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Impact investing[☆]

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ABSTRACT

We show that investors derive nonpecuniary utility from investing in dual-objective Venture Capital (VC) funds, thus sacrificing returns. Impact funds earn 4.7 percentage points (ppts) lower internal rates of return (IRRs) ex-post than traditional VC funds. In random utility/willingness-to-pay (WTP) models investors accept 2.5–3.7 ppts lower IRRs ex ante for impact funds. The positive WTP result is robust to fund access rationing and investor heterogeneity in fund expected returns. Development organizations, foundations, financial institutions, public pensions, Europeans, and United Nations Principles of Responsible Investment signatories have high WTP. Investors with mission objectives and/or facing political pressure exhibit high WTP; those subject to legal restrictions (e.g., Employee Retirement Income Security Act) exhibit low WTP.

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1. Introduction

Do investors knowingly accept lower expected financial returns in exchange for nonpecuniary benefits from investing in assets with both social and financial objectives? 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 (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. Theoretical models consider the implications of these nonpecuniary preferences in a variety of settings (e.g., Andreoni, 1989, 1990; Fama and French, 2007; Hart and Zingales, 2017; Niehaus, 2014), yet these models start from a relatively untested assumption that nonpecuniary motives affect the allocation of capital in a way that reflects an intentional willingness to pay for impact.

A natural starting point is to look for indications of demand for nonpecuniary benefits by the sources of capital themselves. As of April 2019, 2372 organizations representing $86 trillion in asset under management have become 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 indications of demand for investing with a social conscience do not imply that investors readily accept a tradeoff between financial returns and nonpecuniary benefits. For instance, the signing of the UNPRI accords does not imply that a holder of capital necessarily must tilt investment toward impact. Rather, UNPRI investors can comply by adhering to principles of governance within their investing entity.

An important, recent empirical literature on socially responsible investment (SRI) mutual funds shows that the demand for responsibility is growing rapidly (Bialkowski and Starks, 2016), reflecting both preferences and social signaling (Riedl and Smeets, 2017). However, performance in public market SRI has not been statistically different from other mutual funds in this period (see the amalgamation of evidence in Bialkowski and Starks, 2016). Hence, the tilt toward SRI need not reflect a willingness to pay in wealth for nonpecuniary benefits.

Thus, we study a different asset market—impact investing—to ask whether the theoretical assumption that investors are willing to pay for impact holds. Two primary instrument types that receive the largest capital allocation among impact investors are private debt and private equity.[1] While private debt is the largest category, we are not aware of any data sources for private debt impact investments. Instead, we focus on impact funds, which are predominantly Venture Capital (VC) and growth equity funds that are structured as traditional private equity funds but with the intentionality that is the hallmark of impact investing. The Global Impact Investing Network (GIIN) defines impact investing as "investments made with the intention to generate positive, measurable social and environmental impact alongside a financial return."[2] Thus, an impact investor exhibits an intention to generate both positive social or environmental returns and positive financial returns. Green washing investments, which is branding for an appearance of impact intentionality (Starks et al., 2017) and purely for-profit investment in sectors that associate with positive externalities (e.g., health, education, clean energy) do not meet the intentionality criteria. In our data collection, we ensure that we only choose impact VC funds that explicitly market a dual agenda.

Besides the data availability, the VC institutional setting brings an additional advantage. Because VC funds only fundraise at the inception of the fund and investors contractually commit their capital for the duration of the fund (typically ten years), the timing of capital flowing in and out of funds is not a concern in our setting. This institutional feature allows us to focus on the investors' discrete choice to invest in traditional VC funds versus impact VC funds among the observable choice set at a given point in time.

These advantages in the impact-versus-traditional VC market provide us with an ideal setting to identify any ex-ante willingness to pay for impact that investors may exhibit. We ask: (a) whether investors are intentionally willing to forego expected financial returns in exchange for expectation of impact, (b) whether this willingness to pay depends on the source of the capital (e.g., pension fund, bank, or development organization), and (c) whether the evidence points to any attributes (e.g., mission objectives, household versus institutional ownership, the legal or regulatory framework governing the allocation of capital) that explain heterogeneity in investor willing to pay for impact.

Using Preqin data, we construct a sample of 24,000 VC and growth equity (to which we refer together as VC for simplicity) investments by about 3500 investors over the period 1995–2014. These investments reflect 4659 funds—the combination of traditional VC and impact VC funds. We manually isolate 159 of these funds as being impact funds using a strict criterion that the fund must state dual objectives in its motivation. Investors are not all alike in their portfolio choice decisions; thus, we also manually look up the ultimate source of capital for each of the 3500 investors and code them into ten investor types. Our final piece of data coding is to codify the impact agenda themselves in more detail. The impact agenda of impact VCs 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.

Our primary analysis estimates the willingness to pay (WTP) for impact across investor types and attributes. To set the stage for this analysis, we estimate reduced-form regressions of impact fund performance compared to that of traditional VC funds. We show that the annualized internal rate of return (IRR) on impact funds is 4.7 percentage

[1] GIIN annual impact investor survey 2017.

[2] https://thegiin.org/impact-investing/need-to-know/#what-is-impact-investing.

points (ppts) lower than traditional VC funds, after controlling for industry, vintage year, fund sequence, and geography.

Reduced-form estimations suggest investors may be willing to forego returns, but this evidence is not sufficient. Selection in observability of VC fund returns may affect this analysis, and, more fundamentally, ex-post performance estimations do not necessarily reveal ex-ante decisions to invest as a function of expected returns.

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 in a random utility framework) 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 good possesses (e.g., Court, 1939; Griliches, 1961; Rosen, 1974; McFadden, 1974, 1986). Cameron and James (1987) introduce the idea that WTP can be estimated in discrete choices over alternatives. In discrete choice models, the choices made by agents over alternatives can be used to infer the sensitivity of the choice probability to price and other attributes (McFadden, 1974). Cameron and James (1987) note that if one reparameterizes 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 WTP for that attribute.

A relevant example of the method is Huber and Train (2001), who study households that 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 versus conglomerate), making inference as to people's WTP to do business with a more expensive local provider. Analogously, we study the choice of alternatives of funds and ask whether investors exhibit a WTP for the impact characteristic of a fund.

Our empirical analysis relies on two key independent variables: an impact fund dummy variable (the hedonic variable) and an ex-ante estimate of expected return for each fund (the price variable in a hedonic model), which we model using historic data on a fund's characteristics that investors would observe at the time of fundraising. From investors' choices, we find that both the ex-ante expected returns and the impact fund designation positively relate to the probability of investing in a fund. We estimate a logit model over the choice of funds fundraising in a given vintage, including investor fixed effects (i.e., a conditional logit model) or similar-investor dynamic groupings (to capture time-varying investor demand for the asset class). Our specifications include a rich array of fund and investor characteristics to model dimensions of portfolio choice preference. Measuring how sensitive the investment rate is to a fund's expected return allows us then to convert the desirability of impact into a WTP for impact via standard hedonic methodologies.

We address two main methodological concerns with respect to the estimation and inference in our VC setting. First, unlike traditional hedonic models, our price variable is an estimate—the forecast expected returns—and thus has measurement error. This likely induces overdispersion in expected return forecasts and attenuation bias in the expected return coefficient in the logit model. Since WTP has the expected return coefficient in the denominator, attenuation does not affect the sign of the estimated WTP but increases its magnitude. To address the magnitude issue, we apply a shrinkage estimator, which provides an asymptotic correction for the attenuation bias in the expected return coefficient.

Second, investors may have differential exposure or access to opportunity sets of funds to invest in, thus inducing them to have different expected return forecasts for the same fund. Mis-specifying this heterogeneity may induce a bias in the expected return coefficient, thus affecting the magnitude of our WTP estimates. Heterogeneities in expected returns is plausible in our private investment setting, but the exact mechanism is difficult to pin down with precision given the limitation in our knowledge of the actual expected return model or heuristic used by investors. As empiricists, we are agnostic as to whether parsimony versus specificity in the expected return model brings us closer to the true expected return used by each investor. Thus, we use both a parsimonious homogenous expected return model and a heterogenous expected return model to estimate expected returns and report WTP estimates based on both models to generate a range of plausible WTP estimates. Furthermore, we estimate the model under both rationed and expanded opportunity set assumptions and find that our impact coefficient and WTP estimates are consistently positive and stable. Overall, we report that the aggregate WTP for impact is between 2.5%–3.7% in expected IRR.

WTP for impact is not in equal magnitude across investor types. Five noteworthy investor groups exhibit a positive WTP for impact. (i) Development organizations have a high WTP for impact, presumably reflecting their direct impact mission. (ii) Foundations also have a small but positive WTP for impact in some specifications, again reflecting their mission orientation. (iii) Financial institutions—banks and insurance companies—have high WTPs, likely reflecting their incentives to invest in local communities either to comply with the Community Reinvestment Act (CRA) and/or to garner goodwill from the community or politicians/regulators. (iv) Public pension funds have a high WTP for impact, in line with the tendency for state pensions in the US to prefer investments within their home state (Hochberg and Rauh, 2013) to bring spillover economic benefits, nonpecuniary political benefits, and direct social objective benefits. (v) Investors in Europe, Latin America, and Africa have a higher WTP.

We then explore six investor attributes that might capture differential utility from investing in impact across investors; namely, 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 facing regulatory or political 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 focus (i.e., development organizations and foundations) is associated with a positive WTP of 3.4 to 6.2 ppts in expected excess IRR. This result is robust to including the Limited Partner (LP) geography fixed effects interacted with impact (i.e., within each geography, investor mission orientation is positively related to WTP for impact). Likewise, organizations expressing their mission by signing the UNPRI have a similarly higher WTP, especially after their signing. These UNPRI results are robust to including either LP geography fixed effects interacted with impact or LP type fixed effects interacted with impact.

Next, we find that political or regulatory pressure is associated with a positive WTP. In our most conservative models, WTP for impact associated with pressure is 2.3–3.3 ppts in expected excess IRR. Legal restrictions against investments for nonfinancial motives (e.g., the Employee Retirement Income Security Act (ERISA) and the Uniform Prudent Management of Institutional Funds Act (UPMIFA)) are associated with a lower WTP for impact. 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) lower the WTP for impact. In addition to the LP geography-impact interaction, these estimates for attributes (4)-(6) are further robust to including the LP type fixed effects interacted with impact, thus exploiting international (e.g., US versus non-US) differences in laws for a given LP type governing attributes (4)-(6).

Finally, we 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 in each type. Impact funds focused on environmental impact, poverty alleviation, and women or minorities generate the highest WTP estimates. In contrast, impact funds focused on small- and medium-sized enterprises (SMEs) and social infrastructure (e.g. health, education, and mainstream infrastructure) 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.

There is little prior academic work on impact investing by private investment vehicles. Kovner and Lerner (2015) study 28 community development venture capital funds in the US, finding that these funds tend to invest in companies at an earlier stage and in industries outside the VC mainstream and with fewer successful exits. Geczy et al. (2018) analyze contracts of impact funds and show that these contracts provide specific impact goals, indicating that investors intentionally seek impact when investing in these funds.

Our work relates to the broader literature on SRI that dates back as far as Milton Friedman's 1970 doctrine on responsible investing.[3] A survey by Renneboog et al. (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 et al. (2011), and Bialkowski and Starks (2016) show that SRI fund flows are less sensitive to performance than non-SRI flows, while Bollen (2007) shows SRI funds have less volatile flows. Hartzmark and Sussman (2019) show Morningstar sustainability ratings introduced in 2016 resulted in large reallocations of capital toward funds with high sustainability ratings. Similarly, one strand of the SRI literature argues the nonpecuniary 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). In other work, Dimson et al. (2015) provide 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. The above studies highlight the potential importance of nonpecuniary motives when investing, which dovetails with our analysis of the performance of impact funds and investors' WTP for impact.

