The Risk and Return of Impact Investing Funds

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Abstract

We provide the first analysis of the risk exposure and consequent risk-adjusted performance of impact investing funds, private market funds with dual financial and social goals. We introduce a new dataset of impact fund cash flows constructed from financial statements. When accounting for market risk exposure, impact funds underperform the market, though not more so that comparable private market strategies. We exploit known distortions in measures of VC performance to characterize the risk profile of impact funds. Impact funds have substantially lower market beta than VC funds, contradicting the idea of sustainability as a "luxury good." We find that impact fund cash flows do not exhibit positive correlation with a public market sustainability factor, consistent with the idea that private and public market sustainability strategies capture distinct exposures.

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1 Introduction

As major societal problems like climate change and inequality grow, investors and the public have become increasingly interested in whether financial markets can be harnessed to help address these issues. Industry participation in sustainable finance and responsible investing has exploded in recent years, with global sustainable investing assets amounting to $30.7 trillion in 2018, a 34 percent increase in two years (GSIA, 2018). While social and environmental responsibility are often debated in the context of public markets, private markets are uniquely suited to address these challenges because of their dominance in early-stage and growth transactions. At these early stages in companies' lifespans, capital providers exert more influence on both deal sourcing and governance than what they would be able to achieve in public markets (Phalippou, 2017; Gompers et al., 2020).

Impact investing is the practice of using private market strategies to target both financial returns and a social or environmental goal. Although impact investing is a rapidly growing asset class, with $715 billion in assets under management globally, relatively little is known about the financial properties of this approach (Hand et al., 2020; Burton et al., 2021). In particular, to the best of our knowledge no work has addressed the riskiness of impact investing or its financial performance adjusted for market risk exposure.[1]

This paper fills a gap in the literature by characterizing the risk-adjusted return of impact investing and its risk properties relative to other strategies. Three reasons motivate us. First, establishing risk and return properties is a critical component of understanding the feasibility and future of impact investing—even (perhaps especially) if impact investing is not a strategy that maximizes returns. If impact is concessionary, it is essential to describe the magnitude of the potential risk-adjusted concession in order to understand who will be able or willing to participate in these strategies. Likewise, characterizing the riskiness of impact investing can also illuminate how impact investing fits into existing portfolios.[2]

Second but equally important, a large debate over the returns of impact investing reflects divergent theories of the market. Under standard assumptions (perfect and complete capital markets, rational and informed investors), constrained strategies like impact investing must have lower risk-adjusted returns than unconstrained strategies (Brest et al., 2018; Barber et al., 2021). If these standard

[1] Barber et al. (2021) take an important first step in understanding the performance of impact investing by benchmarking impact fund performance using IRRs and multiples. However, without fund cash flows, they are unable to speak to the risk exposure or risk-adjusted performance of impact funds. Similarly, Cole et al. (2020) abstract from risk exposures in their analysis of long-run returns to impact investing.

[2] Some have argued that impact investing is only meaningful when it has additionality, and that impact investments should be motivated by a moral imperative rather than a financial one (e.g. Phalippou (2017)). We do not disagree with these positions. Our focus in this paper is descriptive rather than prescriptive.

assumptions fail, however, the inequality need not hold. This is in line with recent work by Cole et al. (2020), which finds that markets are imperfectly integrated and that impact investing extracts value from this market friction, leading to potentially higher returns than unconstrained strategies. Risk is a critical part of this debate: concessionary *absolute* returns may still be consistent with a profitable strategy if the strategy hedges risks. Profitable risk-adjusted returns for a constrained strategy would provide evidence in favor of the violation of standard market assumptions.

Third, the risk profile of impact investing sheds light on different models about the risk of sustainable and green assets. The covariance of impact investing with the market is in theory ambiguous. On one hand, Bansal et al. (2018) document that socially responsible investing (SRI) in public markets is highly pro-cyclical. Extending this theory to private markets, we might expect the market beta of impact investing to be high, and higher than comparable nonimpact private strategies.[3] On the other hand, Nofsinger and Varma (2014) and Pástor and Vorsatz (2020) find evidence that sustainable mutual funds outperform during market crises. Recent work by Gibson et al. (2019) and Wang and Sargis (2020) suggests that ESG investing in public markets can reduce portfolio risk. This countercyclical view of sustainable investing would correspond to a lower market beta for impact relative to nonimpact strategies. There are additional risk factors that an impact investor may be interested in hedging. For example, evidence indicates that climate risk is a growing concern for investors (Krueger et al., 2020), and that it may be mispriced in financial markets (Andersson et al., 2016; Engle et al., 2020). By focusing on solutions to climate and other risks, impact investing may serve as a hedge for downside risks, implying a potentially lower beta than comparable nonimpact strategies.

Private market funds in general, and impact investing funds in particular, present several challenges for studying risk and return. Infrequent and highly skewed payoffs make it difficult to use traditional linear factor modeling techniques. Small sample sizes and young funds exacerbate these problems. To address these issues in the VC literature, Korteweg and Nagel (2016) develop the Generalized Public Market Equivalent (GPME), an extension of the Public Market Equivalent (PME) first proposed by Kaplan and Schoar (2005). As Korteweg and Nagel (2016) show, although the PME has many useful features for assessing the performance of venture capital, it assumes a restricted market equity premium and risk-free rate. As a result, the PME systematically overestimates the performance of high-beta assets in times of rising public equity markets. This bias grows with the asset's market beta.

Our key insight is to leverage these known biases in performance measures to back out the risk properties of impact investing. Given that our sample time period is one of rising public equity markets,

[3]Previous work has found evidence of a sizeable market beta for venture capital (VC) investing strategies. For example, Cochrane (2005) finds a beta of 1.9.

the distance between PME and GPME (the "PME wedge") informs us about the relative market beta of the underlying asset. If impact investing is a high-beta asset, then its PME wedge will be positive; if it is a low-beta asset (beta less than one), the PME wedge will be negative. Moreover, artificially levering up the strategy, and thus amplifying its beta, should amplify the PME wedge: if unlevered beta is positive, the PME wedge will increase. This reasoning extends to relative properties across strategies. For example, if impact investing has a higher (lower) beta than VC, its PME wedge will be greater (smaller) than the PME wedge of VC.

The same logic can be applied to other factor covariances. We derive the relative covariance of impact investing with different public factors, such as a sustainability index, by estimating PME and GPME with the alternative factor and comparing the new PME wedge across impact and nonimpact strategies. Finally, we extend our model to multiple factors, and test whether impact investing cash flows are spanned by a combination of the market and other factors.

We use two sources of data for impact investing cash flows, both stemming from work done as part of the Impact Finance Research Consortium (IFRC), a cross-school collaboration to build data on impact investing funds. First, as part of the IFRC effort, we collect annual and quarterly financial statements directly from impact funds and manually convert them into a standardized database covering contributions and distributions net of fees, as well as net asset value (NAV), among other variables. Our aim is to eventually make the resulting Impact Finance Database (IFD) available for researchers. As of this writing, the IFD contains cash flows for 62 funds from 1999 through 2017. After restricting analysis to funds targeting market-rate returns and with sufficient data, we are left with 48 distinct funds. Second, we leverage the comprehensive list of past and existing impact funds created by the IFRC, and search for these funds in Preqin. We find cash flows for an additional 46 impact funds, bringing our total sample to 94 funds.

We construct comparison fund groups using fund cash flows from Preqin, and in the appendix include comparisons to Burgiss as well. Benchmark comparison groups serve two purposes. First, benchmarking to a well-understood asset class helps us understand performance in an established context. For this purpose, our first comparison group is the universe of US-based VC funds over the same time period as our sample. We choose VC because it is the asset class most representative of impact funds overall (Geczy et al., 2020), and its risk and return properties have been studied extensively (Korteweg, 2019). The second purpose of benchmarking is to try to isolate the influence of the impact component. As a second comparison group, we match each impact fund in our sample to a Preqin fund with the same vintage, asset type, and as close as possible on size. Perfectly controlling for everything outside impact is not possible, but this smaller benchmark helps us to address the effect of characteristics known to influence risk exposure.

We find that after properly accounting for risk exposure and the rising market equity premium, impact funds underperform the public market by \$0.45 per \$1 invested over the 1999-2017 time period. Market risk exposure alone cannot explain the low returns of impact investing. At the same time, we find VC underperforms public benchmarks by an average \$0.44 per \$1 invested over the same time period. A value-weighted portfolio that goes long \$1 in VC and short \$1 in impact funds has a negative market risk-adjusted return of −\$0.15. The equal-weighted long-short portfolio has a positive market risk-adjusted return of \$0.02. Matched funds perform somewhat better, with a loss of "only" \$0.31 per \$1 invested. A portfolio long in matched funds and short impact yields a value-weighted return of −\$0.05 and an equal-weighted return of \$0.04, neither statistically different from zero. Our results are thus consistent with previous findings that private market strategies have generally underperformed public markets in the past two decades. We show this pattern extends to impact funds, but not more so than comparable private market strategies.

Our findings provide a new perspective for the debate on financial performance and market completeness. On one hand, we confirm that the constrained impact strategy is concessionary relative to the risk-return frontier that can be achieved in public markets. On the other hand, impact returns are not clearly concessionary relative to private market benchmarks after accounting for systematic risk. Since VC participants (for example) could in principle invest in the same deals as impact funds, this points to the failure of one or more assumptions in private markets. Cole et al. (2020) argue that imperfect integration of international capital markets enable profitable impact investing strategies. Other possibilities include information barriers, investor biases, and distortions to competition in both capital and product markets.

Our second main result is that impact investing is substantially less sensitive to movements in public equity markets than VC, and to a lesser extent, than matched funds. The PME overestimates impact performance relative to the GPME in our time period, consistent with a market beta greater than one.[4] When we artificially lever up our impact fund cash flows, the PME wedge increases, also consistent with a positive beta that grows as the strategy is levered up. However, this wedge grows more slowly for impact funds than for VC and matched funds. We can reject that impact beta is close to VC beta. A portfolio that goes long \$1 in VC and short \$1 in impact still has a positive beta, indicating greater market risk exposure for VC than for impact. The difference with matched funds is lower, but still consistent with a particularly low beta for impact. Overall, impact is not as pro-cyclical as we would expect for a "luxury good", or at least not as much as VC. Instead, adding

[4] This statement holds true in times of rising market equity premia, which we show is the case for our sample period.

impact investments to a private market investor's VC portfolio reduces overall market risk exposure.

Third, impact investing captures distinctive risk exposures. While impact fund returns are not spanned by the market and a small growth factor, we cannot reject that a two-factor model with the market and a public market sustainability index does not span impact returns. In contrast, neither of these multifactor models span VC cash flows better than the single-factor market risk model, in the sense that the negative magnitude of absolute returns cannot be explained by exposure to these risk factors. We also consider the model of an investor who cares about sustainability, and invests only in the public market sustainability index. In this setting, impact underperforms the sustainability benchmark, while both benchmarks outperform. This indicates that if investors are targeting exposure to a public sustainability factor, then impact investing is not a profitable means to gain this exposure.

Our work contributes to the broader understanding of SRI and environmental, social, and governance (ESG) factors. Most existing work has focused on public markets, exploring investor taste for "green" strategies (Hartzmark and Sussman, 2019; Krueger et al., 2020; Pastor et al., 2019; Fama and French, 2007) and the pricing of ESG factors (Ilhan et al., 2021; Bansal et al., 2018). Renneboog et al. (2008) provide an overview of SRI in mutual funds. We extend this work to private markets, which present a different set of challenges and opportunities for sustainability-minded investors. Companies seeking capital in the impact investing market are typically orders of magnitude smaller than public companies, with completely different expected growth paths and risk considerations. The potential for impact is also distinct from public market investments. Investors, via funds, have substantially more influence over the development of portfolio companies than they would in public companies.

Data limitations have kept the literature on impact investing sparse, but this paper joins a few others in the burgeoning literature on impact investing. On the descriptive side, Burton et al. (2021) introduce a new database on investor and firm characteristics in impact investing, and provide essential statistics to understand this emerging space; Geczy et al. (2020) detail the contracting and governance practices of impact investing funds.[5] On the theory side, Chowdhry et al. (2019), Oehmke and Opp (2020) and Green and Roth (2020) propose models for the existence and usefulness of impact investing. Two other papers study the financial performance of private impact investing funds: Barber et al. (2021) use a willingness-to-pay model to show that investors accept 2.5%-3.7% lower internal rates of return (IRRs) for impact funds, and Cole et al. (2020) find that a large impact investor's long-run returns *outperformed* the market by 15% over nearly seven decades of investing activity. We provide a new perspective to these two papers by explicitly addressing the risk exposure of impact

[5] Both projects are related to the Impact Finance Database introduced in this paper: Geczy et al. (2020) leverage the contract data portion of the IFD, and several of the individuals involved in the Impact Investment Database described in Burton et al. (2021) also contribute actively to the IFRC.

cash flows.In our sample, impact underperforms relative to public markets, but not more so than comparable strategies after accounting for market risk exposure. An advantage of our data is that we can differentiate impact funds that are explicitly concessionary from funds that state their intention to achieve market-rate returns. Our current results pertain to the latter only.

Last, this paper contributes to a rich asset pricing literature on the risk and return of PE and VC cash flows, starting with Cochrane (2005) and Korteweg and Sorensen (2010). More recently, Ang et al. (2018) estimate a PE-specific return series using a Bayesian approach and assuming a linear factor structure. Gupta and Van Nieuwerburgh (2019) propose a new method to risk-adjust PE returns and estimate factor risk exposures for each cash flow horizon. We build heavily on the GPME approach introduced by Korteweg and Nagel (2016), leveraging the distortions that they document to back out the risk properties of impact and VC funds. This approach allows us to directly compare VC and impact funds in an intuitive way. A key difference between this method annd Gupta and Van Nieuwerburgh (2019) is that the latter uses expectations of stochastic discount factors (SDFs) from dividend strip prices, while we rely on the realized SDF.

The remainder of the paper proceeds as follows. We describe our data in Section 2 and our approach and predictions in Section 3. In Section 4, we show results relative to market exposure, and in Section 5 we introduce other factors. Section 6 concludes.

2 Data

One of the challenges in studying impact investing is the lack of data. We overcome this challenge by creating a new dataset of impact investing cash flows from new and preexisting data sources. This section explains our data sources and construction. We start with the sample of impact funds, then describe benchmark VC and matched funds, followed by summary statistics for all three samples. We also describe the data for the public market replicating portfolios used in the GPME approach, which we further describe in Section 3.2.

2.1 Impact Investing Funds

This paper uses a new data source, the Impact Finance Database (IFD), that we developed as part of the IFRC, a collaboration across the Wharton School of Business, Harvard Business School, and the University of Chicago's Booth School of Business. The IFD encompasses multiple datasets, covering four key aspects of impact funds: their financial cash flows, impact reports, legal documents, and management practices. This paper focuses specifically on the financial component of the IFD.

The goal of the IFRC is to make the IFD available for outside research once there is a critical mass of funds.[6]

With the support of the IFRC, we collect financial statements directly from impact investing funds. These include both audited annual financial statements and intermediate quarterly statements, when available. We carefully convert these raw financial statements into two standardized cash flow panels, one at an annual frequency and the other at a quarterly frequency. The variables that we track include contributions to the fund, distributions out of the fund, and net asset value (NAV). At the time of writing the IFD covers annual cash flows for 62 funds and quarterly cash flows for 48 of these funds. The sample covers vintage years 1999 through 2015, with cash flow data through the end of 2017.

Impact funds include funds that target market-rate returns, as well as funds that target a positive but below-market return. We typically obtain this information from disclosures made during fund-raising, such as prospectuses. For this paper, we focus on market-rate-seeking funds. We also limit our analysis to funds open for at least three years, and with no data gaps at the annual level. This results in an initial dataset of 48 funds.

We augment our IFD sample with data from Preqin. We leverage the comprehensive list of impact funds created by the IFRC to identify 46 additional funds in the Preqin cash flow database, after applying the same filters as above. Preqin impact funds tend to be larger than IFD funds, though still small relative to private equity in general. When compared to Burgiss, Preqin funds appear to be somewhat negatively selected (see Appendix B). This helps to balance out any potential positive selection bias in IFD-participating funds.

Our total sample for analysis consists of 94 funds. We use quarterly data if available (87 funds), otherwise annual data (7 funds). Cash flows reflect returns to LPs net of fees, except for the final distribution when funds are still open at the end of our sample, where we follow Harris et al. (2014) and Korteweg and Nagel (2016) and use NAV as the final distribution. This final cash flow does not account for future fees.

Geczy et al. (2020) analyze the legal documents of funds in the IFD. Virtually all IFD funds display commitments to impact in their contracts. Term lengths are typically ten years, and the largest investors in market rate-seeking impact funds are high net worth individuals and development finance institutions, but investors also include institutional investors and foundations. We check the websites and any available information for the Preqin funds, and retain only ones that clearly signal a dual mandate for the fund, targeting financial and social or environmental returns.

