% in excess financial returns.[18] This magnitude is between 9 and 12% of the cross-sectional standard deviation of 0.32 that we observe in the IRRs of VC funds (see Table 1). It also is in line with the realized return evidence in Table 3, which indicates that impact funds earned IRRs that were about 4.7 PPT lower than traditional VC funds.

Note that this WTP estimate of 0.17 in percentile rank is an *average* effect among all investors in our sample, reflecting their differential odds of choosing to invest in impact funds relative to the odds of choosing to invest in traditional VC funds, wherein the two odds are calculated relative to available investment opportunities (in impact funds and traditional VC funds, respectively). It does not imply that all investors exhibit the same level of willingness to pay or that investors would necessarily have the same level of WTP if they had ten times more investment opportunities to invest in impact funds (i.e., when the industry scales up ten times). In practice, investors are likely to be heterogeneous in their taste for impact with some investors valuing the attribute more than others for social, institutional, legal or regulatory reasons. Nevertheless, this baseline result does suggest that on average investors indeed accept a tradeoff, willingly sacrificing financial returns in expectation when choosing to invest in impact funds.

In column (1), we allow investor's taste for impact to vary across five geographic regions. Circumstantial evidence suggests that demand for impact should be higher for investors active in more recent periods and from Europe. For example, in their 2014 report the Global Sustainable Investment Alliance (GSIA) reports that 59% of total managed assets in Europe are in SRI strategies compared to only 18% of assets in the US, 17% of assets in Australia, and 1% of assets in Asia. This suggests that Europeans value externalities more than North Americans.[19]

[18] See Appendix Table A1, Panel A. Historically, funds in the 40th percentile rank earned an excess return of -2.3% relative to benchmark cohorts, whereas funds in the 60th percentile earned 1.9%. 1.9-(-2.3) = 4.2%. Similarly, To go from the 40th to the 55th percentile, 0.6 – (-2.3) = 2.9% and to go from the 45th to the 60th is 1.9-(-1.0)=2.9%.

[19] Liang and Renneboog (forthcoming) document that the country's legal origin is more strongly correlated with the firm's CSR practice than "doing well by doing good" factors, resulting in civil law firms assuming higher level of CSR than common law firms. Dyck et al. (2016) find that foreign ownership by European institutional investors are associated with higher firm-level environmental and social performance, suggesting that they transplant their social norms into the firms they hold overseas. While a full assessment of culture is beyond the scope of this paper, it is entirely possible that differences in cultural values shape both beliefs and institutions across countries in a way that determines the demand for impact. We use the Hofstede (2010) measures of cultural values at the country level to consider whether cultural values expressed by Europeans differ from those of Americans. We compare the average scores in Europe to those in the United States for three relevant categories – Individualism v Collectivism, Long-Term Orientation, and Indulgence v Restraint. Relative to Americans on a scale of 0 to 100, Europeans have a score tilted at least 25 points toward having a collective agenda versus individualistic agenda, having a long term view of

Our results in column (1) strongly confirm the circumstantial evidence. North Americans have a positive and significant WTP estimate, but it is smaller (at 0.11) than the baseline estimate of 0.17. In contrast, investors from European and from Africa, Latin America, and Eastern Europe have much higher WTP of 0.26 and 0.34, respectively. Results are qualitatively similar using the linear probability model—e.g., North American investors' WTP is 0.11, and developed Europeans' WTP is 0.22. Asian-Pacific investors (both from developed and emerging economies) seem to have negligible WTP for impact, as their impact coefficients in the logit model are not significantly different from zero. In the linear probability model, their impact coefficients are positive and significant, but the magnitudes of their WTP are still small relative to other regions at 0.07 and 0.04, respectively.

This analysis accomplishes a second goal as well. One might push back on our analysis that the ultimate investors are naïve, and those managing capital are "duping" investors to think that they are not in fact trading off returns for impact utility. It would be hard to argue that this might happen more in Europe than in the United States, on average. In the next section, we also present evidence that UNPRI signatories have a positive taste for impact, further suggesting that investors knowingly make the tradeoff rather than unwittingly.

In column (2) we allow the impact coefficient (δ_i) to vary across 10 LP types. Since these LP types are not proportionally distributed across geographic regions, we further include interactions of the impact dummy with geographic dummies as additional control variables in column (3) (with North America as the omitted category).

The two columns (in two models) show consistent patterns of heterogeneity among the ten LP types. In Figure 2, we summarize the WTP results by LP type focusing on column (2) of the conditional Logit model. We find that development organizations, banks, insurance companies and public pensions have large positive WTP (0.22-0.32) when they invest in impact funds. Again using historical return distribution as reported in Table A1, magnitude of 0.25 suggests that these investors on average are willing to give up about 6% in excess IRR when investing in an impact fund, relative to a traditional VC fund with comparative industry geography, and relationship attributes.[20] This group thus exhibits a substantially larger willingness to pay for impact compared to the base estimate of 0.17 in percentile rank (2-3% in

society, and having more restraint versus being indulgent. These values are at least consistent with Europeans putting a higher value on investments that generate positive externalities.

[20] Moving from 30th to 55th percentile implies 0.6-(-5.4) = 6.0. Moving from 35th to 60th implies 1.9-(-4.2) = 6.1.

excess IRR). In the later section, we explore the attributes of these organizations that motivate this willingness to pay. Here, we provide a brief preview of the results: Development organizations are easy to understand, in having a mission with utility over impact. Financial institutions that are in the U.S. also have utility over impact, in the form of compliance with regulation mandating community investing. Likewise, public pensions can gain utility over local benefits from community investment, facing pressure to keep capital in local endeavors. We explore these ideas in the next section.

In contrast to these LP types who appear to accept non-trivial tradeoff in order to invest in impact funds, endowment and private pensions seem to have negligible WTP for impact, as their impact coefficients in the logit model are not significantly different from zero. In the linear probability model, their impact coefficients are positive and marginally significant, but the magnitudes of their WTP are still relatively small at 0.04 and 0.05, respectively. Fiduciary laws and regulations are likely at play here, an idea we explore in more detail below. These organizations are unlikely to invest in impact funds unless there is a strong case that they are not foregoing returns.

A couple of caveats are in order regarding the absolute magnitude of the Table 4 results. First, the willingness to pay estimate is measured over a small portfolio of investments. A given investor may not have the same willingness to pay for impact when scale of impact investing is larger. Likewise, it is worth reinforcing again that even within a given LP type, there is significant heterogeneity in investors' taste for impact. Not all banks may have the same level of WTP for impact.

V.b. WTP by UNPRI Signatories and Time

Since investors signing the UNPRI are doing so with a cost of compliance, it is plausible that they also have higher willingness to pay for impact compared to non-signatories.[21] Likewise,

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[21] Being a UNPRI signatory may reflect different motives across investor types. For asset managers whose clients do not value the SRI options, the cost associated with UNPRI compliance may be too high relative to its benefits. However, some institutional and wealth asset managers (e.g., Robeco) specialize in catering to end investors that demand SRI in their portfolio choices. Being a UNPRI signatory may elevate the credibility of these asset managers in the eyes of their target audience. For direct (non-intermediated) holders of capital, the motivation for signing the UNPRI could be more transparent as a signal of belief in principles. Likewise, signing may be a form of protection. For example, fiduciary investors may use UNPRI compliance as protection against potential lawsuits for breach of fiduciary duty. Consistent with these motives we find – in an unreported analysis where we interact the UNPRI signatory indicator with each of the ten LP types – that *only* the UNPRI signers have significant above market demand for impact among (i) asset managers, (ii) foundations, and (iii) private pensions.

investor, governmental, and media attention given to impact investing has grown in recent years (e.g., yielding the 2013 G7 Social Impact Investment Forum, spearheaded by UK Prime Minister David Cameron). Thus, it's natural to look for temporal variation in the WTP.[22] We use these markers (UNPRI designation and time) to assess the validity of our empirical method and provide more evidence describing WTP across these divisions.