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

2. Data and statistics

2.1. Data and impact funds designation

Our data on funds, investors, and performance come from Preqin's Investor Intelligence and Performance Analyst data sets. We initially search all private equity funds (which include buyout, balanced, and various types of funds of funds) for impact funds. However, the majority of impact funds we identify are venture or growth oriented. Impact buyout funds are a relatively recent phenomenon and were quite rare during much of our sample period. For example, Bain Capital raised its first "Double Impact Fund" only in 2017, and KKR did not set up its impact-investing unit until 2018. Thus, we restrict our study to one of VC and growth equity, which we loosely refer to as VC.

Our first task is to designate funds as being impact or traditional VC, using the criterion that an impact fund must state the dual objectives of generating a positive externality in addition to earning financial returns. To identify such funds, we proceed in the following three steps.

1. We form an impact potentials list, combining (i) text search of articles in Factiva using a list of impact-

[3] "The social responsibility of business is to increase its profits," The New York Times Magazine, September 13, 1970. Also see Geczy, Stambaugh, and Levin (2003).

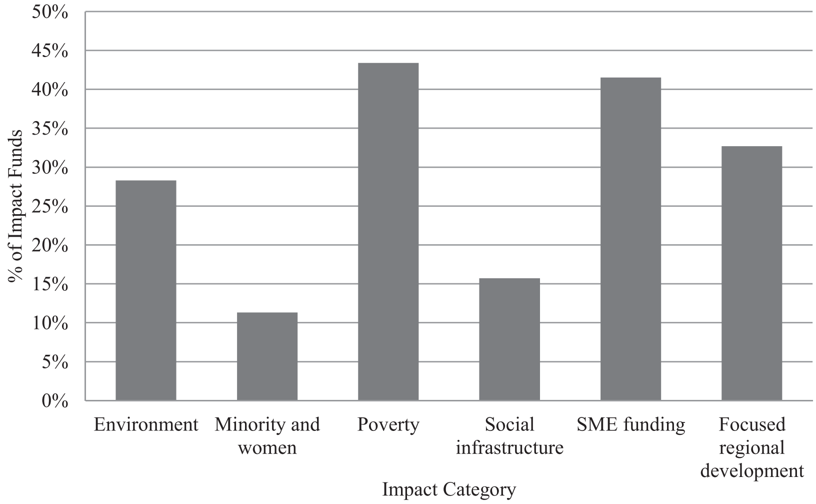

Fig. 1. Distribution of impact categories that impact funds target.
For the sample of 159 impact funds, we identify the impact categories targeted by each impact fund. The figure presents the percentage of sample funds that target each category. Funds can have multiple impact categories. The categories are as follows:
Environment - delivers positive environmental impact (e.g., agriculture, energy, water, and forestry).
Minorities and women - funds firms run by minorities or women.
Poverty - funds firms in impoverished areas.
Social infrastructure - develops infrastructure for societal benefit (e.g., microfinance, health care, schools, and housing).
SME funding - provides capital to SMEs and undercapitalized markets.
Focused regional development - imposes a material geographic constraint on investment.

related keywords[4] to describe funds; (ii) four third-party lists of impact funds and managers (ImpactBase (www.impactbase.org), Impact50 list in ImpactAssets (www.impactassets.org), ethos funds in Preqin (www.preqin.com), and MRI Manager Database in Cambridge Associates (www.cambridgeassociates.com)); and (iii) list of funds with majority geographic focus on countries with GDP per capita less than $1400.[5] Our potentials list consists of 323 VC and growth impact funds once we impose the further restriction that the fund appears in the Preqin Performance Analyst database.

2. We manually read descriptions and online resources about funds and fund families and screen out funds that do not explicitly aim to be double bottom line or state a dual objective. This results in the elimination of 146 funds from the sample (e.g., some large traditional global fund of funds like one managed by HarbourVest Partners that do not bear any resemblance to impact investing).
3. We further restrict the sample to funds with vintage years between 1995 and 2014, and investor information exists for at least one LP per fund in Preqin's Investor Intelligence database. This results in the elimination of 18 funds.

The screening process above results in our final sample of 159 impact funds. Note that 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 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 data set (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 categorize these diverse impact goals, we construct six impact categories: environmental impact, minority and women funding, poverty alleviation, social infrastructure development (e.g., health, education, and mainstream infrastructure), SME funding, and focused regional development (jobs creation and economic development funds in a specific region). 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 six categories, allowing funds to have multiple objectives.

[4] See Table A1 for the list of keywords.
[5] See Table A2 for the list of low GDP per capita countries.

Fig. 1 depicts the percentage of the 159 impact funds for each of stated impact goals. 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 with the most prevalent being poverty alleviation (43%) and SME funding (42%), followed by focused regional development (33%) and environmental impact (28%).

We augment our Preqin data with the list of UNPRI signatories and signing years, which we obtain from UNPRI. As of November 16, 2015, there were 1422 signatories (297 asset owners, 931 investment managers, and 194 professional service managers) who collectively manage $59 trillion. We match UNPRI signatories to our data set using investor names. Investors that are subsidiaries of a UNPRI signatory are also coded as signatories but not investors that are parents of UNPRI signatory subsidiaries.

2.2. Fund statistics

Our analysis focuses on 4659 funds with vintage years from 1995 to 2014. Table 1 presents descriptive statistics for the 4500 traditional VC funds on the left and the 159 impact funds on the right.

Although traditional VC funds are larger than impact funds ($204.6 million versus $129.6 million at the mean and $102 million versus $83 million at the median), the mean commitment size does not differ by impact-versus-traditional VC. When we average across investors in a fund and then calculate the mean of this average across funds, we find that the mean commitment size for impact funds is $27.1 million, which is not significantly different from the mean commitment size of $22.2 million for traditional VC funds. One might wonder if the difference arises because we are more likely to observe commitment 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%). Note that the motivation for our decision to use discrete choice of investments rather than commitments in dollars as the outcome variable is transparent in Table 1; of the 23,986 investments, we observe that only 7867 (32.8%) have data on commitment size.

In terms of realized performance, traditional funds have a mean (median) IRR of 11.6% (7.4%), while impact funds have mean (median) IRR of 3.7% (6.4%). The same pattern emerges for value multiples (VMs) and imputed public market equivalents (PMEs). (Note that we do not observe fund cash flows for our sample funds; thus, the imputed PMEs were calculated using regression coefficients from Table IA.IV of Harris et al. (2014), which use the S&P 500 as a benchmark, and observed IRRs and VMs for our sample funds.) The imputed PMEs for impact funds suggest that they do not beat the public market, on average, while traditional VC funds do (albeit with significant time variation).

Our preferred measure of performance, percentile rank, is based on a fund's performance ranking (either IRR or VM, based on data availability) relative to cohort funds of the same vintage and geography (five regions). Percentile ranks adjust for the large temporal and geographic variation that trouble any inference using the other performance measures, which are notoriously difficult to risk adjust (Korteweg and Sorensen, 2010; Sorensen et al., 2014; Korteweg and Nagel, 2016). In particular, VC funds of vintages from the mid to late 1990s realized very right-skewed IRRs, when impact funds were relatively rare (only 14 of our sample funds have vintage years between 1995 and 1999).

Table 1 reports that traditional funds have a mean (median) percentile rank of 0.49 (0.50), while impact funds have a mean (median) rank of 0.34 (0.28). The difference of 0.15 (0.22) in percentile rank translates to a difference of about 3.0% (4.7%) in excess IRR centered at the median in historical returns. Appendix Table A3 provides the mapping of percentile ranks to excess IRRs, which are calculated as a fund IRR less the median IRR for the fund's vintage year and geography cohort. Although this mapping includes the strong VC return years of the late 1990s, the post-2000 sample yields estimates that are within 1.2 ppts of the full sample mapping for percentile rank differences 0.40 or less.

Table 1 reports a large difference in the standard deviation of IRRs for traditional funds versus impact funds (32.06% versus 15.17%). This difference is not statistically significant, but the magnitude of the difference triggers concern about risk differences. When we look into the source of these standard deviation differences, we find that the difference in return dispersion is again due to the lack of impact funds during the dot.com boom in the 1990s together with the highly right-skewed performance of traditional VCs during this period. Among traditional funds of late 1990s vintage, 22 earned IRRs greater than 100%. From 2000 onwards, the standard deviation of IRRs for traditional and impact funds are similar (16.8% versus 14.7%). Likewise, even in the full sample, the downside risk (measured as the standard deviation of funds with IRRs less than 50%) is statistically and economically the same across traditional (14.3%) and impact (15.2%) funds. Furthermore, our results are quantitatively similar if we restrict our sample to funds from 2000 onwards.

Another potential data concern is the observability of returns among VC funds. Preqin data are similar to other databases in return statistics (Harris et al., 2014), but the observability of returns may vary depending on a fund's impact status. In unreported tests, we use the fact that public pensions are often required to disclose their holdings and returns (Metrick and Yasuda, 2010) to ensure robustness of our results to a setting unlikely to be affected by selection in observability.

Panel B of Table 1 reports the geography of impact-versus-traditional funds. We collapse Preqin codes of the geographic focus of fund investments to eight regions and 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 and a small percentage have no geographic focus (3.5%). Impact funds tilt more toward

Table 1
Fund descriptive statistics, 1995 to 2014.
This table presents fund summary statistics for traditional 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. Imputed PME (public market equivalent) is the fund's PME imputed using regression coefficients in Table IA.IV in Harris et al. (2014) and the fund's available IRR and VM. 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. 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	2005.4	2006.0	5.26	159	2006.7	2008.0	4.44
Fund size ($mil)	4000	204.6	102.0	300.2	147	129.6	83.00	147.3
Capital commitment ($mil)	2717	22.21	14.60	33.85	125	27.09	15.00	32.88
IRR (%)	1207	11.59	7.40	32.06	76	3.70	6.35	15.17
VM - value multiple	1484	1.51	1.22	1.94	91	1.17	1.10	0.56
Imputed PME	1147	1.29	1.09	1.29	65	1.00	0.97	0.42
Percentile rank	1530	0.49	0.50	0.30	94	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		

developing countries including Africa, Latin America, and Emerging Europe than traditional funds.

Panel C of Table 1 reports the industry foci of impact-versus-traditional funds. We collapse 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 code 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." Impact funds are more likely to be energy or diversified funds and are less likely to be IT, health care, or media and communication funds than traditional VC funds.

2.3. Investor (LP) statistics

We categorize investors into nine types by doing manual web searches for each investor in our sample. We refer to these groupings as LP types, reflecting the limited partner designation of investors in private equity. Our goal is to attribute the investing to the source of capital (rather than the intermediary). Thus, for asset managers, we search each manager to uncover whether the asset manager specializes in serving a particular constituent (e.g., public pensions).

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). *Financial institutions* include banks and insurance companies. (When we separately analyze banks and insurance companies, we obtain similar results for each group.) *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).[6] *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).[7] *Foundations*, *Endowments*, and *Public pensions* are self-explanatory. Finally, *Institutional asset managers*, a residual category, include LPs that manage money for a diverse institutional client base (e.g., Adams Street Partners), where the capital appears to be primarily institutional capital with a mixture of constituents.

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 close to 200 distinct LPs participating in the market. The total number of investments by LP type generally mirrors the patterns of LP numbers. The average LP makes 6.9 fund investments. The most active investors are public pensions (15.4 funds per investor), private pensions (8.9 funds), and development organizations (8.3 funds). 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 (17.9%), followed by wealth manager (14.4%), and public pensions (13.4%). Foundations, corporations, and endowments are extremely unlikely to be UNPRI signatories.

The last two rows of Panel A present statistics across the 23,986 investments made by the 3460 LPs. The penultimate row of Panel A, last column, reports that for 33.4% of investments, there is a prior investment relationship between the LP and fund family. The last row of Panel A, last column, reports the home bias rate, which is strikingly large with 75.8% of investments made into funds focusing on the home region of the LP headquarters.

In Table 2, Panel B, we present the regional distribution of LP headquarters. 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 34% of financial institution LPs are in North America. Relative to other LPs, development organization LPs have greater presence in Emerging Europe, Africa, Central and South America, and Emerging Asia-Pacific.