Impact funds share salient characteristics with VC funds. Their function is to raise capital to invest

[6]More information on the data and initiative can be found at https://impactfinanceresearchconsortium.org/.

in private companies, and the legal and compensation structure of impact funds is generally similar to that of VC funds (Geczy et al., 2020). One difference is that impact funds tend to invest across lifecycle stages, with portfolio companies ranging from early stage to mature even within a fund. Impact funds can use both debt and equity, but generally tend to favor equity. The use of equity makes VC a better comparison group than buyout, especially when thinking about how the high leverage structure of buyout funds can affect their market beta. Like VC funds, impact funds also tend to hold minority stakes. Common exits for impact fund portfolio companies are sales and redemptions.

In Figure 1, we report on the geographic focus of the impact funds in our sample. About a third of our funds focus on the Americas, and one fifth on the Middle East and Africa.. Roughly one sixth of our funds are generalist investing across regions, and another sixth focus on Asia and the Pacific. The remaining tenth of funds focus on Europe. Figure 2 reports on the industry focus of funds in our sample, obtained from Preqin for both IFD and Preqin funds. Some funds invest across industries, and therefore appear in multiple categories in the graphic. The most common category for our sample is consumer discretionary, followed by information technology, verticals, healthcare, and financial services (which includes microfinance). Our funds also commonly invest in telecommunications, industrials, business services, energy, and natural resources. A third of our funds simply report a diversified industry focus. The least common industry group, represented by a little under a tenth of our funds, is real estate.

Additionally, we plot the histogram of asset classes for the impact fund sample in Figure 3. A majority of impact funds are equity funds from VC, followed by buyout, expansion, and generalist equity funds. Mezzanine, real assets, and other funds are also represented in the sample, but in much smaller numbers. Lastly, Figure 4 shows the sequence number of the funds in our sample. First-time funds represent about 40% of our sample, second-time funds 32%, third-time funds 16%, and the remaining 12% are later follow-ons.

2.2 Non-impact Funds

We contrast impact investing funds with two benchmarks: VC funds and a group of private market funds matched on asset class, vintage, and size. Comparing impact to these two benchmarks serves two different purposes. The first purpose of benchmark comparison is to contextualize results relative to a known asset class. VC is a well-understood asset class with a robust market. VC and impact share significant similarities and VC is overall the closest asset class to impact, as described above, so examining how the impact market compares to the VC market in a general sense is a useful way to understand impact performance in an established context. The second purpose of benchmarking is to try to isolate the influence of the impact component. For this purpose, we match each impact fund as closely as possible to peer funds on characteristics that may affect risk-return relationships. Our thought experiment is: if an investor has a choice between investing \$1 in our benchmark PE markets or \$1 in the impact market, what are the implications?

Brown et al. (2015) document strengths and limitations of different commercially available data sets for VC and matched benchmark cash flows. We present our main results using benchmark cash flows from Preqin. Preqin gathers information from public sources, direct requests, and requests made under the Freedom of Information Act (FOIA). A strength of Preqin is its accessibility, but a potential weakness is that its sample can be prone to survivorship bias and selection issues. Since we draw on Preqin for part of our impact sample, we use Preqin as our main benchmark, but we show our results are robust to using benchmark cash flows from Burgiss in appendix B. Burgiss provides information management services to institutional investors, and makes anonymized data from these funds accessible to researchers. Burgiss data therefore tends to be less sensitive to survivorship bias and has broader representation. We find VC funds in Burgiss tend to perform slightly better than VC funds in Preqin.

To construct our general VC benchmark, we follow Korteweg and Nagel (2016) and restrict the sample of Preqin funds to funds with at least \$5 million in assets, and funds with a US focus. We include venture, early stage, and late stage fund types, and remove any impact funds that we can identify. To mirror the time period of our impact fund sample, we include VC funds with vintages from 1999 through 2015 and cut off cash flows after 2017. We also drop the funds with less than 3 years of data.

To construct our matched benchmark, we match each impact fund to a fund in Preqin based on general asset class and vintage with the closest size. Because Preqin asset classes are slightly different than the asset classes in the impact sample, we make the following adjustments: we match generalist equity impact funds to balanced Preqin funds and impact generalist, debt, and real estate funds to Preqin general venture funds. This gives us a narrower comparison, but is noisier as a group. We allow for funds with a non-US fund focus, but find that most of the matched sample has a focus on the US. We cut off cash flows for each matched fund based on the final cash flow date in the impact sample. We convert the cash flows to quarterly frequency to better match the structure of the impact fund data.

2.3 Sample Construction and Statistics

Table 1 provides summary statistics for our sample of impact and benchmark funds. Impact funds are smaller than the median VC fund, with a median size of $141 million compared to $280 million for VC funds, though a handful of outliers bring the average size of impact funds higher. Impact funds (by design) have a similar size to the matched group, which has a median size of $179 million. Both absolute performance measures (IRR and multiple) and the PME ratio suggest impact underperforms relative to the benchmarks.

For descriptive purposes, we construct PMEs following Kaplan and Schoar (2005) (see Section 3.1 for more detail). On average, all of the funds underperform the market (i.e., they have a PME less than one). Impact as an asset class is the worst performing group of funds, with an average PME of 0.75. VC funds have a PME of 0.88 and matched benchmark funds have a PME of 0.96.

We have fewer earlier vintage years for our impact funds than for VC funds, and correspondingly fewer cash flows. The matched benchmark funds are explicitly matched on vintage year, and have a similar number of cash flows.

Figure 5 plots the unadjusted performance over vintage years of both the impact and VC funds. Panel (a) shows the performance in terms of IRR and Panel (b) shows total value to paid in (TVPI). For each vintage year, the IRR or TVPI is calculated by taking the median of fund level IRR or TVPI respectively. We use the median because the mean is more sensitive to outliers. Both in terms of IRR and TVPI, the unadjusted performance shows similar patterns. In recent years, VC consistently outperforms impact funds in unadjusted performance, while impact funds do better in earlier years (1999-2000) (though small sample numbers especially in the beginning of the sample period mean these patterns should be read with caution). In Panel (a), we add the annual return of the S&P 500 total return index for each year as a public market comparison point. S&P index returns are more volatile than impact and VC IRRs, and they do not consistently outperform private market strategies in all years.

Figure 6 reports on the timing of distributed cash flows as a percent of fund size for impact funds and VC funds. Overall, the profiles are similar, though statistics are noisier for impact funds at the monthly level. We plot the smoothed cash flow profile at an annual level in Figure 7. The profiles are still similar, with distributions as a percent of fund size increasing in years 5 through 7 of funds. However, the median impact fund has larger payouts than the median VC fund, in addition to a very large final period NAV distribution payout.

2.4 Public Market Replicating Portfolios

To compute the GPME, we require public benchmark portfolios that replicate the capital accumulation and payouts of our private market funds. We use the 1-month T-bill for the risk free rate and the CRSP value-weighted index for the market return. For additional factors, we use the small-growth portfolio return among the six portfolios underlying Fama and French (1993) factors and the Dow-Jones Sustainability World Index. The T-bill rate, CRSP value-weighted index and small growth portfolio return are from Ken French's website and the Dow Jones Sustainability index is extracted from Bloomberg terminal.

3 Characterizing Risk and Return in Private Market Capital

In this section, we review the predominant measurements of performance in the private equity literature and how their various assumptions distort performance evaluation. We then use these distortions to characterize how PME and GPME will behave under different risk properties and generate predictions for our analysis.

3.1 Public Market Equivalent (PME)

Originally developed by Kaplan and Schoar (2005), the PME provides a measure of economic performance for illiquid private equity investments by benchmarking them to what investors would have made, had they invested the same cash flows in the public market. Formally, the Kaplan and Schoar (KS) PME is calculated as follows:

$$PME_{KS} = \frac{\sum_t \frac{distribution_t}{1+R_{mt}}}{\sum_t \frac{call_t}{1+R_{mt}}} \tag{1}$$

where *distribution* is a cash flow from the fund back to the investor, *call* is a cash flow from the investor into the fund, and R_{mt} is the total return on the market from the inception of the fund to the time of the distribution or call.[7] Conceptually, each cash flow is discounted by the opportunity cost for a representative PE investor of an equivalent cash flow invested over the same time period in the public market. The PME improves on previous standards of performance (such the IRR and multiple) by accounting for the opportunity cost of capital.

Sorensen and Jagannathan (2015) demonstrate that the PME is also a valid measure of performance from an asset pricing perspective. Given an investor with log-utility preferences, the PME discount

[7] Later, we redefine the PME as a difference rather than a ratio in order to compare it with the GPME.

rate from time t to $t+1$ can be represented as a stochastic discount factor of the following form:

$$M_{t+1} = \exp(-\log R^m_{t+1}) \tag{2}$$

where R^m_{t+1} is the gross return on the market portfolio. When the cash flows of a PE fund are discounted using this SDF, the PME has the interpretation of an excess return measure accounting for the risk of the market. Importantly, the market return is a proxy for the return on the investor's overall wealth portfolio.

As noted in Korteweg and Nagel (2016), the PME has many useful features for assessing PE fund performance. It is well-suited for the analysis of irregular and skewed cash flows. It also does not require strong distributional assumptions about the return generating process (in papers such as Cochrane (2005) and Ang, Chen, Goetzmann, and Phalippou (2018)).

However, there are important drawbacks to the PME as a measure of performance. Kaplan and Schoar (2005) originally noted that the PME implicitly assumes that systematic risk β is equal to 1. The authors explain that this assumption is the result of the difficulty of estimating risk and return relationships without liquid market prices. Korteweg and Nagel (2016) argue that the PME is particularly distortionary when equity markets are rising. They use the example of jointly log-normal returns. The SDF of the PME implies the following risk-return relationship:

$$\log E[R_{t+1}] = \log E[R_{m,t+1}] - \sigma^2_m + \beta\sigma^2_m \tag{3}$$

This SDF thus restricts the equity premium to the variance of the market return σ^2_m and the (log) risk-free rate to $\log E[R_{m,t+1}] - \sigma^2_m$. Korteweg and Nagel (2016)'s observation is that this relationship is inconsequential for assets with $\beta = 1$ (leading to the risk-return relationship $\log E[R_{t+1}] = \log E[R_{m,t+1}]$). During times of strongly rising equity markets (when $\log E[R_{m,t+1}] - \log R_f > \sigma^2_m$), the SDF will not accurately adjust for market risk exposure if an asset's β is different from one.

3.2 Generalized Public Market Equivalent (GPME)

Korteweg and Nagel (2016) correct for the PME's risk exposure distortion with a new performance measure, the GPME. The GPME is conceptually similar to the PME, but the single-period SDF used to discount PE fund cash flows takes the following form:

$$M^*_{t+1} = \exp(a - br^m_{t+1}) \tag{4}$$

Under this flexible SDF, the PME is a special case when $a = 0$ and $b = 1$. The authors then compound the single-period SDF in order to find the multi-period SDF that can price cash flows over varying time horizons. For each cash flow j, the multi-period SDF is calculated from the first cash flow t to the payoff horizon of cash flow j, represented as $h(j)$.

$$M_{t+h(j)}^{h(j)} = \Pi_{i=1}^{h(j)} M_(t+i) = exp(ah(j) - bf_{t+h(j)}^{h(j)}) \tag{5}$$

In the log-normality example from the previous subsection, this SDF implies the log-linear β pricing relationship in Equation 6 that appropriately accounts for market risk exposure (when a and b are estimated to reflect the market return and risk-free rate). We describe the estimation procedure for parameters a and b in Section 4.1 and Appendix A.

$$\log E[R_{t+1}] = r_f + \beta(\log E[R_{m,t+1}] - r_f) \tag{6}$$

The GPME takes a benchmarking perspective, asking how an investment adds value to an investor's portfolio that would not be attainable from other factors. Instead of using a ratio as in the classic PME formulation in Kaplan and Schoar (2005), the GPME in Korteweg and Nagel (2016) is defined as the sum of discounted distributions minus the sum of discounted contributions, using the multi-period discount rate:

$$GPME_i = \sum_{j=1}^{J} M_{t+h(j)}^{h(j)} \text{Distributions}_{i,t+h(j)} - \sum_{j=1}^{J} M_{t+h(j)}^{h(j)} \text{Calls}_{i,t+h(j)} \tag{7}$$

Each cash flow is discounted to time t, including the initial investment. Moreover, each cash flow is normalized by the size of the fund. Because of this, the GPME can be described as the NPV of \$1 invested in the fund. Under the null hypothesis of no abnormal performance, $E[GPME_i] = 0$.

The GPME has its own limitations. Gredil, Sorensen, and Waller (2019) show that an NPV-based estimator of fund performance may suffer more bias for samples with longer fund life, something we confirm in Appendix C.3. Nonetheless, we show in Appendix B.3 that our results are not due to different fund lives for our benchmark funds. We also show in Appendix C.1 and C.2 that our approach is robust to concerns about finite sample performance and number of cash flows.

3.3 Prediction Development

In this section, we explain how we can characterize risk and performance properties of different asset classes using the properties of PME and GPME. We start with predictions regarding market risk, then move to covariance with other factors. For these predictions, the GPME is defined as in equation 7, and the PME is defined as the special case of the GPME where the SDF parameters in equation 4 are restricted to $a = 0$ and $b = 1$.

3.3.1 Market Risk Predictions

In periods of rising equity markets (i.e., states of the world when the equity premium is higher than what is assumed under the PME), the PME systematically overestimates the performance of high-beta assets when compared to the GPME, and underestimates the performance of low-beta assets. We use this property to back out the asset's covariance with the market, β.

Assuming jointly log-normal VC and market returns, the difference between the log expected return of the GPME and PME can be represented as:

$$(\beta - 1)(\log E[R_{m,t+1}] - r_f - \sigma_m^2) \tag{8}$$

This flows directly from rearranging equations 3 and 6.[8] Notice that this difference reduces to zero when β is one. When β is different than one, our predictions depend on the magnitude of the equity premium.

We say the market equity premium is *sufficiently high* if

$$(\log E[R_{m,t+1}] - r_f - \sigma_m^2) > 0 \tag{9}$$

where $\log E[R_{m,t+1}]$ is the log expected gross return of the market portfolio and σ_m^2 is the variance of the log gross returns of the market portfolio. While this is derived under the assumption of jointly log-normal returns, it should be approximately true in the data. This definition characterizes how much the equity premium observed ex post deviates from what is assumed by the log-utility PME model. If β is greater than 1, then the PME understates the market equity premium and overestimates the abnormal return. The GPME corrects for this distortion. Thus, when the PME overstates abnormal performance ($PME > GPME$) in a one-factor model, we can conclude that β is greater than one.

Our first prediction formalizes the behavior of the SDF when the equity premium is sufficiently high.

Prediction 1 (P1): *When the equity premium is sufficiently high, the parameters of the SDF will not be those of the parameters of the log-utility SDF. That is, for an SDF of the form* $M^*_{t+1} = \exp(a - br^m_{t+1})$,

[8] A full derivation of these expressions can be found in the Appendix of Korteweg and Nagel (2016).

$a \neq 0$ and $b \neq 1$.

When Prediction 1 is true, then the distortions of the PME will be relevant for assets with a β different from one. From Equation 8, we derive the following prediction.

Prediction 2 (P2): *When the market equity premium is sufficiently high, PME overstates abnormal performance for high-beta (β>1) assets and understates abnormal performance for low-beta (β<1) assets. If $PME = GPME$, then $\beta = 1$.*

We use our predictions to compare the β of impact to the β of a set of benchmark funds. From Equation 8, within the same time period, the distortion of PME relative to GPME depends on the magnitude of β. Defining the PME wedge as $PME - GPME$, we make the following prediction.

Prediction 3 (P3): *When the market equity premium is sufficiently high, and all else equal, the relative magnitude of the PME wedge reflects the relative magnitude of the asset's beta. If $(PME - GPME)_{Benchmark} > (PME - GPME)_{Imp}$, then $\beta_{Benchmark} > \beta_{Imp}$.*

We also use artificially levered cash flows to give more accurate bounds on β. This exercise was first developed in Korteweg and Nagel (2016). We simulate increasing β by increasing a leverage factor k applied to fund cash flows and then estimating the PME and GPME of the levered cash flows using the original SDFs. The levered cash flows are calculated as:

$$L_{i,t+h(j)} = C_{i,t+h(j)} + k(C_{i,t+h(j)} - C_{if,t+h(j)}) \tag{10}$$

where $C_{i,t+h(j)}$ are the cash flows from the original fund and $C_{if,t+h(j)}$ are the cash flows from the risk-free rate replicating portfolio which matches the capital call schedule of the original fund while investing in the risk-free asset. Funds are indexed by i, t is time, j denotes cash flow time, $h(j)$ denotes time horizon, and k is a leverage factor. We assume $k \geq -1$, i.e. no net short-selling of the original fund cash flows.

When the asset has a positive β with no leverage, imposing more leverage to the cash flows will inflate the β of levered cash flows. Reversely, if the β of the asset is negative with zero leverage, levering up will decrease β. Thus if the unlevered β of the cash flows is positive, then the PME wedge increases as the artificial leverage factor increases. This reflects the fact that the PME becomes a worse measure of performance as β moves away from one.