Table 5 reports WTP estimated as impact utility heterogeneity across UNPRI designation and time. The first column interacts the impact dummy with the LP UNPRI dummy. Both models show that WTP is positive and significant for both signers and non-signers, but signers' WTP is much larger at 0.31-0.32, compared to non-signers' 0.10-0.13. The second columns test whether WTP for impact shows a secular time trend during our sample period. This is not an obvious prediction because supply is likely evolving as well. We obtain a positive significant WTP in both periods, but the WTP is larger in the later period – a WTP of 0.13 and 0.19 in the pre-2006 (2006 and prior years) and post-2006 periods, respectively. In columns (3), we report estimation results with double interactions of UNPRI designation and time. Consistent with the notion that UNPRI signatories are the main drivers behind the secular increase in investors' WTP for impact, we find that both signers' and non-signers' WTP are larger in the later period, but more dramatically so among the UNPRI signers. Their WTP increase from 0.19 in the pre-2007 period to 0.41 in the 2007-and-post period. The results using the linear probability model are qualitatively similar.

V.c. WTP by Investor Attribute

V.c.1. Discussion of Investor Attributes

In this section, we analyze the origins of varying utility over impact by studying attributes of LP investors that could motivate WTP. Our investor attribute model exploits two sources of variation. First, we study a set of legal restrictions that do not apply to all geographies (e.g., ERISA is a U.S. law). Second, we study combinations of investor attributes (e.g., private U.S. pensions are subject to ERISA *and* reflect constituents who are households) that allow use to compete stories of the cause of WTP.

[22] See Gompers and Metrick (2001) and Bennett, Sias, and Starks (2003) for prior research on temporal variation in institutional preferences for securities in public markets.

Table 6 presents six LP attributes (across columns) and their mapping to the ten LP types (rows). The first three attributes characterize inherent LP features that plausibly affect WTP (positive or negative) for impact. In column one (*Household*), we categorize investors based on the constituents of the capital (organizations or households). Wealth managers and the two types of pensions serve households as the ultimate constituents. In column two (*Intermediated*), we classify the LP types based on whether the capital is intermediated through an asset manager, with an observation that intermediation creates distance between the ultimate owner of capital and those who facilitate capital allocations. In column three (*Mission*), we identify investors that have an impact mission as a primary goal. Development organizations and foundations have explicit organizational goal of generating positive externalities for the region they serve (development organizations) or for the social and environmental goals of their mission (foundations). Implementation of mission objectives may or may not show up in portfolio investments, as many development organizations separate organizational activities (e.g., building schools) from the investment of the organization's capital.

The last three attributes characterize the implicit or explicit rules around investing for impact. In column four (*Pressure*), we identify pressures that encourage impact investment. In the U.S., commercial banks are subject to lending and investment obligations to serve their local low- and moderate-income communities under the Community Reinvestment Act (CRA). Banks are permitted to invest in community development VC as a way to fulfill the investment test part of their CRA obligation (CRA Investment Handbook, 2010, p.24). Likewise, insurance companies in some of the large U.S. states (e.g., Texas, New York, and California) must comply with state-level insurance regulations akin to the CRA that require them to invest in local communities. Even outside of those states, insurance companies in the U.S may face pressure to invest in impact locally in order to preempt passage of a federal CRA-like regulation for insurance (Gainer 2009). Thus, U.S. banks and insurance companies have incentives to invest in impact funds that serve low- to moderate-income communities, especially if such investments garner goodwill from customers. Banks and insurance companies in other countries face less such pressure. Public pensions worldwide, despite commonly being subject to a fiduciary duty standard, may face political pressure to increase the (perceived or real) welfare of voting populations. Public pensions may also face pressure to serve the political interests of their boards, which are often pro-labor and consider local job creation as an important policy goal.

Consistent with this idea, Dyck, Manoel, Morse, and Pomorski (2016) and Andonov, Hochberg, and Rauh (2016) both document that the investments of public pensions are affected by the degree to which the boards governing the pensions are appointed by government officials.

In column five (*Laws*), we highlight legal impediments to impact investing. Foundations, Endowments, and Private Pensions in the U.S. face more restrictive fiduciary standards than their non-U.S. counterparts, while Public Pensions face similar, restrictive fiduciary standards around the world. In the U.S., private pensions are subject to the 1974 Employee Retirement Income Security Act (ERISA). The US Department of Labor's 1994 guidance related to ERISA states that a pension plan fiduciary could consider non-financial factors (such as environmental or social impact) only if doing so would result in the same level of return at the same level of risk as comparable investment alternatives, i.e., it does not adversely affect risk or returns.[23] Public Pensions are subject to state- and national-level legislations regulations worldwide, generally through legislative action. In the U.S., for example, state regulations governing Public Pensions often closely follow ERISA.[24]

Analogous to ERISA, the Uniform Prudent Management of Institutional Funds Act (UPMIFA) governs the management of Foundations and university Endowments in the U.S. and generally imposes fiduciary duties of care and prudence that are similar to those of ERISA (see Geczy, Jeffers, Musto and Tucker (2015)).[25] Furthermore, tax laws in the U.S. create an additional hurdle. The U.S. tax authority requires Foundations to maintain a 5% annual payout rate to keep their tax-exempt status. Foundations can make impact investments designated as program-related investments (PRIs) and count these investments towards the required 5% payout rate if certain eligibility tests are met.[26] While the policy may have been intended to encourage

[23] U.S. NAB (2014). The ERISA guideline issued in 2008 and in effect until 2015 went even further, stating that pensions "… 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" (Johnson (2014)) and that those who consider noneconomic factors could be challenged later for noncompliance with ERISA absent a written record demonstrating no financial sacrifice was made. The new ERISA guideline issued in 2015 withdraws this language and reverts to the original ERISA restrictions. See: https://www.dol.gov/opa/media/press/ebsa/ebsa20152045.htm.

[24] Impact funds are often loath to admit the existence of any trade-offs between the positive externality they generate and the financial return they earn. The careful rhetoric used by impact funds may be an attempt to cater to fiduciary investors' need to appear uncompromising in their search for financial returns.

[25] However, unlike ERISA, UPMIFA provides an additional duty of obedience to the unique charitable mission of the organization. Notwithstanding this duty of obedience provision, we suspect that foundations have been constrained by the UPMIFA because investment decisions are generally detached from pursuit of the organizational mission at U.S. foundations.

[26] Specifically, the PRIs must further the foundation's organization mission, and the financial returns cannot be a primary purpose of the investment. In practice, PRI investors are required to demonstrate that conventional investors

PRIs, the ambiguity around the test outcome and the perceived threat of tax-exempt status loss may subdue Foundations' WTP for impact in their investment portfolio.

In column six (*Charters*), we identify restrictions against impact investment in the form of organizational charters. We exclude from column six the entities already covered by legal restrictions (column five) under the assumption that legal restrictions are more binding. Charters require organizations to maximize value for shareholders, which may constrain investments into impact funds. Charters govern Banks, Insurance, and Corporations, and ensure that management maximizes value to shareholders. Similarly, non-U.S. private pensions are subject to fiduciary responsibility via their parent corporate charters. Institutional Asset Managers, who manage a pool of capital from these entities, are also required by suitability and fiduciary standards to manage investments in the interests of their clients, thereby imposing these restrictions on their investment allocation decisions on behalf of their charter-bound clients. To the extent that institutional asset managers also manage capital on behalf of other clients, our estimates of the effect of charter restrictions will be conservative.

V.c.2. WTP Results by Attribute

Table 7 reports how WTP varies across investor attributes. We report three specifications in each of the two models. In columns (1), we include interactions of impact and investor attributes, which we map from an investors type to attributes using Table 6. In columns (2), we further include interactions of impact and LP geography dummies as additional controls, as in column (3) of Table 4. Finally, in columns (3), we include three of the investor attributes while controlling for interactions of impact and the ten LP types as controls. Note that the three attributes we include in column (3) – *Pressure*, *Charter*, and *Laws* – are functions of both LP types *and* LP geography, and thus can still be simultaneously identified while controlling for the ten LP types. In contrast, the remaining three attributes – *Mission*, *Household*, and *Intermediated* – are linear functions only of the LP types, so we have to exclude them in this specification.

Robustly across columns and models, we find three results relating attributes to impact WTP. We focus on column 2 for ease of exposition. First, investors with *Mission* objectives have a high WTP (25 percentile points in expected returns).