[6] We sort sovereign wealth funds into development organization and government portfolios following Dyck and Morse (2011).

[7] 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.

3. Realized performance results

Our starting point, and the topic of this section, is reduced-form regressions of fund performance. An economic 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 hurts performance. Alternatively, it is possible that the market fails to fully price the opportunities in the sectors that impact funds target (e.g., natural resources, infrastructure development), thus resulting in above-market opportunities for impact funds (though this argument requires a friction in pricing). We consider both possibilities 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 six variations of the following regression:

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

In model (1), 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 model (2), we add controls for fund size, fund sequence number, and vintage year. In model (3), we add controls for fund industry and fund geography.

In the remaining model variations, we introduce time-varying controls for fund industry and geography. Ideally, we would like to include vintage-geography-industry fixed effects, but we lack degrees of freedom to do so (since some geographies and industries have few funds). As a compromise, we consider models with vintage-geography and static industry fixed effects (Model 4), vintage-industry and static geography fixed effects (Model 5), and fixed effects for 60 clusters of vintage year, industry, and geography (Model 6). In the last model, we cluster funds into six three-year vintage groups (1995–1997 to 2010–2012), two geographies (North America/Europe versus the rest of world), and five industry groups (information technology and business services, diversified and consumer discretionary, health care, media and communications, and other industries in Table 1, Panel C).

In each regression, we estimate robust standard errors clustered by vintage year and geography. The six 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) of Panel A, the univariate regression of column (1) reveals that impact funds underperform traditional VC funds by 7.89 ppts ($p<0.01$). When we

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. For development organizations, we manually coded geographic foci of their missions and used them instead of the actual headquarters location. For example, the Inter-American Development Bank is headquartered in the US, but its mission is focused on South and Central America. Standard deviations are in parentheses.

	Dev. org.	Foundation	Financial institutions	Endowment	Corp. & gov't	Institutional	Wealth manager	Private pension	Public pension	Total
Panel A: LP descriptive statistics										
# of LPs	258	453	572	196	404	591	174	440	372	3460
% of total	7.5	13.1	16.5	5.7	11.7	17.1	5.0	12.7	10.8	100.0
# of capital commitments	2147	2770	2473	1287	1513	3541	635	3893	5727	23,986
% of total	9.0	11.5	10.3	5.4	6.3	14.8	2.6	16.2	23.9	100.0
Funds per LP	8.32	6.11	4.32	6.57	3.75	5.99	3.65	8.85	15.40	6.93
	(16.70)	(13.61)	(8.85)	(15.72)	(16.58)	(14.82)	(6.54)	(19.80)	(30.43)	(17.43)
Vintage year	2007.2	2005.8	2005.7	2004.8	2006.6	2005.7	2005.9	2004.7	2005.5	2005.7
	(3.79)	(3.66)	(4.33)	(4.15)	(5.09)	(4.48)	(4.36)	(4.09)	(3.67)	(4.28)
Years of experience	4.39	4.13	3.77	4.64	2.70	3.54	3.67	5.08	7.76	4.34
	(4.47)	(4.69)	(4.38)	(5.39)	(3.46)	(4.30)	(4.58)	(5.23)	(7.52)	(5.11)
% UNPRI signatories	5.4	2.2	11.0	1.5	1.0	17.9	14.4	8.4	13.4	9.0
% Prior relationship	23.7	41.7	22.7	38.8	23.3	25.0	24.6	38.3	41.1	33.4
% Home bias	59.4	78.2	82.4	82.0	72.1	61.5	68.5	78.3	84.5	75.8
Panel B: Regional Distribution of LPs by LP Type (%)										
North America	19	83	34	82	21	32	34	72	62	48
Developed Europe	28	15	36	16	28	40	39	20	29	29
Emerging Europe	5	0	2	0	2	1	2	1	0	1
Africa	5	0	3	1	1	2	1	1	2	2
Central and South America	6	0	1	1	2	1	0	3	2	2
Developed Asia-Pacific	8	1	10	0	20	9	20	2	3	8
Emerging Asia-Pacific	25	0	10	1	24	11	4	0	1	9
Middle East	4	1	4	0	3	5	2	1	1	3

Table 3
The performance of impact funds, vintage years 1995–2012.
Fund performance (Panel A, IRR; Panel B, VM; Panel C, percentile rank) is regressed on a dummy variable for impact funds and controls. Controls include vintage year, log of fund size, log of fund sequence number, fund geography, and fund industry. Models (1) to (3) step in controls without interactions using 5 geographies and 12 industries. Model (4) creates fund group dummy variables based on 6 three-year vintage groups (1995–97 through 2010–12) and 5 fund geographies in place of vintage year and geography FEs of Model (3). Model (5) creates fund group dummy variables based on 6 three-year vintage groups and 12 fund industries in place of vintage year and industry FEs of Model (3). Model (6) creates fund group dummy variables based on 6 three-year vintage groups, 5 fund industries, and North America/Europe v. other funds. The 5 fund industries include (1) information technology and business services, (2) diversified and consumer discretionary, (3) health care, (4) media and communications, and (5) others (energy, industrials, infrastructure, food and ag., materials, real estate). Models that include fund size in the regression lose observations of traditional VC funds with missing fund size. Robust standard errors (in brackets) are calculated by clustering on vintage years and fund geography. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: IRR						
Impact	−7.890***	−9.937***	−4.701**	−4.898**	−4.652*	−5.359**
	[2.548]	[2.386]	[2.282]	[2.440]	[2.555]	[2.520]
Observations	1283	1252	1252	1252	1252	1252
R-squared	0.004	0.146	0.166	0.288	0.19	0.274
Panel B: Value multiple						
Impact	−0.403***	−0.465***	−0.361***	−0.265*	−0.228*	−0.194*
	[0.124]	[0.107]	[0.137]	[0.141]	[0.122]	[0.103]
Observations	1456	1417	1417	1417	1417	1417
R-squared	0.002	0.117	0.125	0.184	0.122	0.204
Panel C: Percentile rank						
Impact	−0.149***	−0.158***	−0.089**	−0.093**	−0.083**	−0.078*
	[0.037]	[0.037]	[0.040]	[0.045]	[0.040]	[0.040]
Observations	1505	1465	1465	1465	1465	1465
R-squared	0.014	0.027	0.068	0.17	0.121	0.164
Controls for all panels in column						
Vintage year FE	NO	YES	YES	NO	NO	NO
Log(fund size)	NO	YES	YES	YES	YES	YES
Log(fund sequence)	NO	YES	YES	YES	YES	YES
Fund geography FE	NO	NO	YES	NO	YES	NO
Fund industry FE	NO	NO	YES	YES	NO	NO
Vintage group*Geography	NO	NO	NO	YES	NO	NO
Vintage group*Industry	NO	NO	NO	NO	YES	NO
Vintage grp.*Industry*Geography	NO	NO	NO	NO	NO	YES

add controls for fund size, sequence number, and vintage year in column (2), the performance spread grows to 9.94 ppts ($p<0.01$). 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 4.70 ppts remains reliably negative. Models (4) to (6) introduce finer controls on industry and geography as discussed above and yield results similar to those of model (3). Thus, industry and geography explain some of the variation in performance between impact and other funds. However, models with industry and geography controls may underestimate the differences between impact and traditional funds if we misclassify some impact funds as traditional funds and if impact funds are more prevalent in some industries and geographies.

The analysis of VMs (Panel B) and percentile ranks (Panel C) are qualitatively similar to the analysis of IRRs. VMs for impact funds are reliably less than those of traditional VC funds, ranging from 0.194 to 0.465 depending on model specification. Percentile ranks for impact fund are also reliably less than those of traditional VC funds, ranging from 7.8 to 15.8 ppts depending on model specification.

These performance results represent one contribution of our analysis, as we show impact funds underperform traditional VC funds. However, this fund-level analysis of realized returns is not immune from concerns of selection in observability of VC fund returns. More fundamentally, ex-post performance estimations do not necessarily reveal ex-ante decisions to invest as a function of expected returns. As motivated in the introduction, we are interested in an intentional WTP for impact if any and its variation across different investors. Thus, we now turn to a WTP model of this ex-ante choice, which builds on the hedonic pricing and resource choice literatures.

4. Willingness-to-pay methodology

This section presents the discrete choice hedonic model for estimating investors' WTP for impact funds, closely following Cameron and James (1987) and Huber and Train (2001). In the original applications of these models WTP might be, for example, a homebuyer's WTP for a porch, estimated from homebuyers' purchase choices among the houses for sale at a cross-section in time. Analogously, WTP in our context is the hedonic value of investing in impact, estimated from investors' choices of investments from investment opportunities available at a cross-section in time.[8] Our WTP model is different from the housing example in that the price variable in our setting

[8] VC fund structures only allow investments at fund formation. Thus, the choice of a VC investment is considered relative to other funds of the same vintage.

is an unobserved expected return, requiring an additional layer of estimation that we discuss in detail below.

4.1. Random utility model of willingness to pay

Consider investor *i* facing a binary choice of whether to invest in fund *j*. A random utility model of latent utility U_{ij}^* from such an investment is given by

$$U_{ij}^* = \beta\mathbb{E}\left[\mathrm{r}_j\right] + \Gamma_1' X_{1,j} + \ \Gamma_2' X_{2,ij} + \mu_i + \ \delta_i \mathrm{IMPACT}_j + \mathrm{e}_{ij} \tag{2}$$

The first terms $\{\mathbb{E}[\mathrm{r}_j],\ X_{1,j},\ X_{2,ij}\}$ and the four parameters $\{\beta,\ \Gamma_1,\ \Gamma_2,\ \mu_i\}$ govern the creation of utility from an investor's portfolio choice. $\mathbb{E}[\mathrm{r}_j]$ is the expected return for fund *j*. $X_{1,\,j}$ is a matrix of nonprice fund characteristics that enter the portfolio choice preference for the investment (e.g., geography, sector, fund size). $X_{2,\,ij}$ is a matrix of investor characteristics governing investor preferences, including the investors' recent intensity of investing in the asset class, the proximity to the investment, and the prior relationship with the VC firm. Beyond these investor-specific variables, investors may differentially value exposure to the asset class within the larger portfolio choice of all of their capital, which we cannot see. Thus, we allow for investor fixed effects, μ_i, as a heterogeneous baseline utility of investing in VC. Investors' VC investment portfolio size may grow or shrink over time, and their baseline utility may fluctuate. Therefore, we also introduce time-varying investment intensity bins, described more fully in the results Section 5.1.

The final term in Eq. (2), IMPACT_j, is a dummy variable equal to one if fund *j* is an impact fund (and zero otherwise). Investors may have specific utility for impact; therefore, we index δ_i by *i*. To make this investor heterogeneity operational, we cluster investors by investor types.[9]

Omitted from Eq. (2) are explicit risk variables that might enter into a standard portfolio choice decision. Differences in liquidity, which might generally carry return implications, are not relevant in our context since investing in the VC asset class—whether traditional or impact—involves liquidity lock-up and no trading. Differences in fund-specific risk might be a concern. We control for the portfolio choice variables $X_{1,\,j}$ to absorb risk differences as they relate to the industry sectors, geography, and size of funds chosen. Yet, residual risk differences could be correlated with a fund being IMPACT. If so, we would expect the ex-post standard deviation of impact VC performance to be different from traditional VC. As discussed in Section 2.2 in conjunction with Table 1, Panel A, we find no such difference except in the dot.com period when some traditional VC funds had outsized IRRs of 100% or more and drove up the skewness of return distribution for traditional funds. In contrast, downside risk is not statistically and economically different between traditional and impact funds. Finally, our results are robust to restricting our sample to 2000 onwards.