Prediction 4 (P4): *When the market equity premium is sufficiently high, the PME wedge increases with k if $\beta_{unlevered} > 0$. The wedge decreases with k if $\beta_{unlevered} < 0$.*

Building on Prediction 2, the PME wedge should be positive when k is such that the levered β is greater than one, and negative when k is such that the levered β is less than one.

Prediction 5 (P5): *When the market equity premium is sufficiently high, the PME wedge is positive when k is such that $\beta_k > 1$, and negative when k is such that $\beta_k < 1$. The wedge crosses the x axis when k is such that $\beta_k = 1$.*

Combining P4 and P5, we can back out approximate asset β by looking at the plot of the PME wedge against the leverage factor k. If the wedge is decreasing, $\beta < 0$; if the wedge is increasing but less than 0 at $k = 0$, then $0 < \beta < 1$; and if the wedge is increasing and greater than 0 at $k = 0$, then $\beta > 1$. We use these predictions to determine whether impact behaves like a "luxury good," in a very pro-cyclical way, or whether it is more of a hedging strategy as suggested by Gibson et al. (2019) and Wang and Sargis (2020).

3.3.2 Predictions for Covariance with Other Factors

So far we have limited ourselves to a CAPM model where the return on the market portfolio represents the return on the investor's wealth portfolio. We may care about covariance with other factors, for example a public sustainability factor. We can use the same intuition for different public market indexes that may reasonably capture alternative assets that represent the impact investor's wealth portfolio.

We start by generalizing Equation 8 to any public-market factor X.

$$(\beta - 1)(\log E[R_{X,t+1}] - r_f - \sigma_X^2) \tag{11}$$

Our predictions now depend on the magnitude of the equity premium for X. The equity premium of public-market factor X is *sufficiently high* if

$$(\log E[R_{X,t+1}] - r_f - \sigma_X^2) > 0 \tag{12}$$

The equity premium is *low* (not sufficiently high) if

$$(\log E[R_{X,t+1}] - r_f - \sigma_X^2) < 0 \tag{13}$$

When the equity premium is low, the PME *overstates* the public equity premium and *underestimates* the abnormal return when $\beta_X > 1$. In that case, when $PME_X > GPME_X$, we can conclude that

$\beta_X < 1$.

Prediction 6 (P6): *If the equity premium is sufficiently high for a public market factor X, then a positive PME wedge implies a $\beta_X > 1$ for that factor.*

If the equity premium is low for a public market factor X, then a negative wedge implies a $\beta_X > 1$ for that factor.

Similarly, we can apply the logic of P4 and P5 and use artificial leveraging in these one-factor models to back out the covariance structure of impact investing returns relative to public market factor X.

Prediction 7 (P7): *If the equity premium is sufficiently high for a public market factor X, then a positive relationship between the PME wedge and the amount of artificial leverage applied to cash flows indicates a $\beta_X > 0$ for that factor.*

If the equity premium is low for a public market factor X, then a negative relationship between the PME wedge and the amount of artificial leverage applied to cash flows indicates a $\beta_X > 0$.

Finally, we can examine the risk profile of impact investing cash flows more generally using multifactor models. In these exercises, we examine what publicly traded factors span impact investing returns. To undertake this analysis, we test whether impact and benchmark cash flows have abnormal performance when discounted with SDFs that account for different risk factors.

Prediction 8 (P8): *If impact investing returns are spanned by public market factors, then the GPME with respect to these factors is zero when cash flows are discounted with a multifactor SDF.*

A significant non-zero GPME with a multifactor SDF indicates that impact investing cannot be replicated with these public market factors.

4 Impact Investing Funds and Market Risk

In this section, we test how constrained impact investing strategies perform relative to public and private markets. To do so, we approximate the return on the impact investor's wealth portfolio with the return on the market and examine implications for risk and risk-adjusted performance relative to the market. We first examine each strategy's performance through PME and GPME, then compare strategies using long-short portfolios. Our third subsection focuses on the market risk exposure, or beta, of each strategy.

4.1 PME and GPME Estimation with Market Factor

We use two SDFs to price impact and PE cash flows: the GPME is abnormal performance when the SDF $M_{t+1}^{GPME} = \exp(a - b\log(R_{m,t+1}))$ is used to price cash flows; the PME restricts this SDF to a special case where $a = 0$ and $b = 1$.

We begin by estimating the parameters for M_{t+1}^{GPME}. We follow Korteweg and Nagel (2016) and create public market replicating portfolios of the risk-free rate and the gross market return, for each impact, VC, and matched fund in our sample. The purpose of these public market replicating portfolios is to create a cash flow series for an investor that invests in and receives distributions from public assets at roughly the same time intervals as the fund cash flow series we are interested in pricing. We then use GMM to find the parameters of the stochastic discount factor such that the expected sum of discounted cash flows across all replicating portfolios is equal to zero. In order to create a consistent measure of performance, we price public market portfolios that replicate impact, VC, and matched funds, and use the one set of parameters throughout our analysis. More details on the estimation method and the relevant assumptions can be found in Appendix A.

The results of our estimation of SDF parameters are in Table 2. In the first column, the PME implicitly assumes that the coefficient associated with the risk-free rate (a) is 0 and the slope coefficient on the market return (b_1) is 1. Our estimates in the second column demonstrate that the ex-post SDF is very different from the PME assumptions. Using the procedure described above to estimate the realized SDF, we find the slope coefficient on the log market return is 3.913 and the coefficient associated with the risk-free rate is 0.195. These estimates are consistent with relatively "hot" equity markets and Prediction 1.

We examine the magnitude of the market equity premium more directly by computing a sample estimate for our sample period:

$$\log \bar{R}_m - r_f - \hat{S}_m^2 \approx 0.002 > 0$$

where $\log \bar{R}_m$ is the natural logarithm of sample expected gross return of the market portfolio and $\hat{S}_m^2$ is the sample variance of the log returns. This is consistent with a *sufficiently high* market equity premium during our time period. The market risk of impact funds is thus a relevant concern for understanding performance, and PME will distort performance upwards for riskier assets.

We now examine how the SDFs from Table 2 price the impact and VC fund cash flows. From equation 7, fund-level GPME is given by:

$$GPME_i = \sum_{j=1}^{J} M_{t+h(j)}^{h(j),GPME} C_{i,t+h(j)}$$

For fund i, cash flow time j, cash flow horizon $h(j)$, and cash flows C. Fund-level PME is given as:

$$PME_i = \sum_{j=1}^{J} M_{t+h(j)}^{h(j),PME} C_{i,t+h(j)}$$

In Table 3, we report the average performance of impact and benchmark (VC and matched) funds under PME and under the market risk GPME SDF, using the SDF parameters from Table 2. We report standard errors in parentheses and p-values of the J-test of whether $(G)PME = 0$ in brackets.[9]

Panel (a) presents our results for impact funds. We find a negative impact PME of −\$0.20 per \$1 of capital committed. The p-value is small, but this in part reflects the fact that the SDF parameters for the PME are assumed ($a = 0$ and $b = 1$) rather than estimated. We also find that the market risk GPME of impact funds is negative and statistically different from zero. After properly accounting for risk, impact funds underperform the market index by \$0.45 per \$1. The overestimation of the PME relative to the GPME suggests that impact has a market β greater than 1, in line with Prediction 2. The underperformance of impact investing relative to public markets is consistent with the general underperformance of constrained strategies.

However, impact's underperformance relative to the market appears to reflect the broader underperformance of VC over the same time period. In panel (b), we show the VC PME is also negative, if slightly less so than the impact PME: an abnormal loss of \$0.13 per \$1 of capital committed. The VC GPME is similar to the impact GPME, at a risk-adjusted loss of \$0.44 per \$1 of capital committed. We can reject zero pricing errors. As with impact, the PME overestimates the performance of VC. These results are consistent with a β of VC larger than 1 (Prediction 2), as has been found in previous literature (see e.g. Boyer et al. (2018),Cochrane (2005)). Appropriately accounting for risk exposure suggests that an investor would fare about equally poorly adding impact or VC to her portfolio. The similar performance of these two private market strategies suggests that private markets are imperfectly integrated, as in Cole et al. (2020).

We report the results for the matched benchmark funds in panel (c). We find a less negative PME of −\$0.03 per \$1 capital committed for this group, and a GPME of −\$0.31. We cannot reject zero pricing errors with either measure. The PME-GPME wedge is larger than impact, but smaller than

[9] For our J-test, we adjust the spectral density matrix for correlation between pricing errors as well as estimation error when applicable (see Appendix A for more details).

VC, suggesting that matched funds have a market risk exposure in between that of impact funds and that of VC funds. A public market equity investor would seem to do slightly better investing in the matched group of funds than in impact. We evaluate this claim next.

4.2 Long-Short Portfolios

We directly test the performance of impact relative to the two PE benchmarks by creating portfolios of cash flows that go long $1 in each benchmark and short $1 in impact funds. This is not a replicable strategy, but is meant to test relative differences in performance between the benchmarks and impact. We do this in two ways. First, we look at equal-weighted long-short portfolios as statistical tests of the PME and GPME differences in Table 3. Second, we consider value-weighted long-short portfolios to give us a better picture of the performance of the asset class as a whole.

4.2.1 Equal-Weighted Long-Short Portfolios

To conduct statistical tests of performance differences in Table 3 between impact and benchmark funds, we use the SDF estimates from Table 2 to price 14 equal-weighted cash flow portfolios that go "long" benchmark funds and "short" impact funds. We create these portfolios by taking equal-weighted averages of all benchmark or impact funds with the same vintage year. Each of the 14 portfolios then corresponds to a vintage year in the impact sample. We normalize each of the long-short portfolios' cash flows so that the portfolios reflect the relative number of funds in each vintage. Another way to think of this exercise conceptually is as the return on a strategy that invests $1 in a randomly selected benchmark fund and sells $1 in a randomly selected impact fund.

We present estimates of the PME and GPME for the 14 equal-weighted portfolios in Table 4. Panel (a) presents results using VC funds on the long side, and Panel (b) presents results using matched funds on the long side (both go short impact funds). The first column in both panels contains the PME estimates that assume the strategy has $\beta = 0$, effectively discounting the long-short cash flows by the risk-free rate. The second column contains the GPME estimates. Both PME and GPME estimates of these strategies are positive, but we can only reject zero pricing errors in the case of the PME, where we restrict the SDF to $a = 0$ and $b = 1$. When we adjust for market risk exposure with the GPME, we can no longer reject zero pricing errors; in other words, we can no longer reject comparable market risk-adjusted performance for impact funds relative to benchmark funds.

4.2.2 Value-Weighted Long-Short Portfolios

We also price value-weighted long-short portfolios in order to better measure relative performance differences between a marginal dollar invested in nonimpact and impact strategies. Conceptually, we invest $1 in the basket of benchmark funds available in our time period, and sell $1 in the basket of impact funds available during the same time.

We do this exercise for two reasons. First, most performance benchmarks across asset classes are market-value weighted. Second, equal weighted portfolios may be more likely to misrepresent performance in the case of impact investing. This is because a marginal dollar invested in impact is more likely to be invested in larger funds, but the impact market as a whole is comprised of very small funds. As a result, equal-weighted portfolios will overweight smaller funds relative to their proportion of capital in the asset class. While equal-weighting measures the return on a randomly selected fund, value-weighting measures the return on a randomly invested dollar.

We approximate this conceptual exercise by creating fund size-weighted portfolios of fund cash flows for each vintage year in the sample. These portfolios are constructed as a short portfolio of impact funds' size-weighted cash flows subtracted from a long portfolio of benchmark funds' size-weighted cash flows. The result is 14 weighted long-short portfolios of cash flows, one for each vintage year in the impact sample. Because the distribution of vintages in the impact fund sample differs from the overall distribution of PE fund vintages, we normalize vintage long-short portfolio cash flows such that the cash flows in each vintage reflects that vintage's size relative to other vintages.

Table 5 presents the PME and GPME estimates of our value-weighted portfolios, using SDF estimates from Table 2. The PME and GPME of this value-weighted long-short strategy reflect the performance of benchmark funds relative to impact funds for an investor with a stake in the basket of impact funds during our sample period. Again, Panel (a) presents results using VC funds on the long side, and Panel (b) presents results using matched funds on the long side. Value-weighting yields smaller estimates than equal-weighting, reflecting the influence of smaller funds and vintages. When smaller funds and vintages are given less weight, the performance of benchmark funds relative to impact funds worsens. PME estimates remain positive but smaller than those in Table 4, and GPME estimates become negative.

On a value-weighted basis, the risk-adjusted returns of going long VC and shorting impact are negative, −$0.15 per $1 of committed capital, and we can reject zero pricing errors. We cannot reject zero pricing errors for PME estimates or for the GPME estimate of the portfolio that goes long in matched funds and short in impact funds. We conclude that impact performs better as a class than VC in our sample period, and neither better nor worse than the sample of matched funds. While constrained strategies do worse on both an absolute and risk-adjusted basis relative to an unconstrained strategy (investing in a public market index), our results suggest that impact investors can do as well as other private market investors. This is potentially due to impact investing extracting value from private market frictions, such as information barriers.

Whether value- or equal-weighted, we find positive PMEs and a postive wedge between the PME and GPME estimates of the long-short strategies. We can conclude that the β of these strategies are not zero because the GPME and PME estimates are not the same. In line with Prediction 3, our results indicate that $\beta_{Benchmark} > \beta_{Imp}$. We examine the relative β of both strategies in more detail in the next section.

4.3 Backing Out Market Risk Exposure Using Artificial Leverage

The relatively small PME wedge of impact relatively to the other private market strategies suggests that impact funds have a low β with public markets. In this section, we use artificial leverage to bound the β of impact relative to our two benchmarks, and thus inform the debate about the risk of sustainable and green assets. We use the SDF estimates in Table 2 to price levered cash flows given in equation 10. We apply this leverage strategy first to the fund cash flows directly, then to the cash flows from our long-short portfolio strategy.

4.3.1 PME-GPME Wedges

We plot the PME wedge for impact and both benchmarks in Figure 8. We create 95% confidence intervals by bootstrapping the wedge estimates 1,000 times. At $k = 0$, there is no additional leverage and the wedge is the difference between the PME and GPME estimates as in Section 4.1. As we increase k to a leverage factor of 1 and 2, we artificially increase the β of the cash flows. Thus, for any asset with a positive β, we expect an increasing wedge with the addition of more leverage (Prediction 4). If an asset is already a high-beta asset at $k = 0$, this additional leverage should lead to an increasing wedge as the PME becomes a more distortionary measure of performance. If an asset has a $\beta = 1$, then the GPME and PME should coincide at $k = 0$ and we would expect to see a positive slope with the addition of more leverage, crossing the x axis at $k = 0$.

We can also apply negative leverage to the cash flows, replicating a decrease in β. Given a high-beta asset, we can determine how much de-leveraging is necessary to achieve a $\beta = 1$ by examining at what value of k the wedge is equal to zero. As k nears -1, the wedge should become negative as levered β falls below one and the PME begins to understate performance.

The line for VC funds is consistent with Predictions 4 and 5: as the leverage factor and thus β increase, the PME wedge increases as well, as we would expect for a high-beta asset. The wedge is also close to 0 around leverage factor -0.5. These two findings, along with those from the previous section, suggest a VC β of approximately $1/0.5 = 2 > 1$.

In contrast, the wedge for impact appears relatively flatter across leverage factors, only slightly increasing in k. A constant wedge would imply a β close to zero, as additional leverage does not affect the wedge magnitude. However, we can reject a zero wedge at $k = 0$ with 95% confidence, suggesting that β must be at least one. The relatively flat slope of the wedge line suggests that β is not much higher than one. We cannot infer more specifics about the absolute level of impact β from Figure 8, but we can rule out that the sensitivity is as large as VC. This reinforces our conclusion from Table **??** that $\beta_{VC} > \beta_{Imp}$.

The matched fund wedge is flatter than the VC line, but steeper than impact. At higher factors of leverage, the separation across the three strategies becomes clearer, with VC most sensitive to market risk, impact least, and the matched benchmark in between. The higher sensitivity of the matched benchmark to leverage factors suggests that impact's lower β is not entirely explained by size, asset class, or vintage. We do not find impact is countercyclical in absolute, but adding impact to a VC portfolio does reduce overall market risk exposure.

4.3.2 Long Short Portfolio Wedges

To supplement this analysis, we also apply artificial leverage to the value-weighted long-short cash flow portfolios from Section 4.2. Applying artificial leverage to the net cash flows is another way to test both whether the β of the benchmarks and impact are different and whether the β of the benchmarks are greater than the β of impact. If a benchmark and impact β are the same, then the β of that long-short portfolio should be zero, and the PME wedge should stay constant as we increase k.