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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. Precisely for this reason, below-market-return loans are popular vehicles for PRIs. In contrast, equity vehicles are relatively rare, possibly because of the perceived risk of violating the PRI eligibility requirement if it makes too much profit ex post.

Second, investors facing *Pressure* from political or regulatory institutions exhibit a high WTP (30 percentile points in performance rank). Some investors are not driven to impact in a vacuum but by the structure deliberately built into their environment by regulation and politics. The number of investments accounted for by the institutions in this category is large, implying that *Pressure*, explicit or implicit, may imply real economy effects for certain geographic areas. More evidence is needed as to the welfare implications of these investment outcomes.

Third, we find that LPs with *Laws* against impact investing have significantly negative WTP for investing into impact funds (-19 percentile points in performance rank). This finding is particularly interesting because we find that having *Charter* Restrictions against impact alone does not materially affect their demand for impact on average. Laws like ERISA and UPMIFA matter. In contrast, shareholders' recourses (e.g., lawsuits and management turnover) do not seem to bind against impact investing in a way that we can identify.

V.c.3. The Effect of Pressure and Home Bias on WTP

In the prior section, we document that *Pressure* results in a high WTP for impact. Specifically, banks and insurance companies within the U.S. are subject to regulatory pressure to invest locally, while public pensions funds worldwide are subject to political pressure to do so. In both of these scenarios, our arguments imply that the pressure induces or reflects a preference for investing in impact closer to home rather than impact *per se*. To support these arguments, we test whether pressure is indeed a local concept. In particular, for these LPs under pressure is local demand for impact statistically distinguished from their overall demand for impact and their overall preference for local non-impact investments?

To investigate this question, we estimate models where the key variables of interest are the triple interaction of *Impact*, *Pressure,* and *Homebias*, which is a dummy variable that equals one if the fund is in the same region as the LP. We estimate three models. In all three models we include standard controls and alternatively include fixed effects for the interaction of impact and LP geography (as in column (2) of Table 7), the interaction of impact and LP type (as in column (3) of Table 7), or both interactions. In columns (1) to (3), we show the *Pressure* WTP results of Table 7 are qualitatively unchanged when we pare down the model to include only the key Impact**Pressure* variable.

The results of interest are provided in columns (4) to (6), in which we present the results of the triple interaction. The key result is the economically large effect of the triple interaction of

Impact, *Pressure*, and *Homebias* across the three model specifications; LPs subject to political pressure are much more likely to invest in impact funds that are close to home. The double interaction of *Pressure* and *Homebias* is also consistently positive, though the economic magnitude is relatively small; LPs subject to political pressure prefer local nonimpact investments, but not to the same extent that they prefer local impact funds. The double interaction of *Impact* and *Pressure* is reliably negative in two model specifications, which suggests that LPs subject to political pressure do not have a general preference for impact funds (and might actually spurn impact funds when they are not locally focused). The double interaction of *Impact* and *Homebias* is either economically small or indistinguishable from zero, which indicates investors do not have a general preference for impact funds that are locally focused. In sum, the impact preferences of LP Types subject to political pressure (public pensions, U.S. banks, and U.S. insurance companies) are restricted to impact funds that are locally focused and the home bias preferences of those institutions to invest in nonimpact funds are small relative to the preference for locally focused impact funds.

V.d. WTP by Impact Utility Category

In this section we examine whether investors' willingness to pay for impact varies by the type of impact that funds pursue. Figure 3 presents the results of the logit model estimation in which we interact the impact dummy with each of the seven impact categories as described in Section II.a. and summarized in Figure 1. Note that these categories are not mutually exclusive, as a given fund can meet the criteria of more than one impact category.

The results indicate that investors exhibit a positive willingness to pay when considering investing in impact funds focusing on social, environmental, women & minority issues, and poverty alleviation. Translated to IRR, this amounts to about 9% in excess IRR, or about one quarter of standard deviation in fund IRR in our sample. These are all arguably categories with high public good or externality content. In contrast, investors exhibit a negative willingness to pay when considering investing in impact funds focusing on SME funding. Notably, 57% of impact funds in the SME category also have a poverty focus and are thus captured by the poverty category; SME funds without a poverty focus often target particular geographic areas (e.g. Oregon Investment Fund) and are unlikely to attract interest from investors other than local financial institutions and pensions. It is also possible that the investors' willingness to pay is a function of the scarcity of investment opportunities in a given category. For example, only 11%

of impact funds have a focus on women and minority. Given the relatively small number of investment opportunities for this fund attribute during the sample period, investors who internalize the externality of advancing women and minority causes may have accepted a larger tradeoff in expected financial returns than they would have otherwise.

VI. Conclusion

In this paper, our goal has been to understand whether investors have utility for positive externalities. We do this in two empirical frameworks designed to identify preference for impact investments. We first document in reduced-form regression analysis that ex post financial returns earned by impact funds are 4.7% lower than those earned by traditional VC funds even after controlling for a host of fund characteristics. If these return differentials are equilibrium results and not ex post surprises, the results suggest investors willingly pay for impact. To examine whether investors in impact funds willingly trade off *expected* financial returns at the time of investment decisions, we estimate investor's willingness to pay for the generation of a positive externality (impact) based on expected fund returns (where expectation is conditional on historical information available to investors at the time) and the impact status of the fund. Our estimation model is a conditional logit model, founded on the hedonic pricing framework derived to estimate investors' willingness to pay from their discrete choice over a set of alternatives (in our case, VC funds). We find that investors choosing to invest in impact funds are on average willing to forgo 17 percentile points in performance rank, or about 3-4% in excess IRR relative to traditional VC funds (or about 9-12% of sample standard deviation in fund IRRs). The overall positive WTP is driven almost entirely by investors from Europe and the smaller pool of VC investors in Latin America and Africa.

The willingness to pay varies considerably over who controls the capital allocation decision. To unpack the heterogeneity across investors we categorize LP investors into ten broad categories. Investors in four of the ten categories – development organizations (0.32), banks (0.29), insurance companies (0.22), and public pensions (0.24) – exhibit reliably positive willingness to pay for impact. In contrast, some investors have no reliable WTP for impact funds, including endowments and private pensions.

To better understand why the investors' willingness to pay for impact varies dramatically across these LP types, we identify six attributes of investors that plausibly affect their willingness to pay for impact. We find that investors with organizational missions and investors who face political and/or regulatory pressure to invest in impact (e.g., banks in the U.S. that face CRA requirements) exhibit a reliably positive WTP for impact. In line with the locally restricted nature of these political and/or regulatory pressures (to generate positive externality for local population), the WTP for impact exhibited by those LPs under *Pressure* is only a WTP for local impact funds. We conclude from these results that investors who can legally internalize externality and/or investors who face exogenous constraints that induce them to deviate from unconstrained financial return maximization are indeed willing to forgo some expected financial return when investing in impact funds.

In contrast, investors who are subject to legal and regulatory restrictions (e.g., U.S. pensions, foundations and endowment subject to ERISA and UPMIFA) against dual-objective investments with potential for financial return sacrifice exhibit a reliably negative willingness to invest in impact. This result suggests that legal restrictions in the form of strong fiduciary duty (as exists in the U.S.) go beyond simply making these high fiduciary investors *ignore* impact utility when making investment decisions; in fact these legal restrictions appear to induce high fiduciary investors to require a *higher* financial return threshold when investing in impact funds relative to when investing in traditional VC funds, perhaps to compensate for the elevated risk of violating their legal duty. Since the number of high-fiduciary LPs affected by such legal restrictions is large (1,258 out of 3,504 in our sample), this finding has important implications for how subtle shifts in legal interpretations of institutions' fiduciary duty may affect investors' willingness to pay for externality generation.

In combination, our results provide compelling evidence that investors are willing to pay for nonpecuniary characteristics of investments. Specifically, investors value the generation of positive externalities when allocating capital. This result indicates that the capital allocation decisions, though certainly governed by the linchpin risk-return tradeoff of wealth maximization in standard utility models, are also shaped by the real world consequences of the investments that people make. The preferences for the generation of positive externalities vary considerably across legal and regulatory environments, investor geography, and time. This variation opens up a number of avenues for future research to explore the factors that govern the variation that we document.