4.2. Logit specification and willingness to pay

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 investment decision U_{ij} corresponds to the latent utility U_{ij}^* as follows:

$$\begin{aligned} U_{ij} &= 1\, iff\, U_{ij}^* \ > 0 \\ U_{ij} &= 0\, iff\, U_{ij}^* \ \leq 0 \end{aligned} \tag{3}$$

Under the assumption that the error term ε_{ij} is distributed *iid* extreme value, this form of random utility can map to a logistic distribution with a mean 0 and variance $\pi^{2/3}$; thus, a logit estimation can uncover the parameters of Eq. (2):

$$\begin{aligned} Logit\left(invest_{ij}\right) = \beta\mathbb{E}\left[\mathrm{r}_j\right] + \Gamma_1' X_{1,j} + \ \Gamma_2' X_{2,ij} + \mu_i \\ + \delta_i \mathrm{IMPACT}_j + \mathrm{e}_{ij}. \end{aligned} \tag{4}$$

Following Cameron and James (1987) and Huber and Train (2001), the WTP for impact (*WTP*) for investor *i* is[10]

$$WTP_i = = \frac{\partial\mathbb{E}\left[\mathrm{r}_j\right]}{\left(\partial \mathrm{IMPACT_j}\right)_i} = \frac{\left({}^{\partial U_{ij}}/_{\partial \mathrm{IMPACT_j}}\right)_i}{{}^{\partial U_{.j}}/_{\partial\mathbb{E}\left[\mathrm{r}_j\right]}} = \frac{\delta_i}{\beta}. \tag{5}$$

4.3. Expected returns formation

Estimation of a discrete choice hedonic model requires a price variable, which in our context is the expected return for each fund, $\mathbb{E}[\mathrm{r}_j]$. As motivated by the literature on the determinants of fund performance (Kaplan and Schoar, 2005; Sorensen, 2007), we estimate expected returns, with estimates denoted $\hat{\mathbb{E}}[\mathrm{r}_j]$, based on fund characteristics observable at the time of investment. We start with the assumption that all investors have the same model for predicting fund returns and later relax this assumption. We begin by considering an investor who is making decisions about VC investments offered in the market in a particular vintage year, say 1995, as an example. The investor forms return expectations based on the information set available for the VC asset class at that point in time. The information set consists of the average asset class return observed recently and a fund-specific skill adjustment. Skill in the VC asset class shows up to the econometrician as persistence in fund series performance. To estimate the strength of persistence and the average observed asset class return, 1995 investors would use data covering vintage funds 1983 to 1990 (because of the time lag in realizing returns in VC).[11] Denoting these 1983 to

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[9] An alternative is to estimate a random effects logit (mixed logit) model of investor choice (Revelt and Train 1998); however, we found the computation to be prohibitive costly given the very extreme choice (1 fund chosen out of about 100) in VC selection. Also, given that many investors only invest in a few funds, the model was not precisely estimable.

[10] Technically, IMPACT is a discrete choice variable; thus the correct form is $WTP_i = \frac{U_i(.IMPACT_j=1) - U_i(.IMPACT_j=0)}{{}^{\partial u}/_{\partial\mathbb{E}[\mathrm{r}_j]}}$. The continuous time version is provided above for readability.

[11] The typical private equity fund invests in companies during years 1 to 5 of the fund's life and liquidates those investments after year 5. It is during this liquidation phase that the fund's performance becomes clear

1990 vintage years as being in set v, we assume the 1995 investors use the following simple linear model to gage parameters:

$$r_{j_v} = \alpha_0^{1995} + \alpha_1^{1995} r_{j_v}^{prior} + \varepsilon_{j_v}. \tag{6}$$

The return r_{j_v} of fund j in these look-back vintage years v is a function of the performance of the prior funds managed by the same VC firm ($r_{j_v}^{prior}$) and the overall asset class performance for funds in vintage pool v (the constant).

Using the coefficients from the estimation of Eq. (6), we apply them to funds that are raising capital in 1995 to forecast expected returns for any 1995 fund j as

$$\hat{\mathbb{E}}\left[r_{j\in 1995}\right] = \hat{\alpha}_0^{1995} + \hat{\alpha}_1^{1995} r_{j\in 1995}^{prior}. \tag{7}$$

We roll forward this process to the remaining vintage years, until we have an estimate of expected returns for each fund j with vintage years from 1995 to 2014.

By definition, these forecast expected returns have measurement error since we do not observe the actual expected returns.[12] In our context, this measurement error is a common problem of overdispersion in expected return forecasts, given by the simple relation:

$$\hat{\mathbb{E}}\left[\mathrm{r}_j\right] = \mathbb{E}\left[\mathrm{r}_j\right] + u, \tag{8}$$

where $\mathbb{E}[\mathrm{r}_j]$ is the true but unobservable expected return and u is measurement error that is uncorrelated with $\mathbb{E}[\mathrm{r}_j]$. The importance of this overdispersion comes when we turn to estimating *WTP* in the logit formation. Overdispersion in $\hat{\mathbb{E}}[\mathrm{r}_j]$ may cause attenuation bias in the $\hat{\beta}$ coefficient on $\hat{\mathbb{E}}[\mathrm{r}_j]$ when we estimate the logit Eq. (4), relative to the true β if we had the precise $\mathbb{E}[\mathrm{r}_j]$. Because $WTP_i = \frac{\delta_i}{\beta}$, attenuation in $\hat{\beta}$ implies an overestimate of *WTP*.

We take two steps to correct the bias. First, we seek to remedy a source of error, which is our inability to observe the soft information entering the assessment of skill. We augment Eq. (6) to include indicator variables as to whether the fund is missing prior fund performance information ($Miss_j^{prior}$), is a first-time fund ($First_j$), and/or is an impact fund ($IMPACT_j$). This augmented model, dropping the vintage subscripts to reduce equation clutter, is given by

$$r_j = a_0 + a_1 r_j^{prior} + a_2 Miss_j^{prior} + a_3 First_j + a_4 IMPACT_j + a_5\left(Miss_j^{prior} * IMPACT_j\right) + a_6\left(First_j * IMPACT_j\right) + \varepsilon_j. \tag{9}$$

In estimating these regressions, we use percentile ranks as the performance measure. Table 4 reports a summary of estimates from the 20 rolling regressions estimating Eq. (9), corresponding to fund expectations formed from 1995 to 2014. In Panel A, we summarize the coefficient estimates and associated t-statistics on the model's independent variables across the set of rolling estimations. Consistent with the literature, prior fund performance carries the vast majority of the explained variation. The only other reliable relationship is that first-time funds tend to have subpar performance.[13]

Second, we employ a correction for the logit estimates attenuation by applying a shrinkage procedure used in practice. Because overdispersion is a common issue in portfolio choice, investors knowingly shrink extreme forecasts toward a global mean, as in the seminal portfolio optimization models of Jorion (1986) and as applied in expected returns or cost of capital estimations in Fama and French (1997).

The shrinkage procedure begins with regressing realized fund return (r_j) on the estimated expected returns $\hat{\mathbb{E}}[\mathrm{r}_j]$:

$$r_j = \gamma_0 + \gamma_1 \hat{\mathbb{E}}\left[\mathrm{r}_j\right] + e_j. \tag{10}$$

Our estimates are $\gamma_0 = \underbrace{0.25}_{p<0.001}$ and $\gamma_1 = \underbrace{0.50}_{p<0.001}$. The γ estimates imply that our $\hat{\mathbb{E}}[\mathrm{r}_j]$ has some information about future returns ($\gamma_1 \neq 0$) but that $\hat{\mathbb{E}}[\mathrm{r}_j]$ is imprecise ($\gamma_1 \neq 1$ and $\gamma_0 \neq 0$). Then, following standard shrinkage procedure, we calculate the shrinkage estimate of expected returns $\hat{\mathbb{E}}_{shrink}[\mathrm{r}_j]$ as the prediction from Eq. (10):

$$\hat{\mathbb{E}}_{shrink}\left[\mathrm{r}_j\right] = 0.25 + 0.50\ \hat{\mathbb{E}}\left[\mathrm{r}_j\right]. \tag{11}$$

Whereas $\hat{\mathbb{E}}[\mathrm{r}_j]$ has a ranking range of 0.16 to 0.72 (on a natural percentile rankings range of 0 to 1), $\hat{\mathbb{E}}_{shrink}[\mathrm{r}_j]$ has a range of only 0.28 to 0.61, reflecting the shrinkage to address imprecision. We use $\hat{\mathbb{E}}_{shrink}[\mathrm{r}_j]$ to estimate Eq. (4).

Importantly, using the true realized returns to shrink the dispersion in estimated expected returns asymptotically eliminates attenuation bias in the logit *WTP* estimation when the following two key assumptions are added to a classic errors-in-variable analysis:

(i) The ex-post residual of realized fund returns relative to true expected returns is uncorrelated

to investors. Thus, a 1995 investor would have a good indication regarding the performance of funds with vintage years 1983 to 1990 because these funds would be 6 to 13 years old in 1995. In contrast, funds with vintage years 1991 to 1994 would still be in their investment phase with no or limited liquidations.

[12] Our forecast model uses fully realized fund percentile rank as dependent variables in Eq. (6), while as of 1995, some of the 1983-1990 vintage funds are yet fully realized (assuming ten-year fund life, 1983-1985 funds are at least ten years old, whereas 1986-1990 funds are still less than ten years old). This may introduce measurement errors to our model in one or more ways. For example, if investors apply interim-to-final rank transition in their true expected return formation using their soft information, our model approximates that with some measurement errors. Alternatively, investors may attempt to isolate the component of performance persistence that is due to skill (and investable) from spurious correlation due to contemporaneous exposures (Korteweg and Sorensen, 2017), in which case our naive model also produces forecast expected return with measurement errors. Furthermore, investors may be heterogeneous in their soft information possessed to form their expected returns. We present our expected return model that incorporates investor heterogeneity in the next section.

[13] We consider a number of robustness checks to ensure our results are not driven by the specific model that we use to predict expected returns. First, our results are robust to alternative specifications of the expected return model of Eq. (5). For example, we add additional lags of past fund performance, fund industry fixed effects, and fund geography fixed effects. These additional variables are not consistently related to fund performance nor does their inclusion materially affect the WTP estimates. Consequently, we opt for the more parsimonious model.

Table 4
Summary of expected return regression models.
In each of 20 forecast years, 1995 to 2014, we estimate a regression of realized fund performance (using percentile ranks) on fund attributes as described in the main text. For example, in the 1995 forecast year we estimate relations between fund attributes and performance using data on 1983–1990 vintage-year funds since the performance and attributes of these funds would be observed by an investor looking to invest in 1995. Panel A summarizes the distribution of the 20 coefficient estimates and associated *t*-statistics across the 20 regressions; Panel B summarizes the number of observations and *R*-squareds across regressions. The interaction terms are only estimated for the last 12 of the 20-year rolling window regressions because there are a small number of impact funds in the early part of the sample.

	Mean [*t*-stat.]	% of |*t*-stats| > 1.96	% of coef. > 0	25th percentile [*t*-stat]	Median [*t*-stat.]	75th percentile [*t*-stat]
Panel A: Coefficients						
R_j^{prior}	0.217	85.0%	100.0%	0.167	0.222	0.280
	[3.12]			[2.93]	[3.23]	[3.95]
$Miss_j^{prior}$	-0.052	15.0%	20.0%	-0.079	-0.051	-0.014
	[-0.94]			[-1.49]	[-1.00]	[-0.42]
$First_j^{prior}$	-0.076	45.0%	10.0%	-0.146	-0.054	-0.019
	[-1.97]			[-3.63]	[-1.67]	[-0.64]
$Impact_j$	-0.203	0.0%	0.0%	-0.292	-0.186	-0.139
	[-1.15]			[-1.35]	[-1.08]	[-0.88]
$Impact_j * Miss_j^{prior}$	-0.033	0.0%	33.3%	-0.160	-0.069	0.067
	[-0.38]			[-0.92]	[-0.31]	[0.24]
$Impact_j * First_j^{prior}$	0.068	0.0%	75.0%	0.004	0.062	0.147
	[0.31]			[0.04]	[0.31]	[0.79]
Panel B: Regression statistics						
Observations	459.4	n.a	n.a	240.0	446.0	649.0
R-squared	6.50%	n.a.	n.a.	3.00%	4.50%	10.20%

with $\mathbb{E}[\mathrm{r}_j]$. Specifically, $\mathrm{cov}(\mathbb{E}[\mathrm{r}_j], \xi) = 0$, where this residual is given by

$$r_j = \mathbb{E}\left[\mathrm{r}_j\right] + \xi. \tag{12}$$

This condition assumes that the unexpected part of realized returns is not systematically higher [or lower] for funds with high expected returns and is the implicit assumption made in the asset pricing literature, which uses realized returns to understand temporal and cross-sectional variation in unobserved expected returns.