We can formalize this intuition in the context of the jointly log-normal model used at the outset of Section 3 in Equation 8. From equation 11, the wedge for benchmark B under jointly log-normal returns is:

$$(\beta_B - 1)(\log E[R_{m,t+1}] - r_f - \sigma_m^2)$$

The wedge for impact is then:

$$(\beta_{Imp} - 1)(\log E[R_{m,t+1}] - r_f - \sigma_m^2)$$

This implies that the wedge of the net cash flows is:

$$(PME_B - PME_{Imp}) - (GPME_B - GPME_{Imp}) = (PME_B - GPME_B) - (PME_{Imp} - GPME_{Imp})$$

Which can then be written as

$$(\beta_B - 1)(\log E[R_{m,t+1} - r_f - \sigma_m^2) - (\beta_{Imp} - 1)(\log E[R_{m,t+1}] - r_f - \sigma_m^2)$$

Given that the equity premium is the same in both samples, this expression reduces to:

$$(\beta_B - \beta_{Imp})(\log E[R_{m,t+1}] - r_f - \sigma_m^2) \tag{14}$$

Given a large market equity premium (relative to σ_m^2), a positive wedge is indicative of $\beta_B - \beta_{Imp} > 0$. A negative wedge indicates that $\beta_B - \beta_{Imp} < 0$. If the equity premium was small (i.e., $\log E[R_{m,t+1}] - r_f < \sigma_m^2$), then the opposite predictions would hold.

What we observe in Figure 9 is a wedge that is increasing in artificial leverage k for both benchmarks. The positive slope of both lines indicates that the β of the net cash flows is positive: as k increases, the GPME becomes more negative and the wedge increases. This is further evidence that the β of both benchmarks is greater than the β of impact, although we note that our confidence intervals are too large to statistically reject a zero wedge at any value of the leverage factor. We see these results as further suggestive evidence that impact investing provides market hedging services beyond its features (size, asset class) as a private equity class.

5 Impact Investing Funds and Other Factors

What other financial risks are inherent in an impact investing strategy? Section 4 characterizes the market β of impact funds, i.e., the covariance of these cash flows with the market. In this section, we use the same tools to characterize the covariance of impact fund cash flows with other factors. We first examine whether private sustainable investing is different from public sustainable investing strategies. Then we test whether additional risk factors span impact investing cash flows.

5.1 Abnormal Performance and Risk Exposure to Other Factors

We can approximate the covariance of impact fund cash flows with any factor by replicating the analysis in Section 4, using a one-factor SDF with the alternative factor of interest in place of the

Market Risk SDF. Predictions 6 and 7 highlight that the interpretation of the analysis depends on the magnitude of the public market premium with that factor. If the market premium for the factor of interest is sufficiently high, then predictions are the same as for the market factor. However, if the market premium is low, our predictions flip.

We investigate impact and benchmark funds' risk exposure to a sustainability index factor. We start by examining the magnitude of the equity premium on the sustainability index by computing its sample estimate:

$$\log \bar{R}_{SI} - r_f - \hat{S}^2_{SI} \approx -0.002 < 0$$

where $\log \bar{R}_{SI}$ is the natural logarithm of sample expected gross return of the sustainability index and $\hat{S}^2_{SI}$ is the sample variance of the log returns. This corresponds to the scenario in which the equity premium is low.We are in the second case of Prediction 6: a negative PME^{SI} wedge would imply a $\beta^{SI} > 1$ with the sustainability index.

Table 6 reports the one-factor SDF estimate and Table 7 gives the PME and GPME estimates using the sustainability index as the public market return of interest. Our estimates show that the ex-post SDF using sustainability as the benchmark is also very different from the SDF with log-utility assumptions. We find a slope coefficient on log sustainability returns of 2.49 and an intercept coefficient of 0.06. The PME and GPME estimates are different between impact, VC, and matched funds. With risk adjustment relative to the sustainability index, VC funds gain \$0.15 and matched funds gain \$0.28 per \$1 capital committed, while impact funds lose \$0.16 per \$1 capital committed. The overperformance of benchmark funds relative to the sustainability index is consistent with a concessionary return for sustainable strategies in public markets. The PME overestimates impact fund performance and underestimates VC and matched fund performance relative to the $GPME^{SI}$. However, given the wide error bands on all of the GPME estimates, we cannot draw conclusions on sustainability β by looking at the "wedge" with zero leverage.

In Figure 10, we show what happens to the wedge for different levels of artificial leverage. Since the sustainability premium is relatively small, we are in the second case of Prediction 7: an increasing wedge, as we see for VC and impact funds, implies negative covariance with the sustainability index. A decreasing wedge, as we see for matched funds, implies positive covariance with the sustainability index. The bounds on these estimates are large and the results should be taken with caution, but they highlight that sustainability in private markets, for example via impact investing, is distinct from sustainability in public markets.

5.2 PME and GPME Estimation with Two Factors

The one-factor GPME model can be extended to incorporate multiple factors. The SDF in this case is

$$M_{t+1}^{GPME} = \exp(a - b' \log(F_{t+1}))$$

where f is the number of public market factors, b is an $f \times 1$ vector of factor loadings, and $\log(F_{t+1})$ is $f \times 1$ vector of public market factor returns at time $t+1$.

We use the simplest multi-factor GPME with $f = 2$ to test whether impact, VC, and matched fund returns can be spanned by additional risk factors. We augment the Market Risk SDF with a sustainability factor or the small-growth portfolio from Fama and French (1993). The results are in Table 8. As in Table 3, Panel (a) provides estimates for impact funds, Panel (b) for VC funds, and Panel (c) for matched funds. In the first column, we repeat the GPME estimates from the one-factor market risk model as a reference. The last two columns correspond to two-factor SDFs with the market and small-growth portfolio (second column) or with the market and sustainability index (third column).

Our first observation is that, consistent with Korteweg and Nagel (2016), adding the small-growth factor has little effect on the GPME for VC funds. Replacing the small-growth factor with the sustainability index produces similar results. For VC funds, we find a negative GPME of $-\$0.42$ to $-\$0.44$ per \$1 of capital committed in all three specifications.

We run the same three models on our impact funds. Similar to Market Risk SDF, we get an abnormal performance of $-\$0.42$ per \$1 invested after adding the small-growth factor. Adding the sustainability index yields a higher estimate of $-\$0.33$. We cannot reject zero pricing errors in this model, which implies that these two factors span impact returns. However, the standard error for this estimate is large. An interval of a single standard error would encompass the GPME estimates in the other two specifications.

For matched funds, we find an abnormal performance of $-\$0.28$ per \$1 committed after adding the small-growth factor, which is similar to $-\$0.31$ with the Market Risk SDF. Adding the sustainability index to the market factor also does not change the estimate much, at $-\$0.30$ per \$1 committed.

For VC funds, we can reject zero pricing errors in all models, and find a significant abnormal loss both economically and statistically. We can reject zero pricing errors for impact funds in the first two models, and find negative performance on par with VC's negative performance. We cannot reject zero pricing errors for impact funds when we add the sustainability index as a factor, though the point estimate remains significantly negative from an economic standpoint. Matched funds appear to perform somewhat better than VC or impact funds, and we cannot reject zero pricing errors in any of the specifications. Whatever additional factor we add, matched funds perform better than impact and VC funds after appropriate risk adjustments, consistent with Section 4.

6 Conclusion

In this paper, we provide a characterization of the risk profile and risk-adjusted performance of impact investing. To do this, we develop a new approach to derive risk properties of private market asset classes, building on insights from Korteweg and Nagel (2016). While we apply it to impact investing in this paper, our approach can easily be extended to examining other private market strategies in the future. We use this to show, for example, that the market beta of impact funds is statistically significantly lower than the market beta of VC funds. When accounting for market risk exposure, impact funds underperform the market but do not perform worse than comparable private market strategies.

Our findings shed light on theories of the market as well as the nature of green assets. Our finding that impact underperforms both the S&P 500 and a public sustainability index is consistent with impact investing as a constrained strategy that necessarily leads to lower returns. We find a similar effect for VC and matched benchmark funds, suggesting that private markets violate perfect and complete market assumptions. Our finding that impact outperforms VC funds in a value-weighted long-short portfolio is consistent with market frictions in private markets overall. Impact investors may be constrained, but seem to be able to capture value that general VC investors miss. This could be due to information barriers, investor biases, or distortions to competition in both capital and product markets.

Risk is an important element in this story. Our finding that the beta of impact is lower than the beta of benchmarks, and in particular VC, is consistent with a counter-cyclical interpretation of impact strategies. Although absolute measures of performance are lower during periods of hot equity markets, impact investing acts as a relative hedge against downside risk.

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Figure 1: Impact Funds by Geographic Focus Area

We plot the number of impact funds in our sample by area of geographic focus.

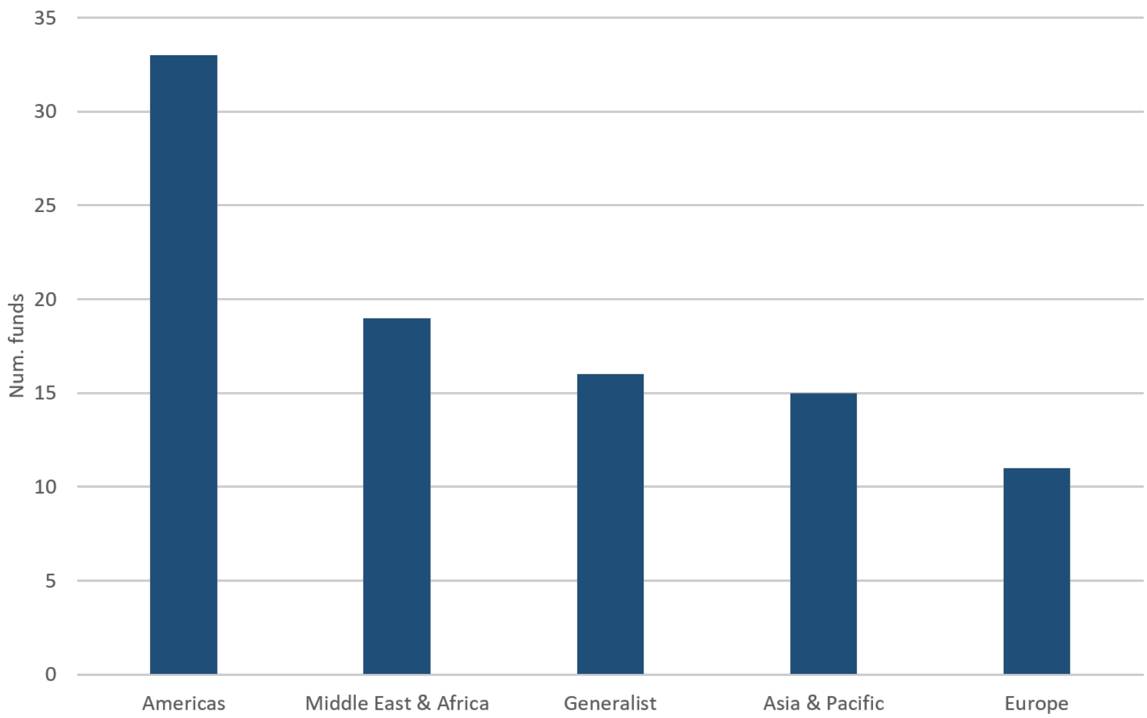


Figure 2: Impact Deals by Industry

We plot the number of impact funds in our sample by area of industry focus. Funds can invest in multiple industries, so the number of funds adds to more than 94.

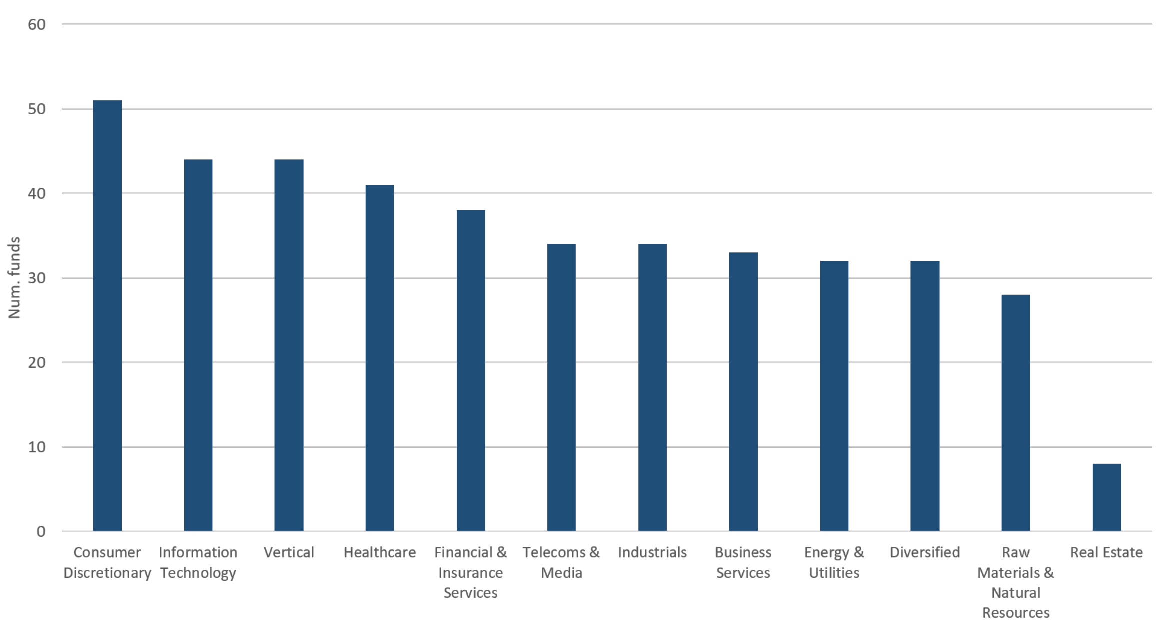


Figure 3: Impact Funds by Asset Class

We plot the number of impact funds in our sample by asset class. VC funds are equity funds that invest with an early stage focus. Other equity funds include late stage and more generalist funds. Buyout funds are equity funds with a buyout focus that use leverage. Debt funds are private funds that originate loans to portfolio companies. Real asset funds invest in physical assets. The remainder of impact funds are generalist, that invest with a variety of styles in companies at various stages.

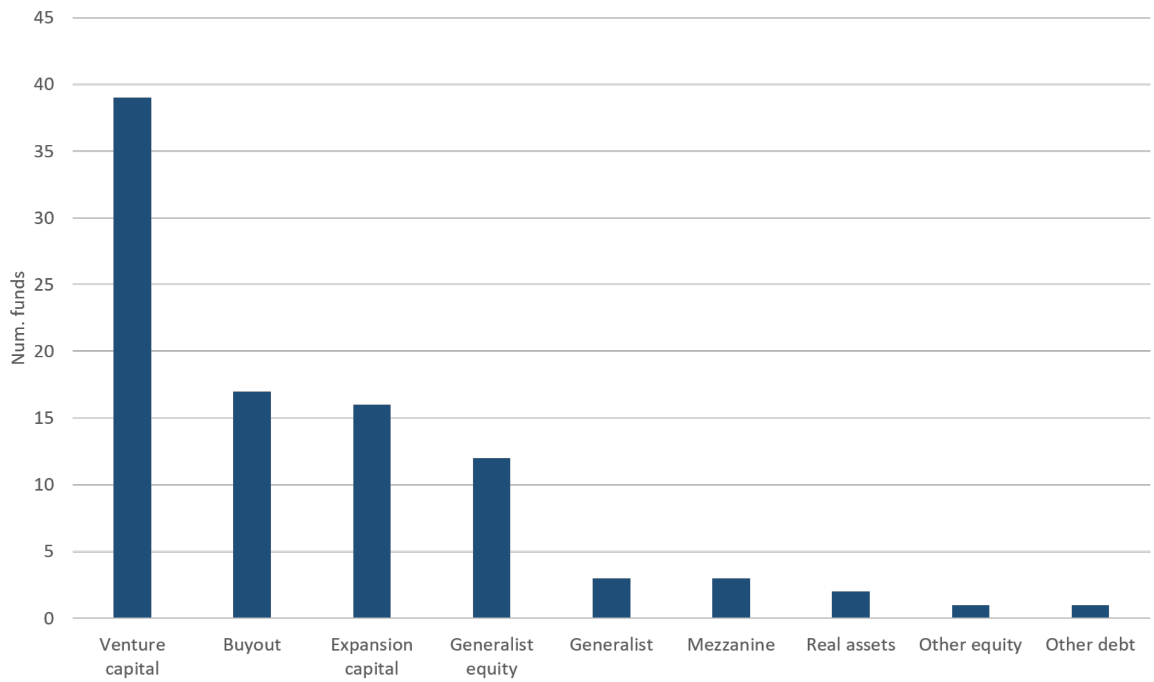


Figure 4: Impact Funds by Sequence Number

We plot the number of impact funds in our sample by sequence number, i.e. whether the fund is first, second, or further along in a series.