Appendix B: 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 B1 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. We identify countries with GDP per capital of less than $1400 according to the IMF 2014 (see Table A2 for the list of 37 countries) and add 66 funds that make investments in these countries according to Preqin. For funds that invest in multiple regions, we require that half of the listed regions be in these poor countries. This results in 843 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 843 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. Finally, we require that there is data on at least one LP per fund in Preqin. This process yields 161 impact funds with a venture or growth focus.

Appendix Table B1: 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	

Table B2: Countries with GDP Per Capital less than $1400

Country	GDP per capita	Country	GDP per capita	Country	GDP per capita
Pakistan	1,343	Haiti	833	Guinea-Bissau	589
Kyrgyzstan	1,299	Benin	822	North Korea	583
Chad	1,236	Sierra Leone	808	Ethiopia	575
Burma	1,221	Mali	754	Guinea	573
Bangladesh	1,172	Uganda	726	Liberia	484
Lesotho	1,130	Rwanda	722	Niger	469
South Sudan	1,127	Burkina Faso	717	Madagascar	449
Tajikistan	1,113	Nepal	699	Congo	437
Cambodia	1,081	Togo	658	Gambia	428
Senegal	1,072	Afghanistan	649	Central African Republic	380
Zimbabwe	1,031	Mozambique	630	Burundi	336
Tanzania	1,006	Eritrea	590	Malawi	242
Comoros	923				

Source: IMF World Economic Outlook 2014

Appendix C: Random-effects Logit Model

Random coefficients logit estimation differs from traditional logit models in that some parameters are allowed to randomly vary across agents (investors or investor types in our case). Following the WTP literature (Revelt and Train 1998), we specify that all investors face the same mapping of expected returns (our "price" variable) to utility and the same investment sensitivity to controls. (Coefficients β and Γ are fixed parameters.) However, we allow our variable of interest, an impact fund indicator, to be random, varying across investors stochastically. Coefficient δ_i is assumed to be distributed normally across the population of investors i (or cluster i of investors), while independent of ε_{ij}, $\mathbb{E}[r_J]$, IMP_j, and X_{ij}.[27] The benefit of the random coefficients model for the WTP application is that the model allows post-estimation inferences about the magnitude of the impact random coefficient for specific investors (or clusters of investors). [28]

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[27] Technically, random coefficient δ_i has mean d_2 and variance σ_2. If μ_i is estimated as a random effect, it has mean d_1 and variance σ_1, allowing μ_i and δ_i are allowed to have an unrestricted covariance σ_{12}. δ_i and μ_i are drawn from normal distributions. The parameters d_1, d_2, σ_1, σ_2, σ_{12}, β and Γ are estimated using maximum log likelihood, using mean-variance adaptive Gauss–Hermite quadrature methods.

[28] We predict δ_i for specific investors (or clusters of investors) by calculating empirical Bayes means using both the estimated model parameters and the observed dependent variables for specific investors (their investment decisions).

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Table 1. Fund Descriptive Statistics, 1995 to 2014

This table presents fund summary statistics for all funds (left columns) and impact funds (right columns). Capital Commitment is the average capital commitment across investors within a fund. IRR is the final or last observed internal rate of return for the fund. VM is the fund's value multiple, and Percentile Rank is the fund's percentile rank relative to similar cohort funds (year, region, and fund type). In Panel B, we present the geography focus of fund investments where each region represents a dummy variable that equals one if the fund invests in the region. In Panel C, we present the industry focus of fund investments. Funds can have multiple geography and industry focuses.

	Traditional VC Funds				Impact Funds			
	N	Mean	Median	Std. Dev.	N	Mean	Median	Std. Dev.
	Panel A: Descriptive Statistics							
Vintage Year	4500	2005.36	2006.00	5.26	159	2006.71	2008.00	4.44
Fund Size ($mil)	4000	204.61	102.00	300.16	147	129.59	83.00	147.26
Capital Commitment ($mil)	2717	22.19	14.60	33.84	125	27.09	15.00	32.88
IRR (%)	1207	11.59	7.40	32.06	76	3.7	6.35	15.17
VM - Value Multiple	1484	1.51	1.22	1.94	91	1.17	1.10	0.56
Percentile Rank	1528	0.49	0.50	0.30	93	0.34	0.28	0.30
Fund Sequence Number	4500	3.95	2.00	5.63	159	3.88	2.00	5.91
	Panel B: Geography Focus of Fund Investments							
North America	4500	0.50			159	0.33		
Developed Europe	4500	0.23			159	0.18		
Emerging Europe	4500	0.06			159	0.09		
Africa	4500	0.02			159	0.23		
Central and South America	4500	0.03			159	0.12		
Developed Asia-Pacific	4500	0.07			159	0.01		
Emerging Asia-Pacific	4500	0.17			159	0.14		
Middle East	4500	0.03			159	0.00		
All Regions	4500	1.10			159	1.09		
	Panel C: Industry Focus of Fund Investments							
Business Services	4500	0.03			159	0.03		
Energy	4500	0.06			159	0.19		
Consumer Discretionary	4500	0.05			159	0.03		
Diversified	4500	0.27			159	0.48		
Industrials	4500	0.04			159	0.06		
Information Technology	4500	0.45			159	0.06		
Health Care	4500	0.22			159	0.06		
Infrastructure	4500	0.01			159	0.05		
Food and Agriculture	4500	0.01			159	0.04		
Materials	4500	0.01			159	0.04		
Real Estate	4500	0.00			159	0.04		
Media and Communications	4500	0.12			159	0.03		
All Industries	4500	1.27			159	1.12		

Table 2. Limited Partner (LP) Descriptive Statistics

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. Funds per LP are the total number of unique fund investments by an LP. Vintage Year is the average vintage year of fund investments. Years of Experience is the number of years since the LPs' first fund commitment (measured at the time of each investment and averaged across all investments for a given LP). The % Prior Relationship is the percent of capital commitments where the LP and fund's general partner (GP) had a prior investment relationship. The % Home Bias is the percent of capital commitments by the LP type where the region of the LP and fund are the same (using the eight major global regions of Panel B). In Panel B, we present the regional distribution of LPs by LP type. Standard deviations are in parentheses.

	Dev. Org.	Found-ation	Bank	Insurance	Endow-ment	Corp. & Gov't	Institu-tional	Wealth Manager	Private Pension	Public Pension	Total
	Panel A: LP Descriptive Statistics										
# of LPs	268	458	260	320	198	416	525	201	440	374	3,460
% of Total	7.7	13.2	7.5	9.2	5.7	12.0	15.2	5.8	12.7	10.8	100.0
# of Capital Commitments	2,159	2,788	657	1,828	1,290	1,531	3,436	675	3,893	5,729	23,986
% of Total	9.0	11.6	2.7	7.6	5.4	6.4	14.3	2.8	16.2	23.9	100.0
Funds per LP	8.06	6.09	2.53	5.71	6.52	3.68	6.54	3.36	8.85	15.32	6.93
	(16.44)	(13.54)	(2.61)	(11.41)	(15.64)	(16.35)	(15.63)	(6.14)	(19.80)	(30.36)	(17.43)
Vintage Year	2007.26	2005.81	2006.22	2005.26	2004.85	2006.59	2005.51	2006.17	2004.67	2005.53	2005.74
	(3.86)	(3.67)	(4.14)	(4.42)	(4.18)	(5.12)	(4.29)	(4.65)	(4.09)	(3.69)	(4.28)
Years of Experience	4.28	4.13	3.00	4.34	4.61	2.65	3.77	3.39	5.08	7.73	4.34
	(4.43)	(4.67)	(3.17)	(5.05)	(5.37)	(3.41)	(4.48)	(4.36)	(5.23)	(7.51)	(5.11)
% UNPRI Signatories	5.2	2.4	8.1	13.8	1.5	1.0	19.6	12.4	8.4	13.6	9.0
% Prior Relationship	23.6	41.6	11.0	26.6	38.8	22.9	25.5	24.0	38.3	41.1	33.4
% Home Bias	59.1	78.3	82.1	82.4	81.9	71.9	61.1	68.6	78.3	84.5	75.8
	Panel B: Regional Distribution of LPs by LP Type										
North America	19	83	15	50	82	23	30	34	72	62	48
Developed Europe	28	15	39	33	16	27	42	38	20	29	29
Emerging Europe	5	0	4	0	0	1	1	2	1	0	1
Africa	5	0	4	3	1	1	3	1	1	2	2
Central and South America	6	0	1	1	1	2	1	1	3	2	2
Developed Asia-Pacific	8	1	15	6	0	20	9	17	2	3	8
Emerging Asia-Pacific	25	0	15	7	1	24	11	4	0	1	9
Middle East	3	1	7	2	0	2	5	4	1	1	3