In venture capital, returns are highly nonlinear and positively skewed. To deal with this issue, our empirical analysis uses percentile ranks relative to cohort funds, which are bounded between zero and one. In theory, these bounds could generate $\mathrm{cov}(\mathbb{E}[\mathrm{r}_j], \xi) < 0$ since an expected percentile rank near one (zero) will have negative (positive) estimation error because of the boundary. In practice, we do not believe these boundary conditions are binding on errors since true expectations of percentile ranks would not approach the boundary; stated differently, investors do not expect to be able to pick the top and bottom performing funds from a cohort. The actual range of percentile ranks that we estimate after shrinkage is 0.28 and 0.61, with a standard deviation of 0.035. This range is a reasonable estimate of the range of ex-ante expected percentile ranks, and they are far from the boundary conditions.

(ii) Measurement error u in forecast expected returns, $\hat{\mathbb{E}}[\mathrm{r}_j] = \mathbb{E}[\mathrm{r}_j] + u$ from Eq. (8), is uncorrelated with the residual in the realized return relative to the true expected return, $\mathrm{cov}(u, \xi) = 0$. We can think of no reason why errors in our forecast returns would be correlated with errors in realized returns.

In Appendix B, we show that the bias in our WTP estimates is positively related to the two covariance terms and is positive if $(cov(\mathbb{E}[\mathrm{r}_j], \xi) + cov(u, \xi) > 0)$. To simplify the analysis below, we also assume the measurement error u in forecast expected returns, $\hat{\mathbb{E}}[\mathrm{r}_j] = \mathbb{E}[\mathrm{r}_j] + u$ from Eq. (8), is uncorrelated to the true expected returns, $\mathrm{cov}(\mathbb{E}[\mathrm{r}_j], u) = 0$; this assumption only affects the absolute magnitude of the attenuation bias if the two assumptions above are violated.

To show how shrinkage with realized returns removes attenuation under (*i*) and (*ii*) from above, imagine a simple model of an outcome variable y (investment in a private equity fund in our case) such that $y = a + b\mathbb{E}[\mathrm{r}_j] + e$, where the econometrician must estimate with $\hat{\mathbb{E}}[\mathrm{r}_j]$ instead of $\mathbb{E}[\mathrm{r}_j]$. The standard estimate of the slope coefficient in the classic errors-in-variable analysis is

$$\text{plim}\left(\hat{b}\right) = \frac{b\sigma^2_{\mathbb{E}[r_j]}}{\sigma^2_{\mathbb{E}[r_j]} + \sigma^2_u} = \lambda b, \tag{13}$$

where $\lambda < 1$ is the attenuation bias. Note that the slope parameter (γ_1) of the shrinkage regression of Eq. (10) yields an estimate of this attenuation bias:

$$\gamma_1 = \frac{cov\left(\widehat{\mathbb{E}}\left[r_j\right],\ r_j\right)}{\sigma^2_{\widehat{\mathbb{E}}[r_j]}} = \frac{cov\left(\mathbb{E}\left[r_j\right] + u,\ \mathbb{E}\left[r_j\right] + \xi\right)}{\sigma^2_{\mathbb{E}[r_j]} + \sigma^2_u}$$
$$= \frac{\sigma^2_{\mathbb{E}[r_j]}}{\sigma^2_{\mathbb{E}[r_j]} + \sigma^2_u} = \lambda. \tag{14}$$

Thus, the shrinkage regression provides a valid correction for the attenuation bias.

4.4. Heterogeneity in expected returns forecast and use

The logit model described in Eq. (4) assumes that investors are homogenous in their forecast of expected returns. In practice, investors may exhibit heterogeneity in their forecast of expected returns because of different forecast mechanisms or because of interest in only a subset of funds (Hochberg et al., 2014; Cavagnaro et al., 2019). The dimension of concern to us is bias at the LP investor type level. Thus, we estimate $\hat{\mathbb{E}}_{type,shrink}[r_j]$ uniquely for each investor type as a robustness check on our results. To implement these expected return forecasts, we limit the set of funds in which an investor has an interest to those funds with investment by investors of the same type (e.g., financial institutions, development organizations, foundations, etc.).[14] Estimating by LP type also allows us to incorporate prior relationships as part of the forecast. Different investor types have different propensities to have a prior relationship with a fund in question, which will provide heterogeneity in the use of soft information.[15] These heterogeneous expected return estimates are correlated with the homogeneous expected returns (with a correlation coefficient of 0.76) but, as anticipated, have more variation (a standard deviation of 0.042 versus 0.035).

Having estimated LP type-specific expected returns for each fund, we then estimate

$$Logit\,(Invest_i) = \beta\ \hat{\mathbb{E}}_{type,shrink}\left[r_j\right] + \Gamma'_1\left[X_{1,j}\right]$$
$$+ \Gamma'_2 X_{2,ij} + \mu_i + \ \delta_{type}\text{IMPACT}_j + \varepsilon_{ij}. \tag{15}$$

Note that we are not after the best or optimal model for predicting future returns—we are after the actual model investors use to form their expectations. On the one hand, some investors might rely on hard information about all funds in the market and use this broad information set in forming expected returns. On the other hand, some investors might examine a narrow set of funds that they are more familiar with (or have access to) and use soft information in forming expected returns. We as econometricians do not know which model is closer to the true model that investors use. We are agnostic about which estimates are superior representations of investor behavior and report estimates from both the homogenous and heterogenous expected return models to generate a range of reasonable WTP estimates.

As a final robustness check in our analysis of WTP patterns across LP types, we allow for the possibility that investors are heterogeneous in their use of expected returns because they face different portfolio choice considerations. The model described in Eq. (15) assumes that investors are homogenous in their use of forecast expected returns, though forecasts vary across LP types. Yet, investors may exhibit heterogeneity in their portfolio diversification model (e.g., preferring investments in a particular industry or geography). Thus, in our analysis of WTP across LP types, we allow heterogeneous expected returns forecasts to interact with the industry and geography.

We amend Eq. (15) to allow for these heterogeneities by investor type:

$$Logit\,(Invest_i) = \beta\ \hat{\mathbb{E}}_{type,shrink}\left[r_j\right]$$
$$+ B'_1\left[X_{1,j} \cdot \hat{\mathbb{E}}_{type,shrink}\left[r_j\right]'\right] + \Gamma'_1\left[X_{1,j}\right]$$
$$+ \Gamma'_2 X_{2,ij} + \mu_i + \delta_{type}\text{IMPACT}_j + \varepsilon_{ij}. \tag{16}$$

The resulting WTP for impact embeds a richer investor type-level application of the role of returns in the portfolio choice model while maintaining a baseline property of hedonic discrete choice models that heterogeneities in the magnitude of the coefficient on the hedonic variable (impact designation in our case) be calculated relative to common coefficients on the price variable (representing the change in utility per unit of price) that are fixed across the choice agents. This WTP calculation is

$$WTP_{type} = \hat{\delta}_{type} \Big/ \left(\hat{\beta} + \hat{B}'_1\left[\bar{X}_{1,j}\right]_{type}\right), \tag{17}$$

where $[\bar{X}_{1,j}]_{type}$ is the average of exposures to the industry, geography, and discretized fund size buckets by investor type.

5. Willingness to pay results

5.1. Aggregate WTP results

Table 5 reports coefficient estimates from the logit model of investment choice, akin to those used in the discrete choice implementations in venture capital (Ljungqvist et al., 2006; Bottazzi et al., 2016). Panel A presents the results using homogenous expected returns (corresponding to Eq. (4)); Panel B uses heterogenous expected returns (Eq. (15) but with a single impact coefficient). The dependent variable is an investment indicator variable. The set of observations are all potential investments into the funds that close in a given year by all of

[14] The forecast $\hat{\mathbb{E}}_{type,shrink}[r_j]$ will only be defined over a subset of funds. Because we are interested in how our estimate of WTP varies when allowing $\hat{\mathbb{E}}_{shrink}[r_j]$ to be instead unique to an investor type, $\hat{\mathbb{E}}_{type,shrink}[r_j]$, we want to reproduce the full data set of funds as the opportunity set for investment. Thus, we fill in $\hat{\mathbb{E}}_{type,shrink}[r_j] = \hat{\mathbb{E}}_{shrink}[r_j]$ for the funds j not estimated by a particular investor type.

[15] For each fund in a given LP type sample, we calculate the average of the relationship dummy variable across all LPs that invested in that fund and add this relationship propensity as an additional independent variable to Eq. (9) when estimating LP type-specific expected returns.

Table 5

The willingness to pay for impact.

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. All columns except column (2) are a logit model with LP investment group controls. LPs are dynamically placed in one of 368 groups according to how many prior three-year investments they make in VC by LP type. Column (2) is a conditional logit model (LP fixed effects). Columns (3) and (4) drop ex-ante top-quartile VC funds and top 15 VCs, respectively, investment opportunities for LPs that have no prior relation with the VC fund families. Column (5) creates an opportunity set assuming that a GP was fundraising in year t (and thus is included in the fund opportunity set for LPs investing in year t) if it closed a fund in year $t+1$ and its predecessor fund was raised in t-5 or older. Column (5) creates an opportunity set assuming that an LP considers investments in year t but does not realize investments until $t+1$. *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 are adjusted for shrinkage. In Panel A, a fund's expected return forecast is homogenous across all investors. Panel B allows heterogeneous forecast for each fund by LP type. The WTP estimate is the ratio of the *Impact* coefficient divided by the *Expected returns* coefficient. Standard controls included in all columns are LP experience (log of years since first fund investment plus one), LP-GP relationship (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), 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. Standard errors in brackets are clustered at the LP level, except for the conditional logit. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Homogeneous expected returns forecast						
Expected returns	3.354***	3.426***	3.248***	2.833***	3.146***	3.307***
	[0.276]	[0.210]	[0.363]	[0.354]	[0.270]	[0.275]
Impact	0.591***	0.585***	0.599***	0.567***	0.590***	0.580***
	[0.0599]	[0.0443]	[0.0645]	[0.0643]	[0.0599]	[0.0595]
WTP estimate	0.176	0.171	0.184	0.200	0.188	0.175
Pseudo R-squared	0.261	0.237	0.264	0.269	0.258	0.263
Observations	3047,430	3047,430	2780,390	2944,643	3301,101	3873,720
Panel B: Heterogeneous expected returns forecast						
Expected Returns	4.655***	4.725***	5.072***	5.022***	4.622***	4.655***
	[0.225]	[0.140]	[0.253]	[0.262]	[0.227]	[0.225]
Impact	0.613***	0.602***	0.650***	0.645***	0.618***	0.613***
	[0.0577]	[0.0422]	[0.0589]	[0.0588]	[0.0579]	[0.0577]
WTP Estimate	0.132	0.127	0.128	0.128	0.134	0.132
Pseudo R-squared	0.263	0.240	0.267	0.272	0.259	0.263
Observations	3047,430	3047,430	2780,390	2704,939	3159,087	3047,430
Model:						
Logit with eynamic LP invest. groups	Yes	–	Yes	Yes	Yes	Yes
Conditional logit model	–	Yes	–	–	–	–
# F.E. (LP or dynamic LP groups)	368	3460	368	368	368	368
Sample restrictions:						
Drop top quartile unless prior relation	–	–	Yes	–	–	–
Drop top 15 VCs unless prior relation	–	–	–	Yes	–	–
Expanded fundraising years	–	–	–	–	Yes	–
Expanded LP investor set	–	–	–	–	–	Yes

the active LPs with at least one fund investment in that vintage year. This crossing of all LPs and all VC funds active in each vintage year yields over three million fund-LP observations, pooled across years. Our main independent variables of interest are *Expected returns* (forecasted and shrunk per the methodology section) and *Impact*. 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 variables capturing paired characteristics between the investor and the fund. 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 (Lerner et al., 2007; Hochberg et al., 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 three-year prior average of the median fund size in the vintage and market (US or non-US).