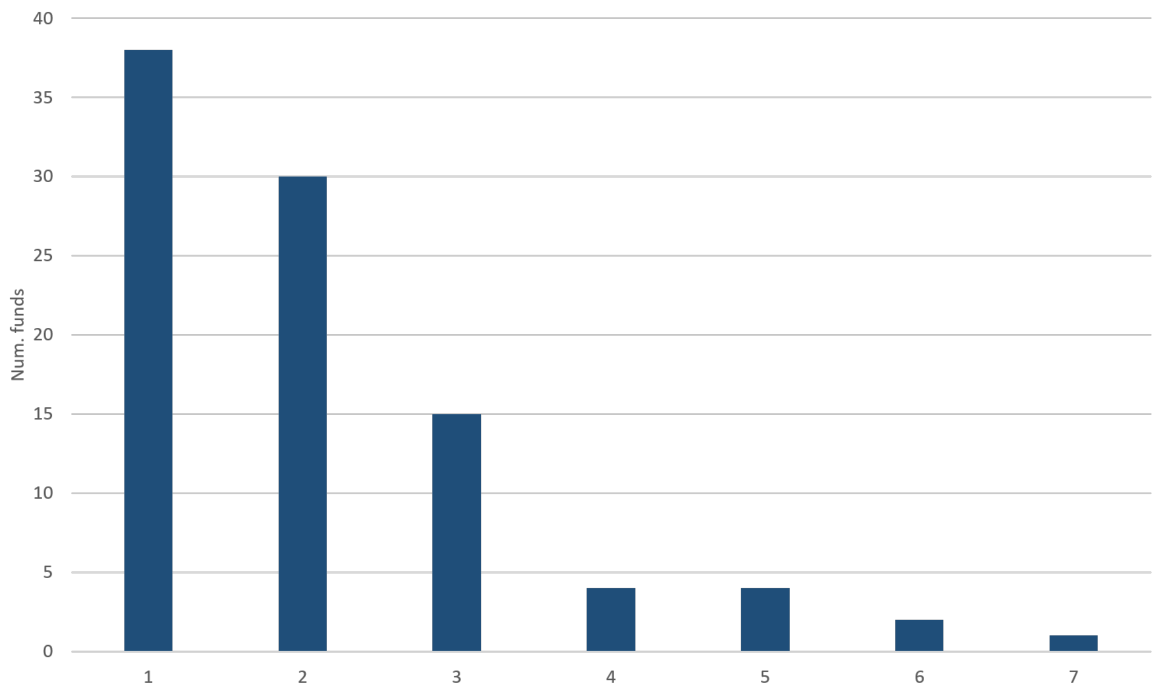


Figure 5: Unadjusted Performance by Vintage

We plot unadjusted performance in terms of IRR and TPVI over vintage years for our impact sample and the VC benchmark. Panel (a) shows the IRR of impact and VC for each vintage year. We add S&P 500 as a comparison of the public market performance over the same year. For S&P 500, we show the annual return for S&P 500 total return index. Panel (b) shows the TVPI of impact and VC for each vintage year. S&P 500 is not added since the TVPI of S&P index is not well defined. For both panels, we use the median of fund-level IRR or TVPI for each vintage year to alleviate the impact of outliers.

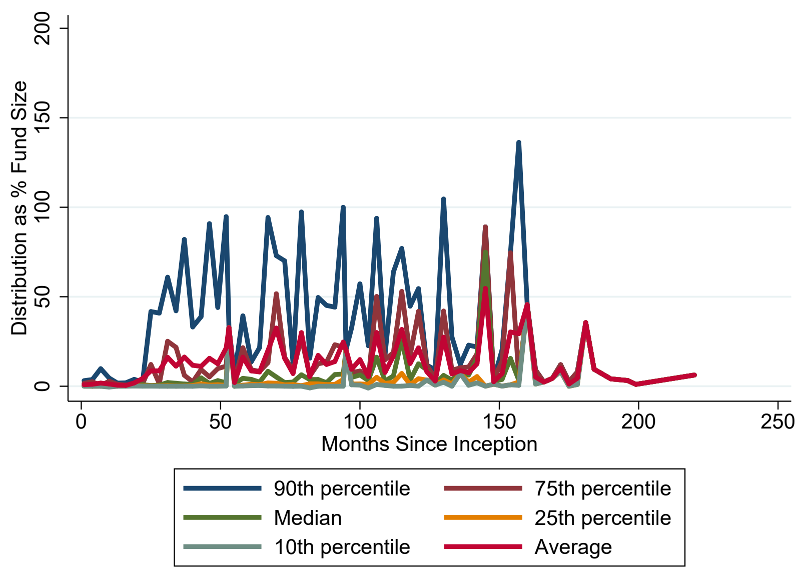
(a) IRR (%) by Vintage

(b) TVPI by Vintage

Figure 6: Distribution as % of Fund Size by Month Since Inception

We plot percentiles of distributions normalized by fund size in each quarter since fund inception. We take percentiles across each quarter that a fund is open in order to characterize the lifespan of the fund. This characterizes the cross-section of fund cash flows at each quarter of fund life. The top panel considers the cross-section of impact funds and the bottom panel plots the percentiles for VC funds. We plot the 10th, 25th, 50th, 75th, and 90th percentiles in addition to the average. The timing of the distribution profile looks similar, although the impact fund sample is considerably noisier than the VC sample.

(a) Impact Funds



(b) VC Funds

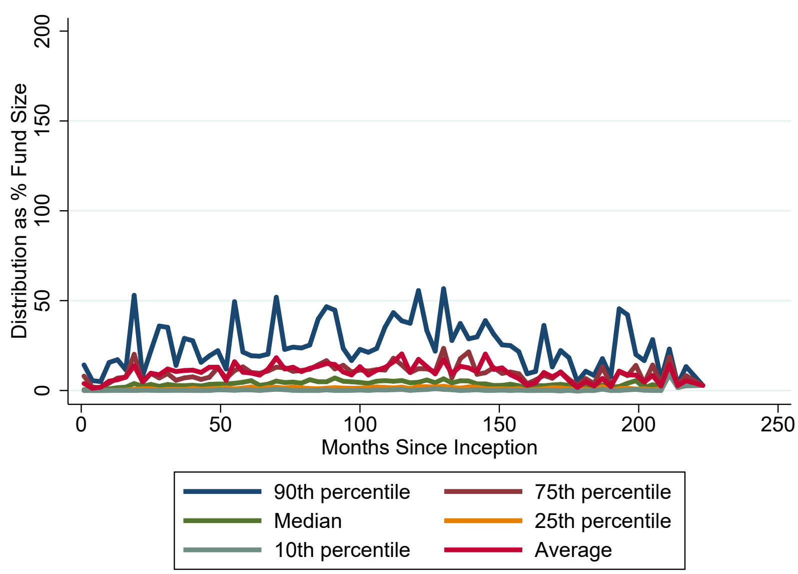
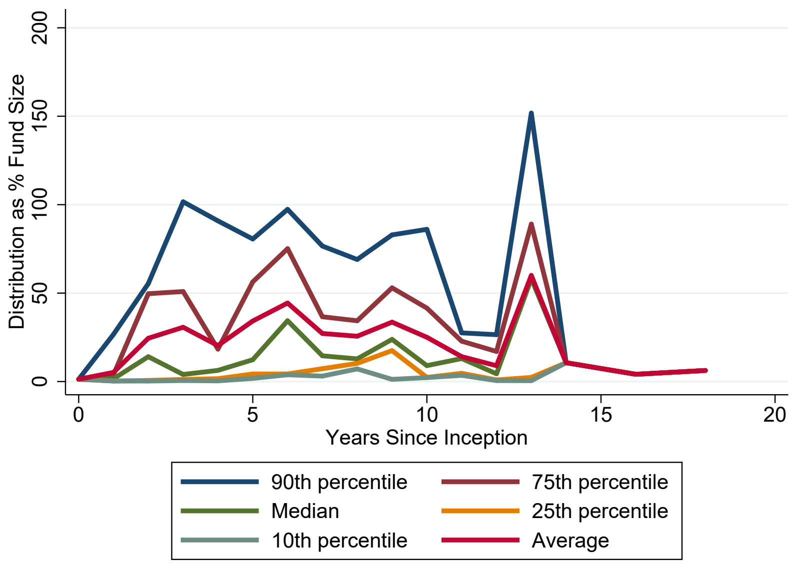


Figure 7: Distribution as % of Fund Size by Year Since Inception

We plot percentiles of distributions normalized by fund size in each year since fund inception. This results in a smoothed version of Figure 6. We sum total distributions in a given year (including the final period NAV) and divide by the total committed capital of the fund. We take percentiles across each year that a fund is open in order to characterize the cross-section of fund. As in Figure 6, the distribution profile looks similar, with an increase in distributions as a percent of fund size around years 5 to 7. The impact funds have very large final period NAV payouts compared to VC funds. Impact's median distribution at each year is higher than for VC funds.

(a) Impact Funds



(b) VC Funds

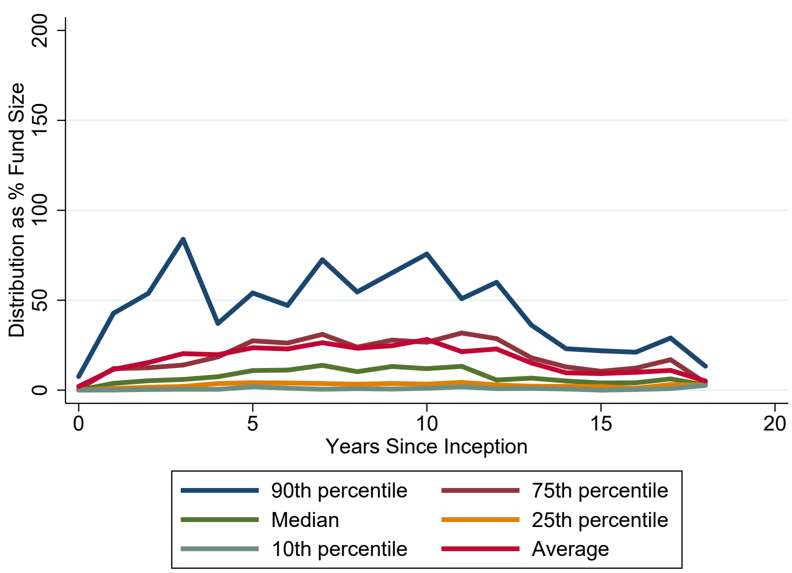


Figure 8: PME-GPME Wedge Using Market Risk SDF

We plot the PME - GPME wedge of artificially levered funds with different leverage k. We create artificially levered funds using impact funds, VC funds, or matched funds respectively, $C^{PE}_{i,t+h(j)}$ and the matched T-bill benchmark funds, $C^{Rf}_{if,t+h(j)}$

$$L^{PE}_{i,t+h(j)} = C^{PE}_{i,t+h(j)} + k(C^{PE}_{i,t+h(j)} - C^{Rf}_{if,t+h(j)})$$

We estimate the market risk SDF using replicating benchmarks for pooled impact and both benchmarks cash flows. We apply the same SDF on different levered cash flows to estimate GPME and use the log-utility CAPM SDF to estimate PME. The wedge is the difference between PME and GPME point estimates. The error bars are 95% confidence interval using bootstrap standard errors from 1,000 bootstrap samples of impact or VC funds.

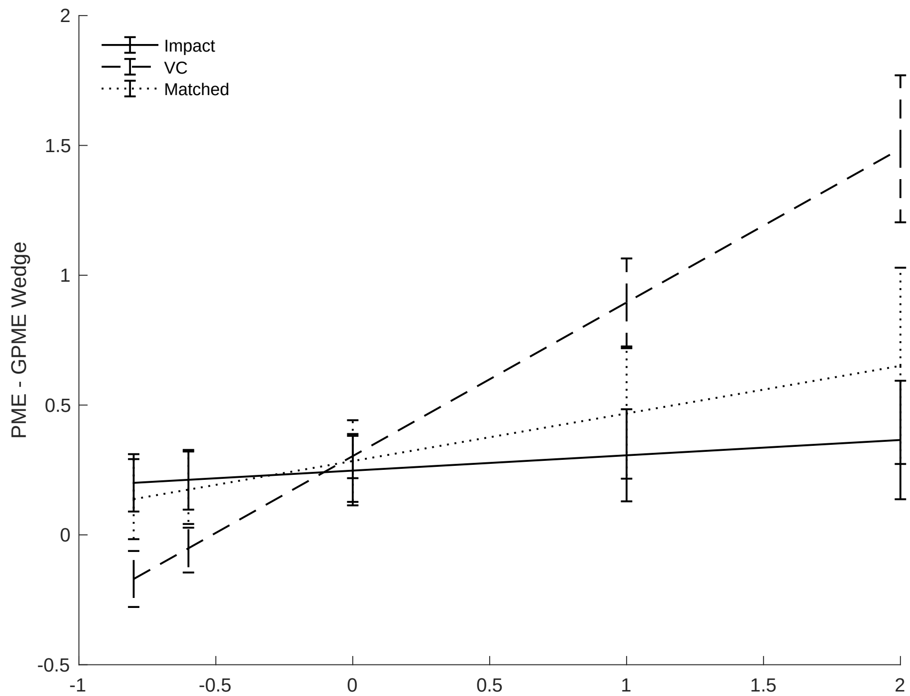


Figure 9: PME-GPME Wedge of Long-Short Portfolio

We create two portfolios, one that is long VC funds and short impact funds, and the other that is long matched funds and short impact funds. Both portfolios presented here are value-weighted. We create artificially levered cash flows of each strategy similar to Figure 8. For each level of artificial leverage k, we plot the difference between the PME and GPME point estimate of the long-short portfolio. The error bars are 95% confidence interval using bootstrap standard errors from 1,000 bootstrap samples of the long-short portfolio.

(a) Value-Weighted

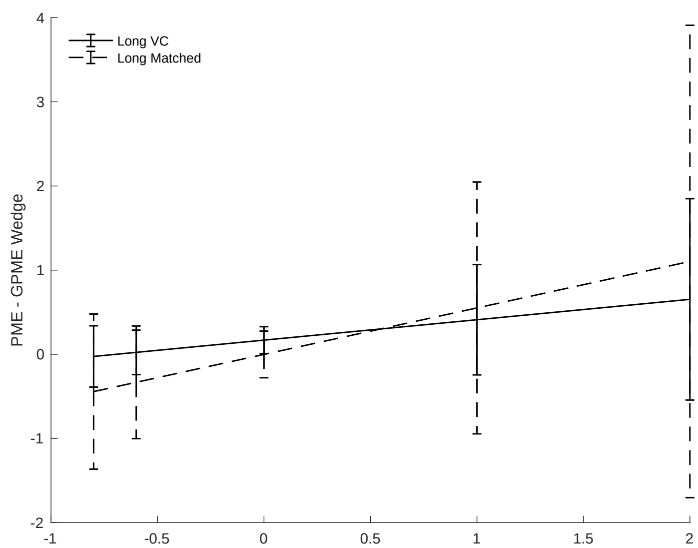


Figure 10: PME-GPME Wedge with Sustainability Index

We plot the PME - GPME wedge of artificially levered funds with different leverage k. We create artificially levered funds as in Figure 8. We estimate the sustainability index SDF using replicating benchmarks for pooled impact and both benchmarks cash flows. We apply the same SDF on different levered cash flows to estimate GPME and use the log-utility CAPM SDF to estimate PME. The wedge is the difference between PME and $GPME_{SI}$ point estimates. The error bars are 95% confidence interval using bootstrap standard errors from 1,000 bootstrap samples of impact or VC funds. Since the sustainability index has a relatively small equity premium relative to the log-utility benchmark (i.e., $\log E[R_{SI,t+1}] - r_f - \sigma^2_{SI} < 0$), a negative relationship between the $PME - GPME_{SI}$ wedge and k indicates $\beta_{SI} > 0$, and a positive relationship between the $PME - GPME_{SI}$ wedge and k indicates $\beta_{SI} < 0$.

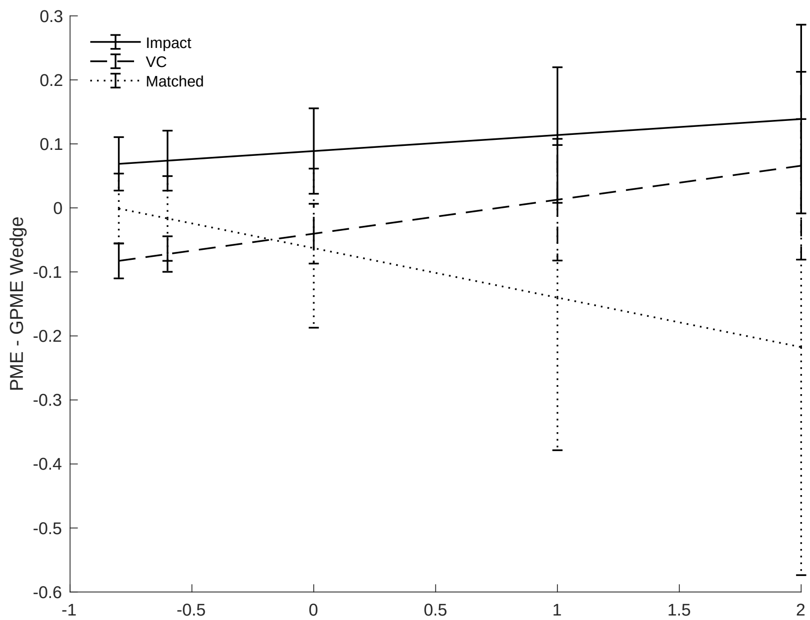


Table 1: Summary Statistics

Impact fund data comes from the IFD. VC and matched fund data come from Preqin. All samples cover vintages from 1997 through 2015 with transaction dates from 1999 to 2017. Impact fund statistics are reported in columns 1-3, VC fund statistics are in columns 4-6, and matched fund statistics are in columns 7-9. We report the mean and median for each sample of funds. The vintage year is the year of fund inception and fund size is the total committed capital raised by the fund, reported in millions USD. The PME is the ratio described in Equation 1, which we calculate using quarterly data when available and annual data for the remaining impact funds. VC and matched PMEs are all calculated using quarterly data. We report other absolute measures of performance, the cash flow multiple and IRR in percent. Finally, we report characteristics about the cash flow profile of each set of funds. Effective years is the number of years funds in each sample are open. We also report the number of total cash flows per fund, as well as the number of contributions and distributions separately.