Table 3. The Performance of Impact Funds, 1995-2014

Fund performance (IRR, VM, or percentile rank) is regressed on a dummy variable for impact funds and fund characteristics (log of fund size, log of fund sequence number, fund geography using five regions, and fund industry using 12 industries). Models that include fund size in the regression lose observations of traditional VC funds with missing fund size. Standard errors are calculated by clustering on vintage years.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	IRR	IRR	IRR	VM	VM	VM	Rank	Rank	Rank
impact	-7.890**	-9.937***	-4.731*	-0.346*	-0.464***	-0.361**	-0.148***	-0.155***	-0.078**
	[3.705]	[2.638]	[2.616]	[0.204]	[0.129]	[0.164]	[0.032]	[0.033]	[0.036]
N - Impact Funds	76	76	76	91	91	91	93	93	93
Observations	1,283	1,252	1,252	1,575	1,518	1,518	1,621	1,563	1,563
R-squared	0.004	0.146	0.166	0.002	0.123	0.131	0.013	0.027	0.068
Controls:									
Vintage Year FE	NO	YES	YES	NO	YES	YES	NO	YES	YES
Log(Fund Size)	NO	YES	YES	NO	YES	YES	NO	YES	YES
Log(Fund Sequence)	NO	YES	YES	NO	YES	YES	NO	YES	YES
Fund Geography FE	NO	NO	YES	NO	NO	YES	NO	NO	YES
Fund Industry FE	NO	NO	YES	NO	NO	YES	NO	NO	YES

Robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Table 4. The Willingness-to-Pay for Impact

Notes: See caption in front of Panel B on the next page.

Panel A: Estimates	Logit model				Linear Probability model			
	(Base)	(1)	(2)	(3)	(Base)	(1)	(2)	(3)
Expected Returns	3.521***	3.491***	3.553***	3.531***	0.0343***	0.0342***	0.0345***	0.0344***
	[0.290]	[0.290]	[0.289]	[0.289]	[0.00342]	[0.00342]	[0.00343]	[0.00343]
Impact Estimates by LP Type								
Dev. Org			1.132***	0.920***			0.0125***	0.0117***
			[0.152]	[0.182]			[0.00285]	[0.00312]
Foundation			0.341*	0.279			0.00325***	0.00291***
			[0.178]	[0.178]			[0.000795]	[0.000801]
Bank			1.040***	0.935***			0.00688***	0.00651***
			[0.188]	[0.237]			[0.00146]	[0.00178]
Insurance			0.773***	0.679***			0.00556***	0.00497***
			[0.140]	[0.152]			[0.00101]	[0.00111]
Endowment			-0.459	-0.513			0.00129*	0.00107
			[0.361]	[0.347]			[0.000716]	[0.000694]
Corporation			0.187	0.102			0.00209**	0.00225*
			[0.186]	[0.236]			[0.000965]	[0.00131]
Institutional			0.254	0.0526			0.00235***	0.00137
			[0.159]	[0.189]			[0.000831]	[0.00112]
Wealth Manager			0.353	0.209			0.00287**	0.00248*
			[0.307]	[0.311]			[0.00129]	[0.00148]
Private Pension			-0.0636	-0.147			0.00164**	0.00125*
			[0.173]	[0.168]			[0.000647]	[0.000639]
Public Pension			0.849***	0.738***			0.00692***	0.00624***
			[0.115]	[0.121]			[0.00112]	[0.00112]
Impact Estimates by LP Geo								
North America		0.397***				0.00358***		
		[0.0846]				[0.000534]		
Developed Europe		0.922***		0.418***		0.00748***		0.00304**
		[0.102]		[0.143]		[0.00107]		[0.00125]
Developed Asia-Pacific		-0.0813		-0.547		0.00230***		-0.00210*
		[0.383]		[0.421]		[0.000586]		[0.00122]
Emerging Asia-Pacific		-0.311		-0.885***		0.00149**		-0.00348***
		[0.270]		[0.299]		[0.000743]		[0.00129]
Africa, Lat.Amer., E. Euro.		1.175***		0.539**		0.00966***		0.00301
		[0.218]		[0.239]		[0.00257]		[0.00280]
Impact	0.593***				0.00458***			
	[0.0600]				[0.000462]			
Standard Controls	YES	YES	YES	YES	YES	YES	YES	YES
Observations	3,047,430	3,047,430	3,047,430	3,047,430	3,047,430	3,047,430	3,047,430	3,047,430

*** p<0.01, ** p<0.05, * p<0.1

Table 4. The Willingness-to-Pay for Impact (continued)

Panel A summarizes estimates from conditional logit and linear probability models. Panel B summarizes the willingness to pay, which is the impact coefficient divided by the expected return coefficient. The dependent variable is a dummy variable that equals one if an LP invests in a fund. Observations are determined by crossing all vintage year funds with LPs that make an investment in that year. Impact equals one for impact funds. Expected Returns are expressed as percentile ranks relative to vintage year cohort funds and are modeled based on known fund characteristics at the time of investment and adjusted for shrinkage. Heterogeneity in investment rates is modeled using LP fixed effects in the linar probability model and dynamic LP group fixed effects in the logit model. Standard controls include the following: LP experience (log of years since first fund investment plus one), LP-GP relationship (a dummy variable that equals one if the LP invested in a prior fund managed by the same fund family, fund-LP geography match (five dummy variables for five regions that equal one if the fund and LP are in the same region), expected fund size, and fixed effects for fund geography (five regions), industry (12 industries), and vintage year. Robust standard errors are shown in brackets. WTP of "--" indicates that the impact coefficient is not significantly different from zero.

Panel A: Estimates	Logit model				Linear Probability model			
	(Base)	(1)	(2)	(3)	(Base)	(1)	(2)	(3)
	Estimates Appear on Prior Page. WTP Calaculations Correspond to Column Numbers							
Panel B: Willingness to Pay (WTP)								
All Investors	0.17				0.13			
WTP by LP Type								
Dev. Org			0.32	0.26			0.36	0.34
Foundation			0.10	--			0.09	0.08
Bank			0.29	0.26			0.20	0.19
Insurance			0.22	0.19			0.16	0.14
Endowment			--	--			0.04	--
Corporation			--	--			0.06	0.07
Institutional			--	--			0.07	--
Wealth Manager			--	--			0.08	0.07
Private Pension			--	--			0.05	0.04
Public Pension			0.24	0.21			0.20	0.18
WTP by LP Geo								
North America		0.11				0.11		
Developed Europe		0.26		0.12		0.22		0.09
Developed Asia-Pacific		--		--		0.07		-0.06
Emerging Asia-Pacific		--		-0.25		0.04		-0.10
Africa, Lat.Amer., E. Euro.		0.34		0.15		0.28		--

Table 5. The Willingness-to-Pay for Impact by UNPRI Signatories and Time

Panel A summarizes estimates from conditional logit and linear probability models. Panel B summarizes the willingness to pay, which is the impact coefficient divided by the expected return coefficient. The dependent variable is a dummy variable that equals one if an LP invests in a fund. Observations are determined by crossing all vintage year funds with LPs that make an investment in that year. Impact equals one for impact funds. Expected Returns are expressed as percentile ranks relative to vintage year cohort funds and are modeled based on known fund characteristics at the time of investment and adjusted for shrinkage. Heterogeneity in investment rates is modeled using LP fixed effects in the linar probability model and dynamic LP group fixed effects in the logit model. All models include standard controls (see text and Table 4 for details). Model (1) also includses UNPRI dummy, and Model (3) includes post2006*UNPRI, post2006*non-UNPRI, and pre2006*UNPRI. Robust standard errors are shown in brackets. *** p<0.01, ** p<0.05, * p<0.1