We first show our aggregate WTP result with two models of investor heterogeneity in terms of their preferences for the VC asset class. In column (1), we absorb investment rate heterogeneities with 368 dynamic (i.e., time-varying) buckets of LP type crossed with the discrete number of prior investments in the previous three years. Each investor group consists of investors of same LP type (e.g., development organization, foundation, pension, etc.) and the same average number of investments per year made in the prior three years. In column (2), the model is conditional logit at the individual LP investor level. The conditional logit levels LPs according to their average likelihood of investing in a VC fund. We prefer the dynamic LP investment groups of column (1). The benefit is in allowing for dynamic appetite for the VC asset class since we cluster together, for example, all foundations have five total investments in the prior three years or public pension funds with 20 investments in the VC asset class in the prior three years, etc.[16]

In Panel A, column (1), the coefficient on impact is 0.591, and the coefficient on expected returns is 3.354 ($p<0.01$ for both coefficients). The WTP estimate is reported as the ratio of these estimates. We find that investors are willing to pay 18 percentile ranks $(0.18=0.591/3.354)$ for impact, where a percentile rank runs from 0 (0th percentile) to 100 (100th percentile). In column (2), estimates from the conditional logit model imply a similar WTP of 17 percentile ranks. A WTP of 18 percentile implies that the average investor is indifferent (obtains identical utility) between investing in an impact fund at the 41 percentile rank of its vintage-geography cohort and investing in a traditional VC fund at the 59 percentile rank. In terms of the expected excess IRR of the fund, this suggests that investors are willing to give up 3.7 ppts in expected excess IRR to invest in an impact fund (see Appendix Table A3 for the mapping of percentiles to excess IRRs). This 3.7 ppts is 11% of a cross-sectional standard deviation of IRRs (0.32).

In Panel B, column (1), the estimated impact coefficient and expected return coefficient are 0.613 and 4.655, which yields a $\mathrm{WTP}=0.13=0.613/4.655$. A WTP of 13 percentile rank suggests that investors are willing to give up 2.5 ppts in expected excess IRR, which is lower than the estimate in Panel A. In Panel B, column (2), conditional logit estimates yield a similar WTP estimate. Overall, our WTP framework suggests that an investor WTP lies between 2.5% to 3.7% in IRR. These WTP estimates are smaller but within one standard error of the performance shortfall that we estimate in the reduced-form regressions of Table 3. Alternatively, a WTP of 13–18 percentile rank suggests that investors are willing to give up 0.13–0.17 in excess PME (see Table A3).

In columns (1) and (2), we assume that the investment opportunity set for all LPs in a given year is the set of funds completing fundraising that year. In practice, opportunity sets may be either more restrictive or more expansive.

One story is that some LPs are more likely to invest in high-performing funds, either due to LP skill differential or to assortative matching between elite VC firms and elite LPs (Cavagnaro et al., 2019; Lerner et al., 2019). Sensoy et al. (2014) show that access disparities between LP types (e.g., endowments versus pensions), as well as returns to such access disparities, largely dissipated in the 1999–2006 period. Yet the possibility remains that some specific LPs continue to enjoy exclusive access to top-performing VC firms that is denied to the rest and that this in turn makes investors that invest in (less exclusive) impact funds appear to accept lower financial returns.

Another possibility is that fundraising campaigns may last longer than a year for some funds. In such cases, funds with vintage year y were effectively fundraising in year y-1, and LPs that were in the market in year y-1 had the opportunity to invest in that fund. Yet another possibility is that for some LPs the fund selection/due diligence may take more than a year. In those cases, LPs that did not pull the trigger until year $y+1$ were effectively looking to invest in year y and had the opportunity to invest in vintage y funds.

Columns (3)-(6) report results of tests where LPs are designed to have either more restricted or expanded opportunity sets. In column (3) and (4), we present estimates using the same empirical model as column (1), except we restrict the possibility of investing in funds managed by elite VC firms only to a subset of LPs that have already invested in the VC firms' previous funds. The two columns differ in the way we define an elite VC firm. In column (3), elite VC firms are those with at least one fund with top-quartile performance (ranked against its vintage cohorts) among the three previous funds. In column (4), we define elite VCs as the 15 VC firms that are chosen as "Best VCs" in Metrick and Yasuda (2010). We find that our impact coefficient and WTP estimates are quite robust to these rationed opportunities sets, with only slight variation across columns.

In columns (5) and (6), we turn to considering an expansion of opportunity sets rather than to a rationing of fund access. In column (5), we assume that the fund raised in year y was also fundraising in year y-1 if more than five years had lapsed between the vintage years of the current fund and the previous fund. Operationally, we treat these funds as being in the market in both y-1 and y. In column (6), we assume that LPs that made no investments in year y but invested in $y+1$ were in fact already looking to invest in year y but passed. Alternatively, some of those LPs with investments in year $y+1$ actually made the commitments into the funds in year y, but the funds did not close until $y+1$. Either way, operationally we treat these LPs as being in the market in both y and $y+1$. In both columns (5) and (6), the sample size expands because either the set of funds (column (5)) or the set of LPs (column (6)) in a given year is greater than in our baseline sample. Again we find that our aggregate WTP estimates are very robust to the expanded opportunity sets, as the results in columns (5) and (6) are very similar to those in column (1).

Before proceeding to the analysis of WTP across different LP types, we estimate the WTP across five geographic regions using the model of column (1) but interacting impact with five regions. We summarize the WTP by region in Fig. 2. Circumstantial evidence suggests that demand for impact should be higher for investors domiciled in Europe. In their 2014 report, the Global Sustainable Investment Alliance (GSIA) reported 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 positive externalities more than others.[17] Our results strongly confirm the

[16] In earlier drafts of the paper, we estimated linear probability models and obtained similar results.

[17] See Liang and Renneborg (2016) and Dyck et al. (2019) for related evidence.

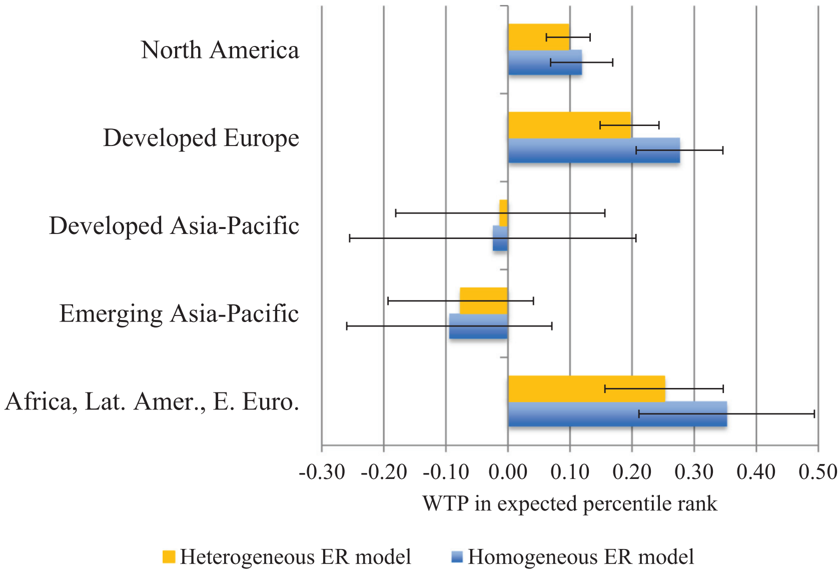

Fig. 2. Willingness to pay (WTP) for impact by geography.
The figure presents estimates of the willingness to pay for impact based on the logit model including the impact coefficient and the impact coefficient interacted with geography using either homogeneous or heterogeneous expected return models. (Geography is not mutually exclusive.) The WTP is the sum of the impact coefficient plus the impact*geography coefficient, all divided by the expected returns coefficient expressed in percentile ranks. Percentiles are based on performance relative to cohort funds. Cohorts are defined by fund vintage year and region. Black bands represent 95% confidence intervals on WTP estimates.

circumstantial evidence. North Americans have a positive and significant WTP for impact, but it is smaller than the baseline estimate (10–12 percentile ranks or 1.6–2.2 ppts in expected excess IRR). In contrast, investors from Developed Europe and from Africa, Latin America, and Eastern Europe have much higher WTP of 20–28 percentile ranks and 25–35 percentile ranks, respectively, corresponding to an expected excess IRR WTP of 4.2 to 8.7 ppts.

5.2. WTP by LP type

In this section, we estimate variation in WTP across LP types. The WTP estimate of 13–18 percentile ranks as reported in Table 5, column (1) is an average effect among all investors in our sample. It does not imply that all investors exhibit the same WTP. 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.

Table 6 presents the results. In all columns we allow investors' taste for impact to vary across nine LP types and five geographic regions. In column (1), we estimate the logit model using homogenous expected returns corresponding to Eq. (4). In column (2), we use heterogenous expected returns corresponding to Eq. (15).

Fig. 3 summarizes the WTP results by LP type. We find that development organizations, financial institutions, and public pensions have large positive WTP for impact with estimates ranging from 13 to 27 percentile ranks (2.5–6.2 ppts in excess IRR). In contrast, endowments, corporations, institutional managers, wealth managers, and private pensions have negligible WTP for impact, as their impact coefficients in the logit model are not significantly different from zero. Foundations have a small positive and statistically significant WTP (6 percentile ranks) in column (2). Although the WTP magnitudes fluctuate across models, the patterns across LP types are very robust.

In addition to testing the null that the individual WTPs are equal to zero, we also test the null hypothesis that LP types have equal WTP; we can easily reject the null hypothesis that the WTP is equal across LP types ($p<0.001$). In pairwise tests of the null hypothesis of equal WTP, we cannot reject the null in pairwise tests for *Development Organizations, Financial Institutions, and Public Pensions*. These are the same LP types that exhibit a robustly positive WTP for impact throughout our analysis. We always reject the null that these three LP types' WTPs are equal pairwise to WTPs of the other six LP types.