	Impact			VC			Matched Benchmark		
	N	Mean	Median	N	Mean	Median	N	Mean	Median
Vintage	94	2009.1	2010	483	2005.9	2006	94	2009.1	2010
Fund Size (Mill$)	93	411.8	141.2	483	382.2	280	94	402.9	178.9
PME	94	0.751	0.765	483	0.882	0.815	94	0.964	0.941
Multiple	94	1.120	1.066	483	1.331	1.183	94	1.411	1.249
IRR (%)	94	-1.084	2.771	483	4.692	4.108	94	9.984	10.006
Effective Years	94	7.5	7	483	11.0	11	94	7.0	6
# Cash Flows per Fund	94	23.0	22	483	30.6	30	94	24.6	22
# Contributions	94	16.0	15	483	19.3	18	94	16.1	15
# Distributions	94	7.0	5	483	11.3	10	94	8.5	7

Table 2: Estimated SDF with Market Risk

The SDF for both PME and Market Risk GPME is given by $M^*_{t+1} = \exp(a - b_1 r^M_{t+1})$. The SDF corresponding to the PME is the SDF for a log-utility model, where $a = 0$ and $b_1 = 1$. The SDF corresponding to the Market Risk GPME relaxes this assumption. We estimate this SDF using benchmark portfolios to replicate pooled VC, matched, and impact fund cash flows, as described in Appendix A.

	PME SDF	Market Risk SDF
a	0	0.195
		(0.069)
b_1	1	3.913
		(0.762)

Table 3: Estimated Performance Relative to Market Risk

We compute PME and GPME relative to the market risk factor using the SDF parameters from Table 2. We report the standard error in parentheses below the estimate, and the p-value of the J-test of whether the estimate is zero in brackets on the third line. Panel (a) estimates performance for impact funds, Panel (b) for VC funds, and Panel (c) for matched funds. All panels use the same SDF parameters.

Panel (a): Impact funds

	PME	Market Risk GPME
Estimate	-0.200	-0.448
(sd)	(0.040)	(0.212)
[J-stat p-value]	[0.000]	[0.034]

Panel (b): VC funds

	PME	Market Risk GPME
Estimate	-0.132	-0.435
(sd)	(0.049)	(0.132)
[J-stat p-value]	[0.007]	[0.001]

Panel (c): Matched funds

	PME	Market Risk GPME
Estimate	-0.026	-0.310
(sd)	(0.022)	(0.209)
[J-stat p-value]	[0.226]	[0.137]

Table 4: Estimated GPME of Equal-Weighted Long-Short Portfolios

We compute PME and Market Risk GPME for two equal-weighted portfolios: Panel (a) estimates performance for a portfolio that is long VC funds and short impact funds, and Panel (b) for a portfolio that is long matched funds and short impact funds. We report the standard error in parentheses below the estimate, and the p-value of the J-test of whether the estimate is zero in brackets on the third line. Both panels use the same SDF parameters from Table 2.

Panel (a): VC-impact

	PME	Market Risk GPME
Estimate	0.153	0.017
(sd)	(0.045)	(0.041)
[J-stat p-value]	[0.001]	[0.687]

Panel (b): Matched-impact

	PME	Market Risk GPME
Estimate	0.113	0.039
(sd)	(0.035)	(0.063)
[J-stat p-value]	[0.001]	[0.530]

Table 5: Estimated GPME of Value-Weighted Long-Short Portfolios

We compute PME and Market Risk GPME for two value-weighted portfolios: Panel (a) estimates performance for a portfolio that is long VC funds and short impact funds, and Panel (b) for a portfolio that is long matched funds and short impact funds. We report the standard error in parentheses below the estimate, and the p-value of the J-test of whether the estimate is zero in brackets on the third line. Both panels use the same SDF parameters from Table 2.

Panel (a): VC-impact

	PME	Market Risk GPME
Estimate	0.022	-0.146
(sd)	(0.054)	(0.074)
[J-stat p-value]	[0.686]	[0.049]

Panel (b): Matched-impact

	PME	Market Risk GPME
Estimate	0.038	-0.046
(sd)	(0.051)	(0.084)
[J-stat p-value]	[0.462]	[0.583]

Table 6: Estimated SDF with Sustainability Index

The SDF for both PME and GPME relative to the Sustainability Index is given by $M^*_{t+1} = \exp(a - b_1 r^{SI}_{t+1})$. The SDF corresponding to the PME is the SDF for a log-utility model, where $a = 0$ and $b_1 = 1$. The SDF corresponding to the SI GPME relaxes this assumption. We estimate this SDF using benchmark portfolios to replicate pooled VC, matched, and impact fund cash flows, as described in Appendix A.

	PME SDF	Market Risk SDF
a	0	0.055
		(0.040)
b_1	1	2.488
		(0.896)

Table 7: Estimated Performance Relative to Sustainability Index

We compute the PME and GPME relative to the Sustainability Index using the SDF parameters from Table 6. We report the standard error in parentheses below the estimate, and the p-value of the J-test of whether the estimate is zero in brackets on the third line. Panel (a) estimates performance for impact funds, Panel (b) for VC funds, and Panel (c) for matched funds. Both panels use the same SDF parameters.

Panel (a): Impact funds

	PME	Market Risk GPME
Estimate	-0.069	-0.157
(sd)	(0.033)	(0.169)
[J-stat p-value]	[0.039]	[0.351]

Panel (b): VC funds

	PME	Market Risk GPME
Estimate	0.112	0.152
(sd)	(0.075)	(0.110)
[J-stat p-value]	[0.137]	[0.164]

Panel (c): Matched funds

	PME	Market Risk GPME
Estimate	0.219	0.282
(sd)	(0.045)	(0.190)
[J-stat p-value]	[0.000]	[0.138]

Table 8: GPME with Multi-Factor SDF

We compute the GPME for different factor models: one-factor model with market factor only, two-factor model with market and small growth, and two-factor model with market and sustainability index. We report the standard error in parentheses below the estimate, and the p-value of the J-test of whether the estimate is zero in brackets on the third line. Panel (a) estimates performance for impact funds, Panel (b) for VC funds, and Panel (c) for matched funds. Both panels use the same SDF parameters; each column has its own set of SDF parameters corresponding to the relevant model.

Panel (a): Impact funds

	Market Factor Only	Market and Small Growth	Market and Sustainability
Estimate	-0.448	-0.421	-0.332
(sd)	(0.212)	(0.177)	(0.292)
[J-stat p-value]	[0.034]	[0.017]	[0.255]

Panel (b): VC funds

	Market Factor Only	Market and Small Growth	Market and Sustainability
Estimate	-0.435	-0.417	-0.422
(sd)	(0.132)	(0.111)	(0.121)
[J-stat p-value]	[0.001]	[0.000]	[0.000]

Panel (c): Matched funds

	Market Factor Only	Market and Small Growth	Market and Sustainability
Estimate	-0.310	-0.280	-0.299
(sd)	(0.209)	(0.175)	(0.292)
[J-stat p-value]	[0.137]	[0.111]	[0.306]

A Estimation Method

A.1 Pricing Cash Flows for Public Market Replicating Portfolios

We follow Korteweg and Nagel (2016) in the construction and pricing of public market replicating cash flows. We pay into the replicating fund at the same time and with the same magnitude as PE fund contributions. When the PE fund makes a distribution at time $t + h(j)$, we assume that public market replicating funds make a payout equal to the sum of

1. Return accumulated since $t + h(j-1)$

2. A fraction π_j of capital in the fund since $t + h(j-1)$:

$$\pi_j = \min\left(\frac{h(j) - p}{10 - p}, 1\right)$$

Where p is time since last payout in years.

This second piece constrains the effective life of the replicating funds to 10 years. In robustness tests, we found little change in results when we extended the effective life of replicating funds beyond 10 years. The final period NAV is treated as a distribution in this set up. This opens our analysis up to potential issues related to the manipulation of NAV by fund managers, as discussed in Brown, Gredil, and Kaplan (2019). We also rely heavily on this single period distribution for very young funds, that have not had many distributions.

We thus have cash flows for PE funds, risk-free rate funds f, and market funds M for the set of both benchmark funds (N_B funds) and impact funds (N_{Imp} funds). As in Korteweg and Nagel (2016), we form the following matrix of cash flows with dimensions $(N_B + N_{Imp}) \times 3 \times J$:

$$Y_{i,t+h(j)} = \begin{pmatrix} C_{i,t+h(j)} \\ C_{if,t+h(j)} \\ C_{iM,t+h(j)} \end{pmatrix}$$

Pricing errors for each i of the $N_B + N_{Imp}$ funds are:

$$u_i(\theta) = \sum_{j=1}^{J} M_{t+h(j)}^{h(j)}(\theta) Y_{i,t+h(j)}$$

We form the GMM estimator as:

$$\hat{\theta} = \ \arg\ \min_{\theta}\left(\frac{1}{N}\sum_{i} u_i(\theta)\right)' \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \left(\frac{1}{N}\sum_{i} u_i(\theta)\right)$$

Where we put positive weight only on the replicating funds to ensure that our SDF perfectly prices these cash flows. Importantly, the set of u_i is for all $N_B + N_{Imp}$ funds. We pool the cash flows together in order to have a consistent SDF for comparing benchmark and impact funds. Additionally, the GMM procedure requires both a large number of funds and non-overlapping time periods.

Estimating the SDF from the pooled set of replicating funds requires an assumption that our replicating funds' cash flow profiles are relatively similar to the original set of benchmark and impact funds. This assumption is also present in Korteweg and Nagel (2016). On top of this assumption, we also need to assume that the timing of cash flows between VC, matched, and impact funds are similar. This assumption allows us to use the same SDF to price VC, matched, and impact fund cash flows, attributing differences in performance to group-level differences rather than to bias in the timing of cash flows. Because we have more VC replicating funds in our SDF estimation, a violation of this assumption will result in a GPME that reflects differences in the realization of the SDF for each set of cash flows more than it reflects differences in performance between VC, matched, and impact funds. Fortunately, Figures 6 and 7 provide evidence in favor of the similarity of cash flow profiles: distributions are steady between years 3 and 10.

With the parameters of the SDF that correctly prices the benchmark cash flows, we discount cash flows of impact, VC, and matched funds separately. We use a J-statistic to test whether the pricing errors of each set of funds are jointly zero. Thus we test whether the GPME estimates for $i \in N_{VC}$ are jointly zero separately from whether the GPME estimates for $i \in N_{Imp}$ are jointly zero, and likewise for $i \in N_{Match}$.

A.2 Spectral Density Matrix Adjustments

There is potentially substantial correlation between the u_i from the previous section if they are measured over overlapping time periods. We follow Korteweg and Nagel (2016) and correct for this correlation using the following spectral density matrix in our tests:

$$\hat{S} = \hat{\Lambda}^{\frac{1}{2}}\hat{\Gamma}\hat{\Lambda}^{\frac{1}{2}}$$

Where the matrix of correlations is given by:

$$\hat{\Gamma} = \left[\frac{1}{N}\sum_i \text{diag}(u_i \circ u_i)\right]^{-\frac{1}{2}} \left(\frac{1}{N}\sum_i u_i u_i'\right) \left[\frac{1}{N}\sum_i \text{diag}(u_i \circ u_i)\right]^{-\frac{1}{2}}$$

And the diagonal matrix of variances is given by:

$$\hat{\Lambda} = \frac{1}{N}\sum_k \sum_i \max(1 - d(i,k)/\bar{d}, 0)\text{diag}(u_i \circ u_k)$$

$$\text{where } d(i,k) = 1 - \frac{\min[t(i)+h(i), t(k)+h(k)] - \max[t(i), t(k)]}{\max[t(i)+h(i), t(k)+h(k)] - \min[t(i), t(k)]}$$

Our analysis extends Korteweg and Nagel (2016) by estimating the SDF on a set of benchmark funds that are a superset of the funds that are ultimately used to construct group-level GPME estimates. Specifically, we estimate SDF using the pooled sample (long sample) and incorporate the SDF point estimate and standard error in predicting GPME estimates on the impact, matched, and VC fund sample respectively (limited sample). We therefore adjust the spectral density matrix to account for estimation error, following the methods developed in Stambaugh (1997) and Lynch and Wachter (2013):

$$\hat{S} = \begin{bmatrix} \hat{S}_{11} & \hat{S}_{11}\hat{B}_{21}^T \\ \hat{B}_{21}\hat{S}_{11} & \hat{\Sigma} + \hat{B}_{21}\hat{S}_{11}\hat{B}_{21}^T \end{bmatrix}$$

where $\hat{S}_{11}$ is the $(K+1) \times (K+1)$ spectral density matrix estimated from the pooled-sample pricing errors using the Korteweg and Nagel (2016) method, where K is the number of benchmark funds for the corresponding VC payoffs. $\hat{B}_{21}$ is the coefficients of a multivariate regression of the limited sample moments on the long sample moments and $\hat{\Sigma}$ is the residual matrix of the moment regressions.

The final spectral density matrix, $\hat{S}^{\mathcal{L}}$ also needs to account for the difference in sample length, so we further adjust the block entries as follows:

$$\hat{S}^{\mathcal{L}} = \begin{bmatrix} \lambda\hat{S}_{11} & \lambda\hat{S}_{11}\hat{B}_{21}^T \\ \lambda\hat{B}_{21}\hat{S}_{11} & \hat{\Sigma} + \hat{B}_{21}\hat{S}_{11}\hat{B}_{21}^T \end{bmatrix}$$

where λ is the ratio of the sample length of the limited and long sample,

$$\lambda = \frac{N_{short}}{N}$$

In our case, the limited-sample moments are exactly the same as the subset of corresponding long-sample moments, since the long sample is the super-set of funds in the limited sample. Therefore, we have

$$\hat{B}_{21} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

The resulting adjusted spectral density matrix $\hat{S}^{\mathcal{L}}$ is a $(2K+2) \times (2K+2)$ matrix, including the moments from VC payoff and benchmark payoffs from both the long and limited sample.

Note that, we do not need to use the efficient estimators developed by Lynch and Wachter (2013) as we are using a pre-specified weighting matrix instead of the optimal weighting matrix $W = S^{-1}$. Thus, the variance of moment conditions is

$$var(g) = (I - d(d'Wd)^{-1}d'W)\hat{S}(I - Wd(d'Wd)^{-1}d')$$

where W is a $(2K+2) \times (2K+2)$ zero matrix with diagonal entries of 1 for corresponding benchmark fund payoffs of the pooled sample, which are the only moments used to estimate the SDF. And a J-test on GPME is

$$g_{VC} var(g_{VC})^{-1} g_{VC} \sim \chi^2(1)$$

B Robustness

B.1 Results in Burgiss Data

Table B.1: Summary Statistics

Impact fund data comes from the IFD and Preqin. VC and matched fund data come from Burgiss. All samples cover vintages from 1997 through 2015 with transaction dates from 1999 to 2017. Impact fund statistics are reported in columns 1-3, VC fund statistics are in columns 4-6, and matched fund statistics are in columns 7-9. We report the mean and median for each sample of funds. The vintage year is the year of fund inception and fund size is the total committed capital raised by the fund, reported in millions USD. The PME is the ratio described in Equation 1. We report other absolute measures of performance, the cash flow multiple and IRR in percent. Finally, we report characteristics about the cash flow profile of each set of funds. Effective years is the number of years funds in each sample are open. We also report the number of total cash flows per fund, as well as the number of contributions and distributions separately.