Panel A: Model Estimates	Logit model			Linear Probability model		
	(1)	(2)	(3)	(1)	(2)	(3)
Expected Returns	3.520***	3.508***	3.505***	0.0343***	0.0343***	0.0342***
	[0.291]	[0.289]	[0.290]	[0.00343]	[0.00342]	[0.00342]
Impact Estimates by LP Char.						
UNPRI	1.091***			0.0109***		
	[0.112]			[0.00202]		
non-UNPRI	0.440***			0.00359***		
	[0.0655]			[0.000425]		
pre-2006		0.439***			0.00323***	
		[0.0748]			[0.000508]	
post-2006		0.679***			0.00529***	
		[0.0713]			[0.000550]	
pre2006_UNPRI			0.682***			0.00539***
			[0.143]			[0.00176]
pre2006_non-UNPRI			0.368***			0.00285***
			[0.0879]			[0.000540]
post2006_UNPRI			1.428***			0.0146***
			[0.137]			[0.00259]
post2006_non-UNPRI			0.463***			0.00387***
			[0.0768]			[0.000469]
Standard Controls	YES	YES	YES	YES	YES	YES
Observations	3,047,430	3,047,430	3,047,430	3,047,430	3,047,430	3,047,430
Panel B: Willingness to Pay (WTP)						
UNPRI	0.31			0.32		
non-UNPRI	0.13			0.10		
pre-2006		0.13			0.09	
post-2006		0.19			0.15	
pre2006_UNPRI			0.19			0.16
pre2006_non-UNPRI			0.10			0.08
post2006_UNPRI			0.41			0.43
post2006_non-UNPRI			0.13			0.11

Table 6. Limited Partner (LP) Types and Attributes related to Impact Motives

The table lays out attribues of the LP investor types listed in the first column. Column 2 indicates whether the primary constituents of the capital are households (v. organization). Column 3 indicates whether the constituent capital is intermediated as opposed to directly invested by the constituent or an administrator (e.g., foundations and pensions). Column 4 indicates whether impact is a primary goal of the constituent. Column 5 identifies legal and political pressure to invest with impact. Finally, hte last two columns identify laws (e.g., ERISA) and charters (e.g., corporate charters) that restrict impact investment.

Limited Partner	Household	Intermediated	Mission	Pressure toward Impact	Laws Restricting Impact	Charters Restricting Impact
Development Organizations	--	--	yes	--	--	--
Foundations	--	--	yes	--	yes UPMIFA and PRI (U.S.)	--
Banks	--	--	--	yes Community Reinvestment Act (U.S.)	--	yes
Insurance	--	--	--	yes State regulation modeled after CRA (U.S.)	--	yes
Endowments	--	--	--	--	yes UPMIFA (U.S.)	--
Corporate & Government Portfolios	--	--	--	--	--	yes
Institutional Asset Managers	--	yes	--	--	--	yes
Wealth Managers	yes	yes	--	--	--	--
Private Pensions	yes	--	--	--	yes ERISA (U.S.)	yes (non-US)
Public Pensions	yes	--	--	yes Political pressure	yes State & National Laws	--

Table 7. The Willingness-to-Pay for Impact by Investor Attribute

Panel A summarizes estimates from conditional logit and linear probability models. Panel B summarizes the (incremental) willingness to pay, which is the impact coefficient (interacted with attributes) divided by the expected return coefficient. The dependent variable is a dummy variable that equals one if an LP invests in a fund. Observations are determined by crossing all vintage year funds with LPs that make an investment in that year. Impact equals one for impact funds. Expected Returns are expressed as percentile ranks relative to vintage year cohort funds and are modeled based on known fund characteristics at the time of investment and adjusted for shrinkage. Heterogeneity in investment rates is modeled using LP fixed effects in the linar probability model and dynamic LP group fixed effects in the logit model. All models include standard controls (see text and Table 4 for details) plus the six LP attribute dummies. Model (1) also includses impact dummy, Model (2) includes Impact*LP Geo dummies, and Model (3) includes Impact*LP Type dummies. Robust standard errors are shown in brackets. WTP of "--" indicates that the impact coefficient is not significantly different from zero. WTP of "--" indicates that the impact coefficient is not significantly different from zero.

Panel A: Model Estimates	Logit model			Linear Probability model		
	(1)	(2)	(3)	(1)	(2)	(3)
Expected Returns	3.553***	3.535***	3.544***	0.0344***	0.0343***	0.0344***
	[0.289]	[0.289]	[0.290]	[0.00342]	[0.00343]	[0.00343]
Impact Estimates by Investor Attribute						
Mission	1.025***	0.890***		0.00415***	0.00363***	
	[0.316]	[0.300]		[0.00117]	[0.00114]	
Household	0.570**	0.356*		0.00117	0.000468	
	[0.226]	[0.215]		[0.000971]	[0.000971]	
Intermediated	-0.114	-0.143		-0.00224**	-0.00239**	
	[0.183]	[0.180]		[0.000976]	[0.00100]	
Pressure	1.001***	1.058***	0.767***	0.00583***	0.00575***	0.00556***
	[0.137]	[0.146]	[0.288]	[0.000979]	[0.000982]	[0.00198]
Charter	0.235	0.201	0.670	-0.00256	-0.00273	0.00291
	[0.296]	[0.285]	[0.507]	[0.00180]	[0.00180]	[0.00324]
Laws	-0.886***	-0.682***	-0.944***	-0.00693***	-0.00591***	-0.00407*
	[0.205]	[0.226]	[0.356]	[0.00181]	[0.00215]	[0.00230]
Impact	0.0857			0.00642***		
	[0.330]			[0.00187]		
LP Attributes	YES	YES	YES	YES	YES	YES
Impact*LP Geo	No	YES	No	No	YES	No
Impact*LP Type	No	No	YES	No	No	YES
Standard Controls	YES	YES	YES	YES	YES	YES
Observations	3,047,430	3,047,430	3,047,430	3,047,430	3,047,430	3,047,430
Panel B: Incremental Willingness to Pay (WTP)						
Mission	0.29	0.25		0.12	0.11	
Household	0.16	0.10		--	--	
Intermediated	--	--		-0.06	-0.07	
Pressure	0.28	0.30	0.22	0.17	0.17	0.16
Restrictions by Charter	--	--	--	--	--	--
Restictions by Laws	-0.25	-0.19	-0.27	-0.20	-0.17	-0.12

*** p<0.01, ** p<0.05, * p<0.1

Table 8. Interactions of Home Bias, Pressure, and Impact on Willingness to Pay

Panel A summarizes estimates from conditional logit and linear probability models. Panel B summarizes the (incremental) willingness to pay, which is the impact coefficient (interacted with attributes) divided by the expected return coefficient. The dependent variable is a dummy variable that equals one if an LP invests in a fund. Observations are determined by crossing all vintage year funds with LPs that make an investment in that year. Impact equals one for impact funds. Expected Returns are expressed as percentile ranks relative to vintage year cohort funds and are modeled based on known fund characteristics at the time of investment and adjusted for shrinkage. Heterogeneity in investment rates is modeled using LP fixed effects in the linar probability model and dynamic LP group fixed effects in the logit model. All models include standard controls (see text and Table 4 for details) plus the double interaction of *Impact* and *Pressure* in columns (1) to (3) or the triple interaction of *Impact*, *Pressure*, and *Homebias* in columns (4) to (6). The models introduce controls for the interaction of impact and LP geography (columns 1 and 4), impact and LP Type (columns 2 and 5), or both (columns 3 and 6). Robust standard errors are shown in brackets. WTP of "--" indicates that the impact coefficient is not significantly different from zero.