One explanation for our results might be that investors look as if they are willing to pay for impact, but in reality they erroneously expect returns on impact funds to be comparable to those earned on other VC funds. Because this story would be applicable to investors new to impact investing but not for investors repeatedly choosing impact VC funds, we can test this prediction. In untabulated results, we reestimate the specification of Table 5 column (1) modified to include the impact dummy interacted with an indicator for an LP having prior impact investing experience. We find that both the impact indicator and the interaction term are positive and significant, with the interaction term coefficient being twice as large as the impact coefficient. Put simply, investors with prior investments in impact funds are much more likely to invest in impact. This result combined with the PME result that impact funds, on average, do not beat the market ex post (Table 1) suggests that our main results

Table 6
Willingness to pay for impact by investor type.
Presented are coefficients and willingness-to-pay estimates from investment choice logit models. The columns vary in their estimation or use of the expected return forecast. Column (1) implements a homogenous model to forecast expected returns, where we estimate a single estimate of the forecast expected returns by fund using all funds in the dataset. Columns (2) and (3) use LP-type specific expected return forecasts but forecast with a smaller set of information (only funds invested by the investor type). Column (3) uses the same forecast as column (2) and also interacts these forecasts with fund characteristics (industry, geography, and size). Column (4) drops the expected return forecast variable altogether. Note that WTP is reported only for columns (1)-(3). Standard errors clusted at the LP level are in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

	(1)		(2)		(3)		(4)
Expected returns forecast:	Homogenous ER forecast		Heterogenous ER forecast by LP type				No forecast
Reported from logit:	Estimates	WTP	Estimates	WTP	Estimates	WTP	Estimates
Expected return	3.364***		4.591***		5.568***	Note: Not comparable to columns (1) and (2).	
	[0.275]		[0.223]		[1.584]		
Impact estimates by LP type:							
Development org.	0.906***	0.27***	0.738***	0.16***	0.980***	0.14***	0.595***
	[0.180]		[0.183]		[0.155]		[0.180]
Foundation	0.267	–	0.299*	0.06*	0.469***	0.07***	0.00261
	[0.179]		[0.179]		[0.178]		[0.178]
Financial institution	0.765***	0.23***	0.710***	0.15***	0.852***	0.13***	0.483***
	[0.144]		[0.144]		[0.122]		[0.141]
Endowment	−0.518	–	−0.443	–	−0.300	–	−0.802**
	[0.346]		[0.346]		[0.360]		[0.343]
Corporation	−0.0188	–	0.0655	–	0.238	–	−0.316
	[0.233]		[0.224]		[0.194]		[0.232]
Institutional	0.0872	–	0.233	–	0.501***	0.08***	−0.187
	[0.182]		[0.182]		[0.157]		[0.181]
Wealth manager	0.121	–	0.23	–	0.449	–	−0.142
	[0.329]		[0.332]		[0.335]		[0.325]
Private pension	−0.153	–	−0.0746	–	0.0834	–	−0.440***
	[0.168]		[0.168]		[0.174]		[0.165]
Public pension	0.730***	0.22***	0.832***	0.18***	1.028***	0.16***	0.430***
	[0.121]		[0.119]		[0.107]		[0.121]
Region*Impact F.E.	YES		YES		YES		YES
ER interacts with portfolio choice variables	NO		NO		YES		NO
Standard controls	YES		YES		YES		YES
Pseudo R-squared	0.261		0.264		0.276		0.260
Observations	3047,430		3047,430		3047,430		3047,430

are capturing investors' preferences rather than inaccurate beliefs.

As a robustness check of observed variation in WTP across LP types, we allow for variation in the portfolio choice considerations of LPs as described in Eq. (16) with results summarized in column (3). The general pattern of WTP across LP types is quite similar with the exception of institutional LPs that have a greater WTP when we consider portfolio choice considerations.

Finally, column (4) of Table 6 reports a model where we exclude the forecast expected returns. Forecasted expected returns, from our main specification, are lower for impact funds. Thus, we expect that, by excluding these forecasts, the coefficients on impact interacted with the investor types should be lower, as this variable is picking up a lower desirability for the fund associated with missing variable of expected returns. Indeed, this is what we find. The coefficients on all the impact interactions with investor type shift negatively, while the patterns of relative magnitudes of impact coefficients across investor types align exactly with our previous specifications.

5.3. Attributes

5.3.1. Discussion of investor attributes

In this section, we analyze the origins of varying utility over impact by studying attributes of investors that could motivate WTP. Table 7 presents six investor attributes (across columns) and their mapping to the ten LP types (rows). The first three attributes characterize inherent LP features. *Household* categorizes investors based on the constituents of the capital (organizations or households). *Intermediated* classifies 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. *Mission* identifies investors (development organizations and foundations) that have an impact mission as a primary goal.

The last three attributes (*Pressure*, *Laws*, and *Charters*) characterize the implicit or explicit rules governing different investors' ability and desire to invest in impact funds. For these attributes, we exploit the fact that laws govern-

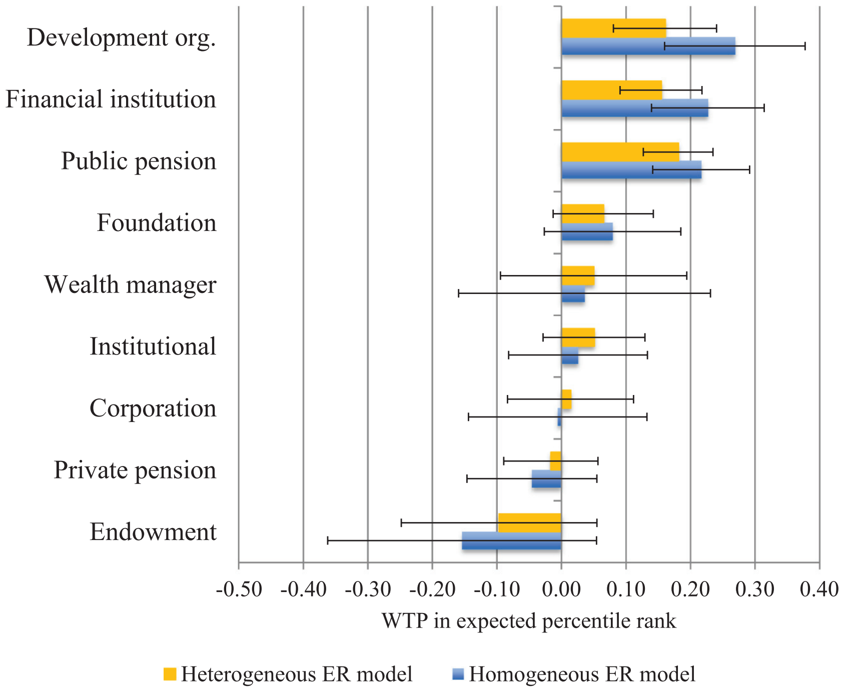

Fig. 3. Willingness to pay (WTP) for impact by investor type.
The figure presents estimates of the willingness to pay for impact derived from the logit estimation of Table 6, column (1) (homogeneous expected return model) and column (3) (heterogeneous expected return model). The WTP magnitude is the ratio of the impact coefficient for the LP type divided by the expected returns coefficient expressed in percentile ranks. Percentiles are based on performance relative to cohort funds, where cohorts are defined by fund vintage year and region. Black bands represent 95% confidence intervals on WTP estimates.

ing these rules vary by geography, thereby allowing us to estimate the WTP associated with these rules within an LP type fixed effect model. Although we do not claim causal identification, this within-LP-type estimation strategy offers suggestive evidence that rules may directly affect WTP for impact.

Pressure (column (4)) identifies regulatory or political pressures that encourage impact investment. Worldwide, public pensions, despite commonly being subject to a fiduciary duty standard, may face political pressure to increase the (perceived or real) welfare of voting populations.[18] Likewise, financial institutions worldwide may have incentives to invest in impact funds that serve low- to moderate-income communities if such investments garner goodwill from customers or regulators. However, in the US, additional regulations (or the threat to regulate) are imposed on financial institutions in a way not operative in other countries. Specifically, US commercial banks are subject to investment obligations to serve their local low- and moderate-income communities under the CRA (CRA Investment Handbook, 2010, p.24). Likewise, insurance companies in some of the large US 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 US may face pressure to invest in impact locally to preempt passage of a federal CRA-like regulation for insurance (Gainer, 2009). We exploit this geographic variation by coding *Pressure* equal to one for US financial institutions (banks and insurance companies), as well as for public pensions worldwide, and zero for others.

Laws (column (5)) identifies investors facing fiduciary duty legal restrictions against impact investing. While most public pensions worldwide face formal (legal or regulatory) restrictions to act solely for the benefit of pension recipients by achieving target investment returns and providing liquidity while minimizing risks and costs, regulations concerning investing principles of other entities such as endowments, foundations, and private pensions are typically less restrictive. However, in the US, foundations, endowments, and private pensions face more restrictive fiduciary standards than their non-US counterparts. US private pensions are subject to the 1974 ERISA, which states that a pension plan fiduciary could consider nonfinancial 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.[19]

[18] 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 et al. (2016) and Andonov, Hochberg, and Rauh (2018) both show that the investments of public pensions are affected by the degree to which the boards governing the pensions are appointed by government officials.

[19] U.S. National Advisory Board (NAB), 2014. Private capital, public good. 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

Table 7
Limited partner (LP) types and attributes related to impact motives.
The table summarizes investor attributes by LP type (column (1)) and region. Column (2) indicates whether the primary constituents of the capital are households (versus 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. The 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 (US)	–
Financial institutions	–	–	–	yes Community Reinvestment Act & state regulation modeled after CRA (US)	–	yes
Endowments	–	–	–	–	yes UPMIFA (US)	–
Corporate & government portfolios	–	–	–	–	–	yes
Institutional asset managers	–	yes	–	–	–	yes
Wealth managers	yes	yes	–	–	–	–
Private pensions	yes	–	–	–	yes ERISA (US)	yes (non-US)
Public pensions	yes	–	–	yes Political pressure	yes State & national laws	–

Likewise, the UPMIFA, which governs the management of US foundations and university endowments, imposes fiduciary standards similar to those of ERISA (see Geczy et al., 2015). However, unlike the ERISA, the UPMIFA provides an additional duty of obedience to the unique charitable mission of the organization. Furthermore, tax laws in the US create an additional hurdle on foundations. The US tax authority requires foundations to maintain a 5% annual payout rate to keep their tax-exempt status; impact investments in the form of program-related investments (PRIs) can count if certain eligibility tests are met.[20] While the policy may have been intended to encourage 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.

Charters (column (6)) identifies restrictions against impact investment in the form of organizational charters, excluding investors already covered by legal restrictions (column (5)) under the assumption that legal restrictions are more binding. Charters require organizations to maximize value for shareholders, which may constrain investments into impact funds. The list of organizations bound by charters includes financial institutions, corporations, non-US private pensions (subject to fiduciary responsibility via their parent corporate charters), and institutional asset managers (subject to fiduciary standards of the institutional sources of capital).

Finally, as we noted in the introduction, both the number of and the dollar amount of assets managed by organizations that are UNPRI signatories have sharply increased in the recent years. Since investors signing the UNPRI are

on the basis of any factor outside the economic interest of the plan" (p.12 of Johnson, K., 2014, "Introduction to Institutional Financial Duties," International Institution for Sustainable Development research report) 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.

[20] 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 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.

Table 8
The willingness to pay for impact by investor attribute.
This table presents logit model estimates (Panel A) and willingness-to-pay estimates (Panel B) including variables to test the incremental willingness to pay for investor attributes. In columns (1) to (3), a fund's expected return forecast is homogenous across all investors. Columns (4) to (6) allows heterogeneous forecast for each fund by LP type. All columns include the interaction of the impact variable with the six LP attribute dummies, a UNPRI signatory dummy variable (that is one for LPs that signed the UNPRI), and a UNPRI post-signing dummy variable. Columns (2) and (5) add in the interaction of the impact variable with the LP geography. Columns (3) and (6) further add the ten LP types and impact interactions. All models include standard controls (see text and Table 5 for details). Standard errors clustered at the LP level are in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Homogenous ER forecast			Heterogenous ER forecast		
Panel A: Model estimates						
Expected returns	3.393***	3.381***	3.386***	4.609***	4.607***	4.608***
	[0.276]	[0.276]	[0.276]	[0.223]	[0.223]	[0.222]
Impact estimates by investor attribute						
UNPRI signatory	0.411***	0.317**	0.357***	0.377***	0.284**	0.328**
	[0.132]	[0.140]	[0.134]	[0.135]	[0.142]	[0.136]
UNPRI post-signing	0.737***	0.702***	0.754***	0.791***	0.764***	0.802***
	[0.211]	[0.211]	[0.211]	[0.219]	[0.219]	[0.218]
Mission	0.916***	0.884***		0.866***	0.764**	
	[0.322]	[0.313]		[0.332]	[0.318]	
Household	0.370	0.319		0.422*	0.277	
	[0.234]	[0.219]		[0.240]	[0.228]	
Intermediated	−0.206	−0.224		−0.0528	−0.052	
	[0.178]	[0.178]		[0.180]	[0.179]	
Pressure	0.987***	1.005***	0.553**	0.957***	0.996***	0.569**
	[0.138]	[0.145]	[0.229]	[0.139]	[0.147]	[0.234]
Charter	0.14	0.196	0.404	0.238	0.203	0.382
	[0.305]	[0.293]	[0.515]	[0.315]	[0.305]	[0.517]
Laws	−0.835***	−0.711***	−0.942***	−0.652***	−0.526**	−0.935***
	[0.211]	[0.222]	[0.353]	[0.216]	[0.226]	[0.353]
Impact	0.0668	n/a	n/a	−0.0472	n/a	n/a
	[0.336]			[0.347]		
Panel B: Incremental willingness to pay (WTP)						
UNPRI signatory	0.12***	0.09**	0.11***	0.08***	0.06**	0.07**
UNPRI post-signing	0.22***	0.21***	0.22***	0.17***	0.17***	0.17***
Mission	0.27***	0.26***		0.19***	0.17**	
Household	–	–		0.09*	–	
Intermediated	–	–		–	–	
Pressure	0.29***	0.30***	0.16**	0.21***	0.22***	0.12**
Restrictions by charter	–	–	–	–	–	–
Restictions by laws	−0.24***	−0.21***	−0.28***	−0.14***	−0.11**	−0.2 ***
Standard controls	YES	YES	YES	YES	YES	YES
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
Pseudo *R*-squared	0.262	0.262	0.262	0.264	0.264	0.264
Observations	3047,430	3047,430	3047,430	3047,430	3047,430	3047,430