	Impact			VC			Matched Benchmark		
	N	Mean	Median	N	Mean	Median	N	Mean	Median
Vintage	94	2009.1	2010	1,017	2006.7	2007	94	2009.1	2010
Fund Size (Mill$)	93	411.8	141.2	1,017	305.5	221.9	94	379.5	142.7
PME	94	0.751	0.765	1,017	0.981	0.863	94	1.085	0.974
Multiple	94	1.120	1.066	1,017	1.466	1.227	94	1.618	1.399
IRR (%)	94	-1.084	2.771	1,017	7.343	5.255	94	14.748	10.821
Effective Years	94	7.5	7	1,017	10.273	10.75	94	7.271	7.625
# Cash Flows per Fund	94	23.0	22	1,017	27.197	26	94	23.340	23.5
# Contributions	94	16.0	15	1,017	17.812	17	94	15.149	15
# Distributions	94	7.0	5	1,017	9.384	8	94	8.191	8

Table B.2: Estimated SDF with Market Risk

The SDF for both PME and Market Risk GPME is given by $M^*_{t+1} = \exp(a - b_1 r^M_{t+1})$. The SDF corresponding to the PME is the SDF for a log-utility model, where $a = 0$ and $b_1 = 1$. The SDF corresponding to the Market Risk GPME relaxes this assumption. We estimate this SDF using benchmark portfolios from Burgiss to replicate pooled VC, matched, and impact fund cash flows, as described in Appendix A.

	PME SDF	Market Risk SDF
a	0	0.176
		(0.065)
b_1	1	3.716
		(0.729)

Table B.3: Estimated Performance Relative to Market Risk

We compute PME and GPME relative to the market risk factor using Burgiss benchmarks and the SDF parameters from Table B.2. We report the standard error in parentheses below the estimate, and the p-value of the J-test of whether the estimate is zero in brackets on the third line. Panel (a) estimates performance for impact funds, Panel (b) for VC funds, and Panel (c) for matched funds. All panels use the same SDF parameters.

Panel (a): Impact funds

	PME	Market Risk GPME
Estimate	-0.197	-0.432
(sd)	(0.040)	(0.270)
[J-stat p-value]	[0.000]	[0.110]

Panel (b): VC funds

	PME	Market Risk GPME
Estimate	-0.074	-0.352
(sd)	(0.055)	(0.107)
[J-stat p-value]	[0.181]	[0.001]

Panel (c): Matched funds

	PME	Market Risk GPME
Estimate	0.059	-0.145
(sd)	(0.052)	(0.262)
[J-stat p-value]	[0.258]	[0.579]

Table B.4: Estimated GPME of VC-Impact Long-Short Portfolio

We compute PME and Market Risk GPME for a portfolio that is long VC funds and short impact funds. We report the standard error in parentheses below the estimate, and the p-value of the J-test of whether the estimate is zero in brackets on the third line. Panel (a) estimates performance for the value-weighted VC-impact portfolio, Panel (b) for the equal weighted VC-impact portfolio. Both panels use the same SDF parameters from Table B.2.

Panel (a): VC-impact value-weighted long-short portfolio

	PME	Market Risk GPME
Estimate	0.104	-0.076
(sd)	(0.067)	(0.056)
[J-stat p-value]	[0.124]	[0.170]

Panel (b): VC-impact equal-weighted long-short portfolio

	PME	Market Risk GPME
Estimate	0.220	0.025
(sd)	(0.070)	(0.041)
[J-stat p-value]	[0.002]	[0.548]

Table B.5: Estimated GPME of Matched-Impact Long-Short Portfolio

We compute PME and Market Risk GPME for a portfolio that is long matched funds and short impact funds. We report the standard error in parentheses below the estimate, and the p-value of the J-test of whether the estimate is zero in brackets on the third line. Panel (a) estimates performance for the value-weighted matched-impact portfolio, and Panel (b) for the equal-weighted matched-impact portfolio. Both panels use the same SDF parameters from Table B.2.

Panel (a): VC-impact value-weighted long-short portfolio

	PME	Market Risk GPME
Estimate	0.456	0.583
(sd)	(0.205)	(0.351)
[J-stat p-value]	[0.026]	[0.097]

Panel (b): VC-impact equal-weighted long-short portfolio

	PME	Market Risk GPME
Estimate	0.514	0.724
(sd)	(0.207)	(0.378)
[J-stat p-value]	[0.013]	[0.056]

Figure B.1: PME-GPME Wedge Using Market Risk SDF

We plot the PME - GPME wedge of artificially levered funds with different leverage k. We create artificially levered funds using impact funds, VC funds, or matched funds respectively, $C^{PE}_{i,t+h(j)}$ and the matched T-bill benchmark funds, $C^{Rf}_{if,t+h(j)}$

$$L^{PE}_{i,t+h(j)} = C^{PE}_{i,t+h(j)} + k(C^{PE}_{i,t+h(j)} - C^{Rf}_{if,t+h(j)})$$

We estimate the market risk SDF using replicating benchmarks for pooled impact and both benchmarks cash flows. We apply the same SDF on different levered cash flows to estimate GPME and use the log-utility CAPM SDF to estimate PME. The wedge is the difference between PME and GPME point estimates. The error bars are 95% confidence interval using bootstrap standard errors from 1,000 bootstrap samples of impact or VC funds.

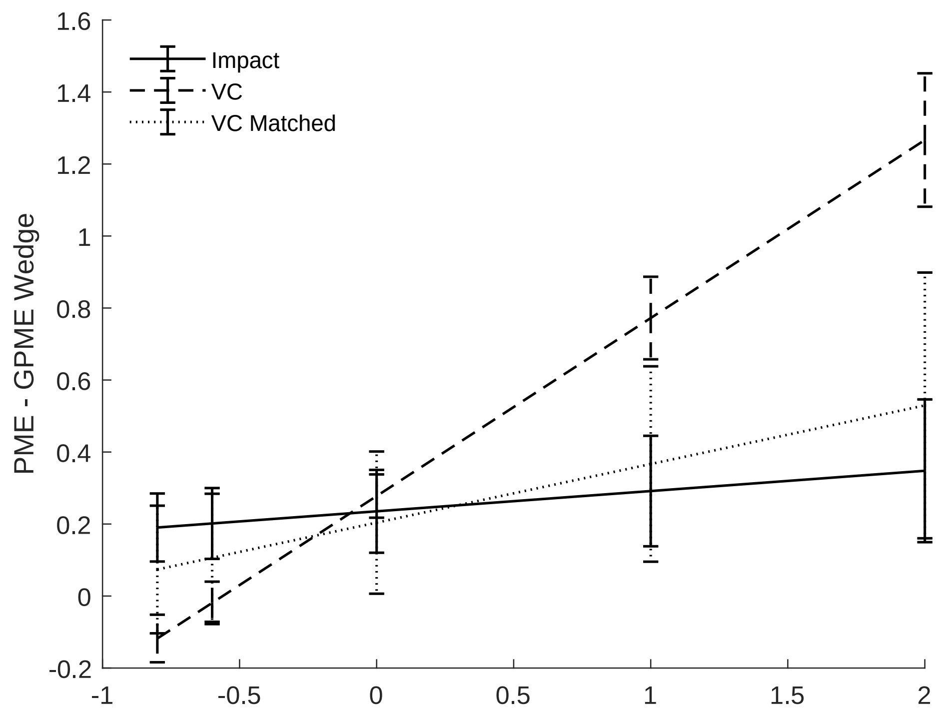


Figure B.2: PME-GPME Wedge of Long-Short Portfolio

We create two portfolios, one that is long VC funds and short impact funds, and the other that is long matched funds and short impact funds. Both portfolios presented here are value-weighted. We create artificially levered cash flows of each strategy similar to Figure 8. For each level of artificial leverage k, we plot the difference between the PME and GPME point estimate of the long-short portfolio. The error bars are 95% confidence interval using bootstrap standard errors from 1,000 bootstrap samples of the long-short portfolio.

(a) Value-Weighted

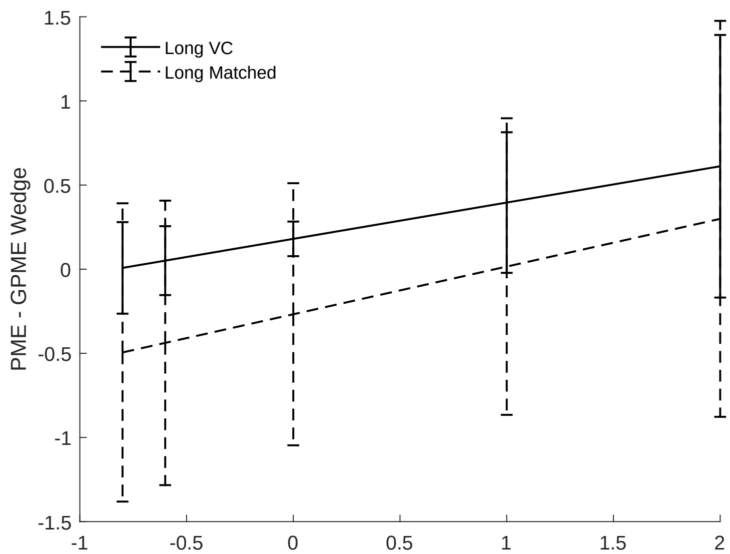


Table B.6: Estimated SDF with Sustainability Index

The SDF for both PME and GPME relative to the Sustainability Index is given by $M^*_{t+1} = \exp(a - b_1 r^{SI}_{t+1})$. The SDF corresponding to the PME is the SDF for a log-utility model, where $a = 0$ and $b_1 = 1$. The SDF corresponding to the SI GPME relaxes this assumption. We estimate this SDF using benchmark portfolios to replicate pooled VC, matched, and impact fund cash flows, as described in Appendix A.

	SI PME SDF	SI SDF
a	0	0.046
		(0.039)
b_1	1	2.282
		(0.904)

Table B.7: Estimated Performance Relative to Sustainability Index

We compute the PME and GPME relative to the Sustainability Index using the SDF parameters from Table B.6. We report the standard error in parentheses below the estimate, and the p-value of the J-test of whether the estimate is zero in brackets on the third line. Panel (a) estimates performance for impact funds, Panel (b) for VC funds, and Panel (c) for matched funds. Both panels use the same SDF parameters.

Panel (a): Impact funds

	SI PME	SI GPME
Estimate	-0.065	-0.142
(sd)	(0.033)	(0.233)
[J-stat p-value]	[0.050]	[0.540]

Panel (b): VC funds

	SI PME	SI GPME
Estimate	0.192	0.198
(sd)	(0.084)	(0.093)
[J-stat p-value]	[0.022]	[0.034]

Panel (c): Matched funds

	SI PME	SI GPME
Estimate	0.337	0.356
(sd)	(0.085)	(0.239)
[J-stat p-value]	[0.000]	[0.136]

Figure B.3: PME-GPME Wedge with Sustainability Index

We plot the PME - GPME wedge of artificially levered funds with different leverage k. We create artificially levered funds as in Figure 8. We estimate the sustainability index SDF using replicating benchmarks for pooled impact and both benchmarks cash flows. We apply the same SDF on different levered cash flows to estimate GPME and use the log-utility CAPM SDF to estimate PME. The wedge is the difference between PME and $GPME_{SI}$ point estimates. The error bars are 95% confidence interval using bootstrap standard errors from 1,000 bootstrap samples of impact or VC funds. Since the sustainability index has a relatively small equity premium relative to the log-utility benchmark (i.e., $\log E[R_{SI,t+1}] - r_f - \sigma_{SI}^2 < 0$), a negative relationship between the $PME - GPME_{SI}$ wedge and k indicates $\beta_{SI} > 0$, and a positive relationship between the $PME - GPME_{SI}$ wedge and k indicates $\beta_{SI} < 0$.

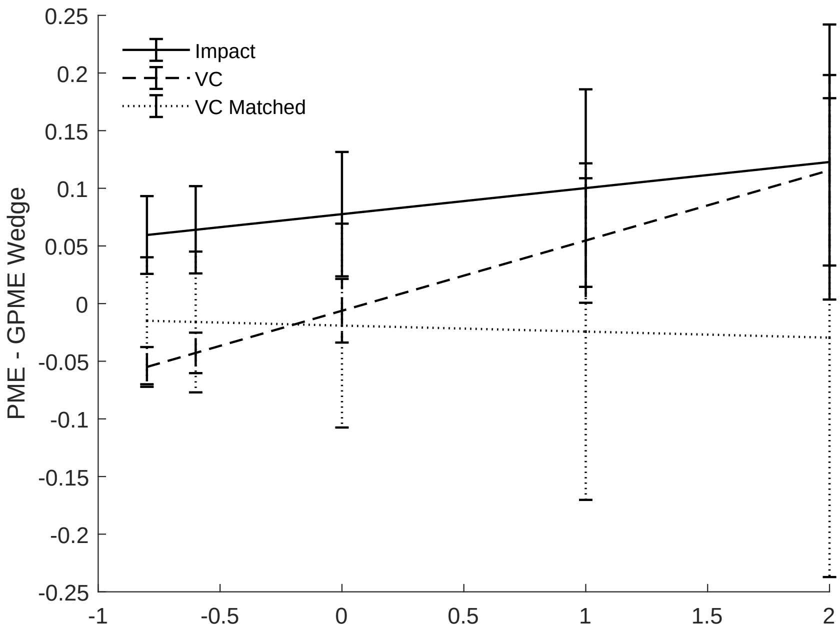


Table B.8: GPME with Multi-Factor SDF

We compute the GPME for different factor models: one-factor model with market factor only, two-factor model with market and small growth, and two-factor model with market and sustainability index. We report the standard error in parentheses below the estimate, and the p-value of the J-test of whether the estimate is zero in brackets on the third line. Panel (a) estimates performance for impact funds, Panel (b) for VC funds, and Panel (c) for matched funds. Both panels use the same SDF parameters; each column has its own set of SDF parameters corresponding to the relevant model.

Panel (a): Impact funds

	Market Factor Only	Market and Small Growth	Market and Sustainability
Estimate	-0.432	-0.415	-0.327
(sd)	(0.270)	(0.239)	(0.544)
[J-stat p-value]	[0.110]	[0.082]	[0.548]

Panel (b): VC funds

	Market Factor Only	Market and Small Growth	Market and Sustainability
Estimate	-0.352	-0.332	-0.433
(sd)	(0.107)	(0.096)	(0.163)
[J-stat p-value]	[0.001]	[0.001]	[0.008]

Panel (c): Matched funds

	Market Factor Only	Market and Small Growth	Market and Sustainability
Estimate	-0.145	-0.108	-0.237
(sd)	(0.262)	(0.239)	(0.541)
[J-stat p-value]	[0.579]	[0.651]	[0.662]

B.2 Matched Benchmark by Asset Class, Vintage, Sequence Number, and Size

In our main analysis, we construct our matched benchmark by matching each impact fund to a fund in Preqin with the same vintage and general asset class, and closest size. In this section, we perform an alternative matching process in order to address the concern that some of the performance differences of impact funds compared to our benchmarks are due to the fact that impact funds are relatively new, that is they are early in their fund sequence. In particular, we match on the same vintage and general asset class, and closest sequence number and size. We does not match exactly on sequence number because there are not always some Preqin funds with the exact same vintage, asset class and sequence number as each impact fund in our sample.

The last three columns of Table B.9 show the summary statistics of the selected funds with this alternative matching procedure. The matched funds have almost identical sequence number distribution as impact funds, even if we are not matching exactly on sequence number. The size difference between this matched benchmark and impact is larger than our main analysis because with sequence number as the additional matching criterion, there are less candidate Preqin funds to be chosen from with the closest sequence number as impact funds.

Table B.9: Summary Statistics of Alternative Matched Funds

Impact fund and VC fund in columns 1-3 and 4-6 are the same as in Table 1. Columns 7-9 reports the summary statistics of the matched benchmark on vintage, asset class, sequence number, and size. We report the mean and median for each sample of funds. All variables are defined in the same way as Table 1.

	Impact			VC			Matched Benchmark		
	N	Mean	Median	N	Mean	Median	N	Mean	Median
Vintage	94	2009.1	2010	483	2005.9	2006	94	2009.1	2010
Fund Size (Mill$)	93	411.8	141.2	483	382.2	280	92	478.7	265
Sequence Number	94	2.11	2	483	4.05	3	94	2.55	2
PME	94	0.751	0.765	483	0.882	0.815	94	0.960	0.907
Multiple	94	1.120	1.066	483	1.331	1.183	94	1.423	1.325
IRR (%)	94	-1.084	2.771	483	4.692	4.108	94	9.386	9.742
Effective Years	94	7.5	7	483	11.0	11	94	7.1	6.3
# Cash Flows per Fund	94	23.0	22	483	30.6	30	94	25.1	23
# Contributions	94	16.0	15	483	19.3	18	94	16.9	17
# Distributions	94	7.0	5	483	11.3	10	94	8.2	6

We pool this alternative matched benchmark with the impact sample and VC benchmark to re-estimate the SDF in Table B.10. We get a similar SDF with only a slightly larger b_1. (3.945 versus 3.913). We use this SDF to calculate the GPME for impact sample, VC, and matched benchmark. Since the realized SDF does not change much, the GPME for impact and VC are almost identical as expected. The GPME on the alternative matched benchmark is also similar to our main analysis (-0.316 versus -0.310). Figure B.4 plots the re-estimated PME-GPME wedge versus the leverage factor. Despite a slightly lower slope of these alternative matched funds than in the benchmark case, it is still higher than impact funds while lower than VC funds. Both the GPME table and the leverage plot give the exact same conclusion as describe in our main analysis. Thus, our results hold even controlling for sequence number on our matched benchmark funds.