Panel A: Estimates	Logit Model						Linear Probability Model					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Expected Returns	3.508***	3.562***	3.536***	3.548***	3.613***	3.582***	0.0343***	0.0345***	0.0344***	0.0346***	0.0348***	0.0347***
	[0.290]	[0.289]	[0.289]	[0.290]	[0.290]	[0.290]	[0.00343]	[0.00343]	[0.00343]	[0.00343]	[0.00343]	[0.00343]
Impact*Pressure	0.603***	0.765***	1.124***	-0.924***	-0.741*	-0.423	0.0041***	0.0056***	0.0080***	-0.000737	-0.000364	0.00272
	[0.125]	[0.288]	[0.316]	[0.286]	[0.436]	[0.455]	[0.00103]	[0.00198]	[0.00232]	[0.00065]	[0.00209]	[0.00237]
Pressure*Homebias				0.283***	0.293***	0.289***				0.0024***	0.0025***	0.0025***
				[0.0761]	[0.0765]	[0.0764]				[0.00066]	[0.00066]	[0.00067]
Impact*HomeBias				-0.226*	-0.155	-0.207				0.000343	0.000283	0.000489
				[0.135]	[0.128]	[0.129]				[0.00115]	[0.00106]	[0.00113]
Impact*Pressure*Homebias				2.009***	1.944***	1.977***				0.0170***	0.0165***	0.0167***
				[0.307]	[0.304]	[0.304]				[0.00310]	[0.00314]	[0.00315]
LP Attributes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Impact*LP Geo	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes
Impact*LP Type	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Standard Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,047,430	3,047,430	3,047,430	3,047,430	3,047,430	3,047,430	3,047,430	3,047,430	3,047,430	3,047,430	3,047,430	3,047,430
Panel B: Incremental Willingness to Pay (WTP)												
Impact*Pressure	0.17	0.21	0.32	-0.26	-0.20	--	0.12	0.16	0.23	--	--	--
Pressure*Homebias				0.08	0.08	0.08				0.07	0.07	0.07
Impact*HomeBias				-0.06	--	--				--	--	--
Impact*Pressure*Homebias				0.57	0.54	0.55				0.49	0.47	0.48

*** p<0.01, ** p<0.05, * p<0.1

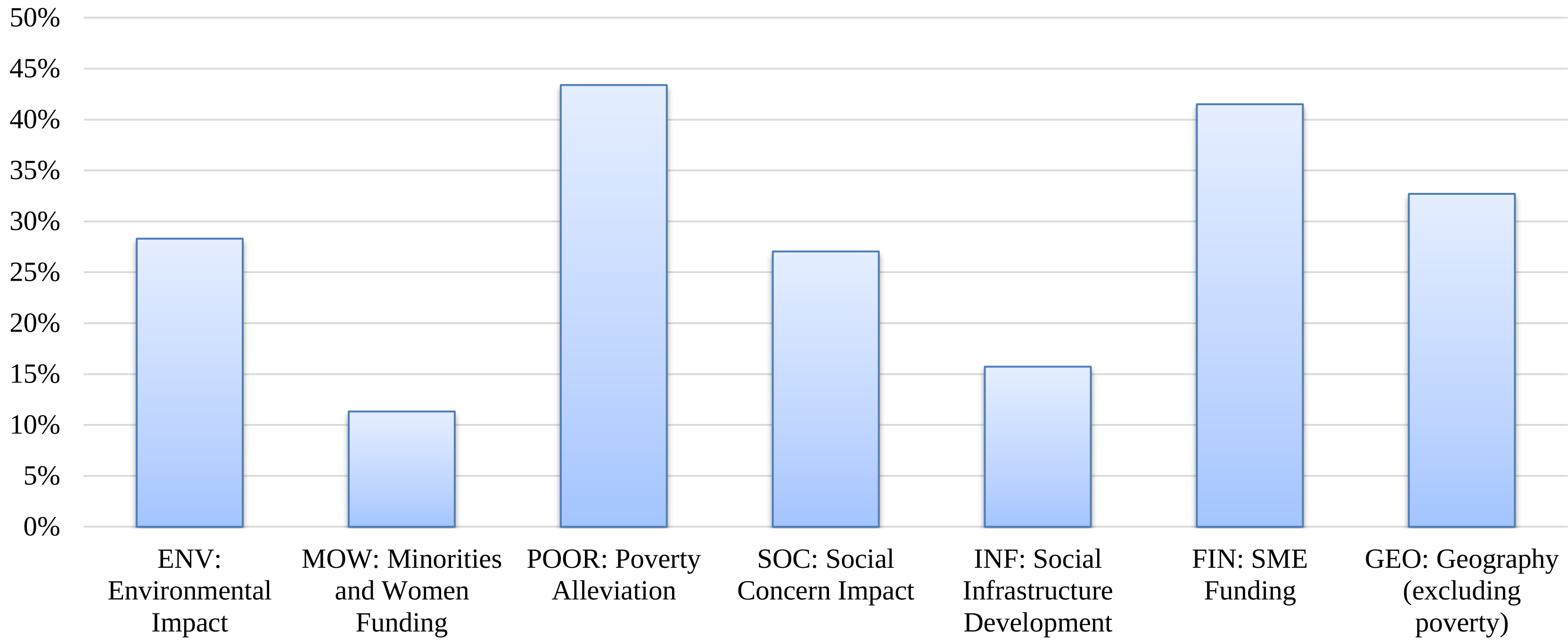

Figure 1. Distribution of Impact Categories that Impact Funds Target

For the sample of impact funds, we identify the impact categories targeted by each impact fund. The figure presents the percentage of sample funds that target each category. The numbers in the bars reflect counts of funds. Funds can have multiple impact categories. The categories are as follows:

Environmental Impact, delivers positive environmental impact (e.g., agriculture, energy, water, and forestry)

Minorities and Women Funding, funds firms run by minorities or women

Poverty Alleviation, funds firms in impoverished areas

Social Concern Impact, addresses social concerns or measures the social impact of its investments

Social Infrastructure Development, develops infrastructure for societal benefit (e.g., microfinance, health care, schools, and housing)

SME Funding, provides capital to SMEs and undercapitalized markets

Geography (excluding poverty), imposes a material geographic constraint on its investment criteria but is not focused on poverty alleviation