doing so with a cost of compliance, it is plausible that they also have higher WTP for impact compared to nonsignatories because of a mission objective. This mission objective may be a fixed attribute for the investor or may reflect some time-varying interest in generation of nonpecuniary benefits from their portfolios. Thus, we introduce two final variables, an indicator variable that takes a value of one if the investor is a UNPRI signatory and an indicator variable that takes a value of one for UNPRI signatories in the years after signing.

5.3.2. WTP results by attribute

Table 8 reports the role of investor attributes in generating WTP for impact. The specification is again the logit estimation with dynamic LP investment groups. Columns (1)-(3) present the results using homogenous expected returns; columns (4)-(6) are for heterogenous expected returns. The columns differ as follows. Column (1) and (4) provides the baseline logits. Column (2) and (5) includes fixed effects for LP geography interacted with impact. This forces the estimation to identify attributes' effects beyond regional preferences for impact. Column (3) and (6) includes LP type interacted with impact fixed effects. The inherent LP type attributes—*Mission, Household*, and *Intermediated*—do not vary by geography and thus drop in this specification.

We report three main attributes results that inform our understanding of investors' WTP for impact. First, having a mission objective increases investors' WTP for impact.

Investors with *Mission* objectives have a WTP for impact of 17–27 percentile ranks (3.4–6.2 ppts in expected excess IRR). We also find evidence supporting a mission objective in considering the coefficients on UNPRI variables. Both the *UNPRI signatory* and the *UNPRI post-signing* variables have positive and significant coefficient across columns. The WTP of being a *UNPRI Signatory* is 6–12 percentile ranks, while that for *UNPRI post-signing* is an additional 17–22 percentile ranks. UNPRI signing captures both temporal and cross-sectional differences in investors' WTP for impact.

Second, investors facing *Pressure* from political or regulatory institutions exhibit a high WTP. In the saturated model of columns (3) and (6), the estimated WTPs for *Pressure* are 12–16 percentile ranks (2.3–3.3 ppts in excess IRR). This evidence is consistent with the interpretation that investors facing *Pressure* returns to satisfy the pressure they face from constituents or to comply with regulators to allocate capital to investments that generate positive externalities.

In auxiliary analyses, we find the effect of *Pressure* can be linked to a preference for local investments by investors that face pressure to invest with impact. We previously noted that financial institutions within the US 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, the mechanism of pressure acts locally. We test whether pressure is a local concept and find that indeed this is the case: investors subject to pressure are much more likely to invest in impact funds that are focused on generating externalities at home than abroad or in another unrelated region (see Appendix Table A4).

Third, we find that *Laws* of fiduciary duty against dual-agenda impact investing have a significantly negative effect on decisions to invest in impact. In the saturated model of columns (3) and (6), the estimated WTPs for *Laws* are −20 to −28 percentile ranks (−4.2 to −6.7 ppts in excess IRR). Laws like the ERISA and UPMIFA matter. In contrast, we find that having *Charter* restrictions against impact alone does not materially affect their demand for impact, on average; shareholders' recourses (e.g., lawsuits and management turnover) do not seem to bind against impact investing in a way that we can identify.

Note that our results are a mixture of utility from regulatory compliance, social signaling, and preferences as underlying investor motivations. We do not attempt to disentangle the sources of utility across different investors, but our results have some counterparts in the literature. Akin to our *Mission* result, Riedl and Smeets (2017) show that both signaling and preferences explain investors' SRI decisions. Yet, in our data, investors that are subject to regulatory *Pressure* may be more driven by the signaling benefits or regulatory compliance. For example, financial institutions may be interested in impact investing as a method of complying with regulator or fostering local goodwill (a form of social signaling). Likewise, pension managers may have signaling incentives over the distilling perception of local job creation that drives portfolio decisions (Dyck et al., 2016; Andonov et al., 2018). As a counterpoint, Bauer et al. (2019) find in an experiment using a Dutch pension program that retirees themselves support allocating more of their retirement portfolios to sustainable investments even when they expect financial returns to be lower. Disentangling between these underlying mechanisms is an important question that we leave for future research.

5.4. WTP by impact category

In this section we examine whether investors' WTP for impact varies by the impact category (e.g., the environment, women and minority businesses, poverty). Fig. 4 presents the results of the logit model estimation of Table 5, column (1) but interacts the impact dummy with each of the six impact categories we describe in Section 2.1. 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 WTP when considering investing in impact funds focusing on environment, poverty, and women or minority issues. Investors are willing to forego 15–22 percentile ranks (3.0–4.7 ppts in excess IRR) in performance when investing in these impact categories. Notably, these are all arguably categories with high public good or externality content. In contrast, investors do not exhibit significantly higher WTP when considering investing in impact funds focusing on SME funding relative to nonimpact funds. However, 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.

6. Conclusion

Our goal has been to understand whether investors are willing to accept lower financial returns for nonpecuniary benefits of intentional impact investing. We show that ex-post financial returns earned by impact funds are 4.7 ppts lower than those earned by traditional VC funds, even after controlling for a host of fund characteristics. To examine whether investors in impact funds willingly trade off expected financial returns at the time of investment decisions, we use a hedonic pricing framework of WTP for impact. We find that impact investors are, on average, willing to forego 13 to 18 percentile ranks of vintage-geography benchmarked performance or about 2.5 to 3.7 ppts in expected excess IRR.

From the perspective of portfolio companies that are financed by impact funds, investors' willingness to accept lower return implies lower cost of capital for the portfolio companies. Assuming 20% carried interest and 2% management fees, back-of-the-envelope calculations for mature funds in the sample suggest that companies that get funded by impact funds generate an excess gross (i.e., gross-of-fees) VM that is 0.29 to 0.43 lower than those funded by traditional VC funds (see Appendix C for details). The mean (median) fund-level gross value multiple in the mature fund sample is 2.3 (1.5). Thus, the WTP for

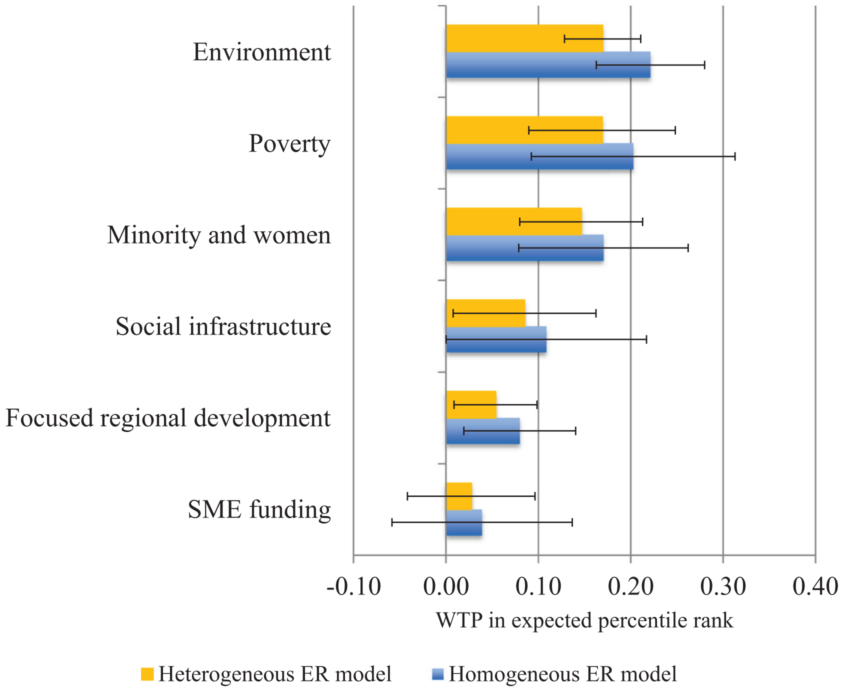

Fig. 4. Willingness to pay (WTP) by impact category.
The figure presents estimates of the willingness to pay for impact by impact category using either homogeneous or heterogeneous expected return models. Estimates are based on a variation of Table 5, column (1) that includes an interaction of impact with the impact type category. The WTP is calculated as the sum of the coefficient on impact and the coefficient on impact*category, all divided by the coefficient on expected returns (expressed in percentile ranks). Percentiles are based on performance relative to cohort funds, defined by fund vintage year and region. Black bands represent 95% confidence intervals on WTP estimates.

impact funds suggests an economically meaningful reduction (e.g., 0.3 reduction is 20% of the median firm's multiple) in the cost of capital for the portfolio companies that they finance.

WTP varies considerably over who controls the capital. To unpack the heterogeneity across investors, we categorize investors into nine broad categories. Investors in three of the nine categories—development organizations, financial institutions, and public pensions—exhibit reliably positive WTP for impact. We then delve into what attributes of investors affect investors' WTP for impact. Not surprisingly, investors with organizational missions and investors that are PRI signatories (especially post signing) have high WTP. In addition, we find that investors facing political and/or regulatory pressure (e.g., banks and insurance companies in the US that face CRA and other equivalent requirements) and those benefiting from political or local goodwill exhibit a higher WTP for impact. In contrast, laws that discourage the sacrifice of financial returns for impact (e.g., ERISA and UPMIFA in the US) may reduce the WTP for impact. Since the number of high-fiduciary LPs affected by such legal restrictions is large (1258 out of 3504 in our sample), this finding has important implications for how subtle shifts in legal interpretations of institutions' fiduciary duty may affect investors' WTP for impact. For example, in the US, the IRS and Treasury issued guidance on mission-related investments in September 2015, assuring that it is possible for private foundations to make a prudent investment using the foundation's assets that advances the foundation's charitable purpose, even if the investment offers a lower rate of return, higher risk, or lower liquidity than alternative investments that do not further charitable purposes. To the extent that (either real or perceived) risk of a tax penalty from making impact investments had a negative effect on their WTP prior to this ruling, this regulatory shift may affect foundations' WTP in the future years. Moreover, recent growth in fundraising by impact buyout and impact infrastructure funds by mainstream General Partners (GPs) like KKR and Bain Capital is consistent with asset managers meeting investors' demand for dual-bottom-line funds. Since a positive loading on the impact implies lower performance sensitivity in fundraising, these GPs may find the impact designation valuable for their objective of maximizing net present value of future fee revenues (Chung et al., 2012).

In combination, our results provide compelling evidence that investors are willing to pay for nonpecuniary characteristics of investments. 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 WTP for impact varies considerably across legal and regulatory environments, investor geography, and time. This variation opens up a number of avenues for future research that explores the factors that govern the variation that we show.

Appendix

Supplementary material associated with this article can be found, in the online version, at http://jfe.rochester.edu/appendix.htm.

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