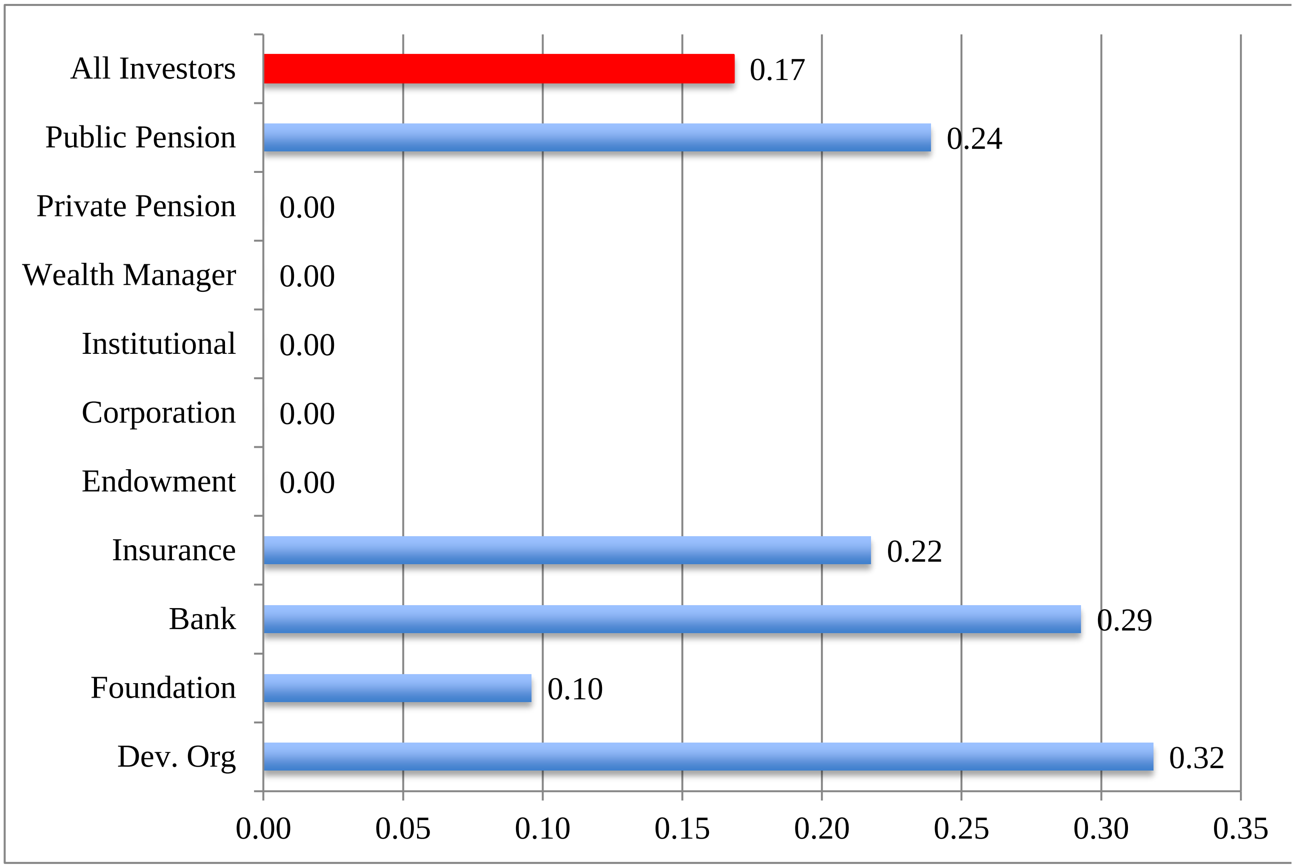

Figure 2. Willingness to Pay for Impact by Investor Type

The figure presents the logit model estimates of the willingness to pay for impact based on the baseline model for all investors and model (2) for each LP Type (see Table 4). The WTP is expressed in percentile ranks, where percentiles are based on performance relative to cohort funds. Cohorts are defined by fund vintage year and region.

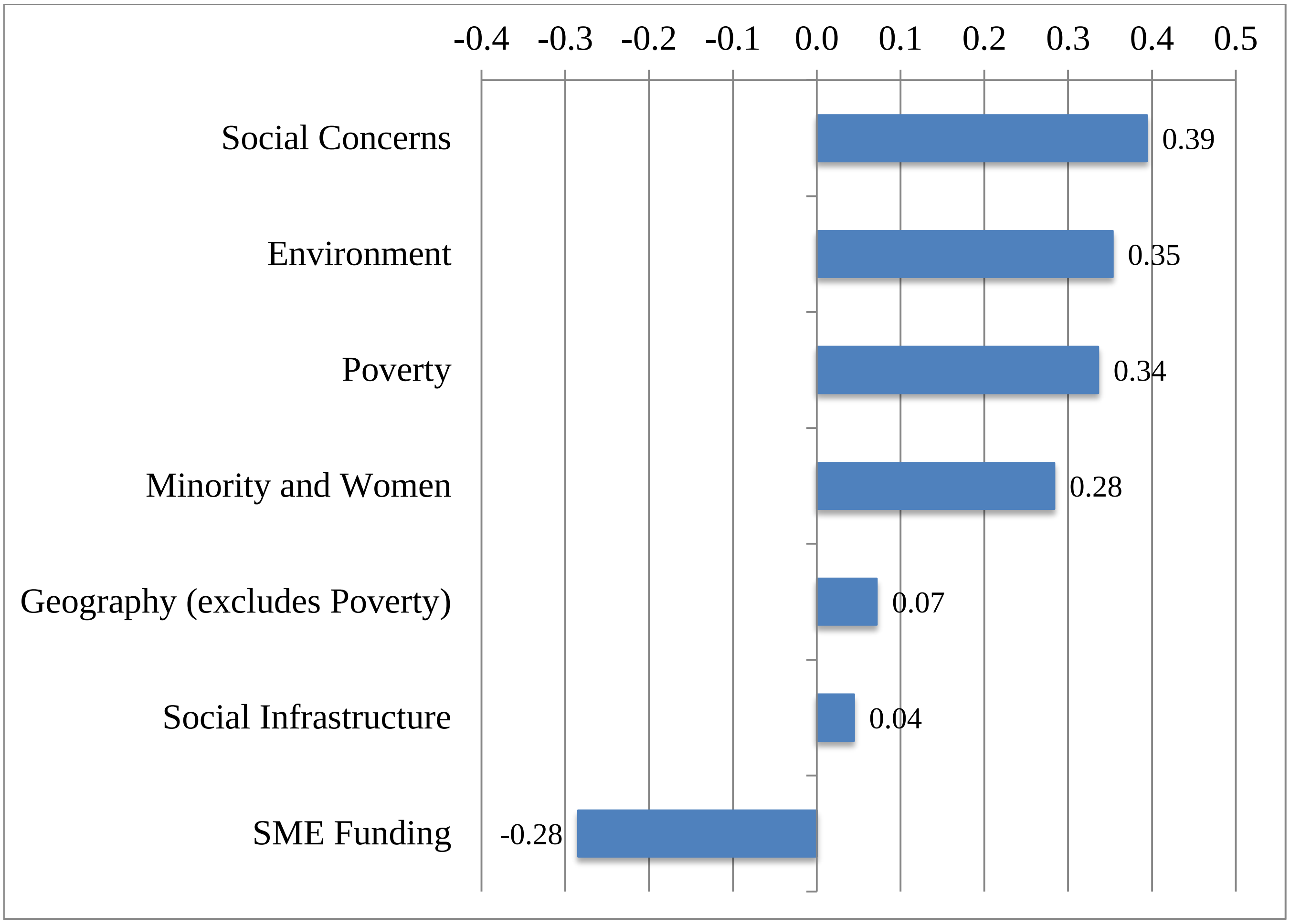

Figure 3. Willingness to Pay by Impact Category

The figure presents estimates of the willingness to pay for impact by impact category. Estimates are based on variation of model (1) of Table (4). The WTP is expressed in percentile ranks, where percentiles are based on performance relative to cohort funds. Cohorts are defined by fund vintage year and region.

Table A1. Distribution of IRR and VM for VC Funds, 1995 to 2012

The table reports the distribution of funds' final (or last reported) internal rate of return (IRR) or value multiple (VM). Excess IRR (or VM) is the fund's IRR less the median IRR (or VM) for cohort funds. Cohorts are defined by vintage year and geography.

Percentile	IRR	Excess IRR	VM	Excess VM
5th	-14.5	-24.0	0.34	-0.88
10th	-9.5	-15.9	0.51	-0.67
15th	-6.1	-12.2	0.67	-0.53
20th	-3.5	-9.8	0.79	-0.43
25th	-1.4	-7.6	0.87	-0.35
30th	0.5	-5.4	0.95	-0.26
35th	2.5	-4.2	1.00	-0.18
40th	4.3	-2.3	1.08	-0.12
45th	5.9	-1.0	1.14	-0.05
50th	7.3	0.0	1.21	0.00
55th	8.4	0.6	1.28	0.03
60th	9.9	1.9	1.36	0.10
65th	11.2	3.4	1.44	0.18
70th	13.1	4.9	1.52	0.27
75th	15.3	6.9	1.63	0.36
80th	18.3	9.2	1.76	0.49
85th	23.0	12.1	1.93	0.68
90th	30.7	18.8	2.22	0.93
95th	46.7	32.1	3.04	1.76
Interquartile Range	16.7	14.5	0.76	0.71
N	1,283	1,283	1,575	1,453

Table A2. Summary Statistics on Coefficients from Expected Return Model

In each of 20 forecast years, 1995 to 2014, we estimate a regression of realized fund performance on fund attributes as described in the main text. This table summarizes the distribution of the 20 coefficient estimates. The interaction terms are only estimated for the last 12 of the 20 year rolling window regressions because there are few impact funds; there are only two impacts funds prior to 1995.

	Mean across Years [Mean Std. Error]	% of Coef. > 0	25th Percentile	Median	75th Percentile
R_j^{-1}	0.207	95%	0.160	0.215	0.270
	0.076				
$Miss_j^{-1}$	-0.053	20%	-0.083	-0.052	-0.014
	0.045				
$First_j^{-1}$	-0.103	10%	-0.147	-0.054	-0.020
	0.044				
IMP_j	-0.203	0%	-0.292	-0.186	-0.139
	0.187				
$IMP_j *Miss_j^{-1}$	-0.032	33%	-0.157	-0.069	0.067
	0.224				
$IMP_j *First_j^{-1}$	0.069	75%	0.007	0.062	0.147
	0.187				
Observations	458.75		239.750	0.044	0.056
R-squared	6.5%		3.0%	4.7%	10.4%

Standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1