Table B.10: Estimated SDF with Market Risk (Impact+VC+Alternatively-Matched Funds)

The SDF for both PME and Market Risk GPME is given by $M^*_{t+1} = \exp(a - b_1 r^M_{t+1})$. The SDF corresponding to the PME is the SDF for a log-utility model, where $a = 0$ and $b_1 = 1$. The SDF corresponding to the Market Risk GPME relaxes this assumption. We estimate this SDF using benchmark portfolios to replicate impact, VC, and alternatively matched funds, as described in Appendix A.

	PME SDF	Market Risk SDF
a	0	0.197
		(0.070)
b_1	1	3.945
		(0.765)

Table B.11: Estimated Performance Relative to Market Risk

We compute PME and GPME relative to the market risk factor using the SDF parameters from Table B.10. We report the standard error in parentheses below the estimate, and the p-value of the J-test of whether the estimate is zero in brackets on the third line. Panel (a) estimates performance for impact funds, Panel (b) for VC funds, and Panel (c) for alternatively matched funds. All panels use the same SDF parameters.

Panel (a): Impact funds

	PME	Market Risk GPME
Estimate	-0.200	-0.451
(sd)	(0.040)	(0.218)
[J-stat p-value]	[0.000]	[0.038]

Panel (b): VC funds

	PME	Market Risk GPME
Estimate	-0.132	-0.439
(sd)	(0.049)	(0.132)
[J-stat p-value]	[0.007]	[0.001]

Panel (c): Matched funds

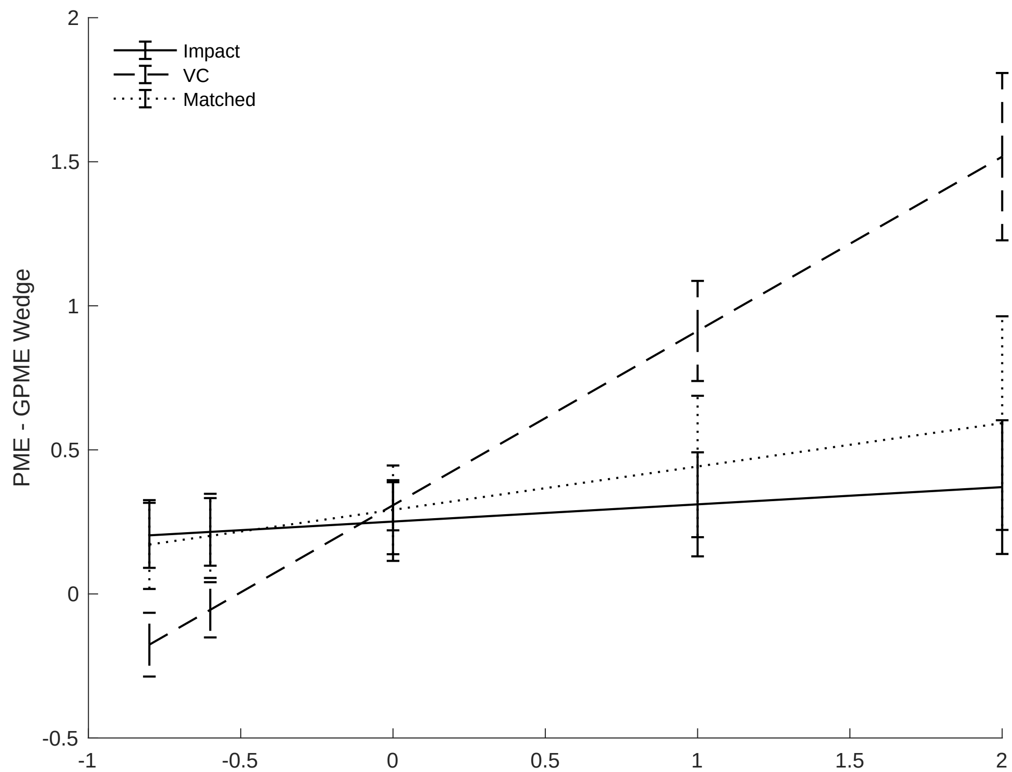
	PME	Market Risk GPME
Estimate	-0.024	-0.316
(sd)	(0.027)	(0.218)
[J-stat p-value]	[0.365]	[0.148]

Figure B.4: PME-GPME Wedge Using Market SDF

We plot the PME-GPME wedge of artificially levered funds with different leverage k. We create artificially levered funds using impact, VC, and alternatively matched funds respectively, $C^{PE}_{i,t+h(j)}$ and the T-bill benchmark funds, $C^{Rf}_{if,t+h(j)}$:

$$L^{PE}_{i,t+h(j)} = C^{PE}_{i,t+h(j)} + k(C^{PE}_{i,t+h(j)} - C^{Rf}_{if,t+h(j)})$$

We estimate the market risk SDF using replicating benchmarks for pooled impact, VC, and alternatively matched cash flows. We apply the same SDF on different levered cash flows to estimate GPME and use the log-utility CAPM SDF to estimate PME ($a = 0$ and $b_1 = 1$). The wedge is the difference between PME and GPME point estimates. The error bars are 95% confidence interval using bootstrap standard errors from 1,000 bootstrap samples.



B.3 VC Sample Matching Fund Life

This section addresses the concern raised by Gredil, Sorensen, and Waller (2019) that an NPV-based estimator of fund performance may suffer more bias for samples with longer fund life. In Section C.3, we confirm in simulations that the estimated PME-GPME wedge is more sensitive to changes in β as the fund life increases. To control for fund life in our VC sample, we match the fund life distribution of our VC benchmark sample to our impact sample and re-estimate the PME and GPMEs.[10] We take a two-step process to match the fund life distribution: (i) we match the vintage distribution of the VC sample to the vintage distribution of our impact sample by keeping all of the VC funds in the most populated impact vintage year (2010), and then randomly drop VC funds in other vintage years in proportion to the impact vintage distribution; (ii) for each vintage year, we cut off VC fund cash flows at the mean impact fund life within that year. The last three columns of Table B.12 show the summary statistics of the VC sample matched by fund life. We can see that while maintaining similar size as the full VC sample, this matched sample follows closely the vintage and effective years distribution of the impact fund sample.

Table B.12: Summary Statistics of VC Matched by Fund Life

Impact fund and VC fund in columns 1-3 and 4-6 are the same as in Table 1. Columns 7-9 reports the summary statistics of the fund-life-matched sample constructed by the process described above. We report the mean and median for each sample of funds. All variables are defined in the same way as Table 1.

	Impact Funds			All VC Funds			VC Matched by Fund Life		
	N	Mean	Median	N	Mean	Median	N	Mean	Median
Vintage	51	2009.5	2010	483	2005.9	2006	144	2009.4	2010
Fund Size (Mill$)	51	95.3	74.4	483	382.2	280	144	370.0	286
PME	51	0.777	0.767	483	0.882	0.815	144	1.002	0.933
Multiple	51	1.123	1.081	483	1.331	1.183	144	1.429	1.274
IRR (%)	51	1.526	3.327	483	4.692	4.108	144	12.42	9.328
Effective Years	51	6.7	6.0	483	11.0	11	144	6.5	5.8
# Cash Flows per Fund	51	18.7	16	483	30.6	30	144	23.0	21
# Contributions	51	13.3	12	483	19.3	18	144	16.0	16
# Distributions	51	5.4	2	483	11.3	10	144	7.0	5

We pool the fund-life-matched VC sample with the IFD impact sample and re-estimate the SDF in Table B.13. Despite having a larger b_1, the SDF is consistent with the relatively "hot" equity markets in our main results. In Figure B.5, we plot the re-estimated PME-GPME wedge as a function of the artificial leverage factor, separately for fund-life-matched VC and impact funds. There is still a much higher slope for the matched VC funds, suggesting that impact funds have a lower β than VC even after controlling for fund life. This confirms and strengthens our main results that impact funds have a substantially lower market beta than venture capital funds.

[10] This robustness test was conducted with the original sample of 51 impact funds. We are working on repeating this for the expanded sample of 94 impact funds.

Table B.13: Estimated SDF with Market Risk (Impact+Fund-Life-Matched VC)

The SDF for both PME and Market Risk GPME is given by $M_{t+1}^{*} = \exp(a - b_1 r_{t+1}^{M})$. The SDF corresponding to the PME is the SDF for a log-utility model, where $a = 0$ and $b_1 = 1$. The SDF corresponding to the Market Risk GPME relaxes this assumption. We estimate this SDF using benchmark portfolios to replicate pooled fund-life-matched VC and impact fund cash flows, as described in Appendix A.

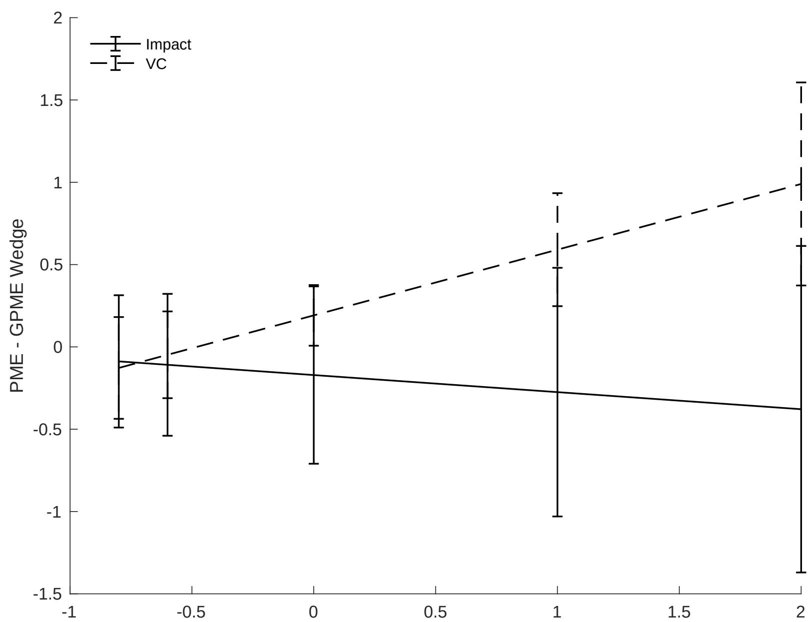
	PME SDF	Market Risk SDF
a	0	0.331
		(0.113)
b_1	1	4.683
		(0.875)

Figure B.5: PME-GPME Wedge Using Market Risk SDF (Impact+Fund-Life-Matched VC)

We plot the PME-GPME wedge of artificially levered funds with different leverage k. We create artificially levered funds using impact funds or fund-life-matched VC funds respectively, $C_{i,t+h(j)}^{PE}$ and the T-bill benchmark funds, $C_{if,t+h(j)}^{Rf}$:

$$L_{i,t+h(j)}^{PE} = C_{i,t+h(j)}^{PE} + k(C_{i,t+h(j)}^{PE} - C_{if,t+h(j)}^{Rf})$$

We estimate the market risk SDF using replicating benchmarks for pooled impact and fund-life-matched VC. We apply the same SDF on different levered cash flows to estimate GPME and use the log-utility CAPM SDF to estimate PME ($a = 0$ and $b_1 = 1$). The wedge is the difference between PME and GPME point estimates. The error bars are 95% confidence interval using bootstrap standard errors from 1,000 bootstrap samples.



C Simulations

C.1 Finite-Sample Performance of PME-GPME Wedge

Our main result uses the difference in the PME-GPME wedge between impact and VC funds as an indication of their difference in β. As stated in Section 3.3, this method is based on the following equation:

$$\log E[R_{GPME}] - \log E[R_{PME}] = (\beta - 1)(\log E[R_{m,t+1}] - r_f - \sigma_m^2) \tag{15}$$

This equation shows that in true expectations, we can have a one-to-one relationship between the PME-GPME wedge and β. However, the relationship is not exact when we estimate the wedge in finite samples, especially in small samples like ours. In particular, our results depend on the fact that the following relationship holds in the finite sample:

$$\log E[R_{GPME}] - \log E[R_{PME}] = f(PME - GPME) \tag{16}$$

where f is an strictly increasing function.

We verify this relationship using Monte Carlo simulations. To create simulated fund cash flows, we first assume that the log market return follows

$$f_t = r_f + \gamma\sigma^2 - \frac{1}{2}\sigma^2 + \sigma\varepsilon_t \tag{17}$$

where $\varepsilon_t \sim N(0,1)$, r_f is a constant log risk-free rate, γ is risk aversion coefficient, and $Var(f_t) = \sigma^2$.

This specification guarantees that the log SDF with the form

$$m_t = a - \gamma f_t \tag{18}$$

prices the risk-free rate and market factor perfectly in population, with $a = (\gamma - 1)r_f + \frac{1}{2}\gamma(\gamma - 1)\sigma^2$.

We then model fund returns with any arbitrary β as

$$r_t = r_f + \beta\gamma\sigma^2 - \frac{1}{2}\beta^2\sigma^2 + \beta\sigma\varepsilon_t + \eta_t - \frac{1}{2}\omega^2 \tag{19}$$

One can easily show that such fund returns satisfy the definition of β:

$$\beta = \frac{Cov(r_t, f_t)}{\sigma^2} = \frac{Cov(r_t, \sigma\varepsilon_t)}{\sigma^2} \tag{20}$$

They also satisfy the (log-)linear beta pricing relationship inferred by the SDF:

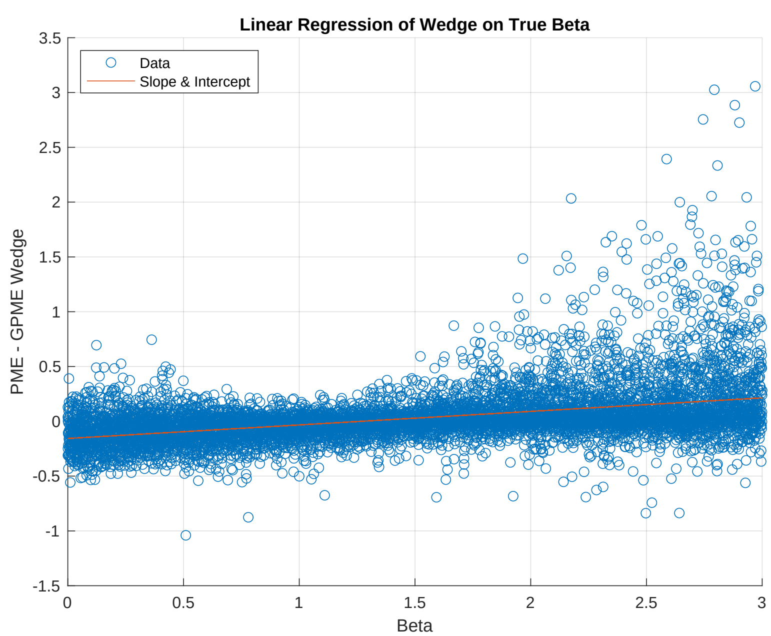
$$\log E[R_t] - r_f = \beta(\log E[F_t] - r_f) = \beta\gamma\sigma^2 \tag{21}$$

where $r_t = \log R_t$ and $f_t = \log F_t$.

We simulate the irregularly-spaced fund cash flows following the approach in the Online Appendix of Korteweg and Nagel (2016). We use the same notation of market and fund-specific parameters in the simulations. Specifically, we choose number of time periods $T = 19$, reflecting the fact that the time period spanned by fund cash flows in our sample is from 1999 to 2017. We set the log risk-free rate $r_f = 0.02$, market volatility $\sigma = 0.15$, and risk aversion $\gamma = 2$. For fund-specific parameters, in the baseline simulation, we choose number of funds $N = 585$, which is the total number of funds in our pooled sample with impact, VC, and VC matched funds. The parameters of idiosyncratic shocks are $\omega = 0.25$ and $\rho = 0.1$. Finally, we choose the number of cash flow realizations $J = 25$ and fund life $h^{max} = 9$, both reflecting the median value in the summary statistics in Table 1.

We simulate 10,000 iterations of our sample with the parameters above. In each simulation, we randomly draw a β from a uniform distribution from 0 to 3. We then estimate the PME-GPME wedge in the simulated finite sample of fund cash flows in each iteration. In Figure C.1, we plot the wedge against the true fund β. The true β and the true expected return difference are in one-to-one correspondence and thus can be used interchangeably.

Figure C.1: Simulated PME-GPME Wedge vs. True β



We supplement the plot with a linear regression in Table C.1 which regresses PME-GPME wedge on the true β. We get a statistically and economically significant positive efficient on β, demonstrating that the finite sample estimation of the wedge goes in the same direction as true β. We conclude that the wedge can be used as a valid indicator to compare the VC β with the impact β in our main analysis.

Table C.1: Simulated PME-GPME Wedge on β

	(1) PME-GPME Wedge
Beta	0.1235***
	(37.877)
Constant	-0.1564***
	(-41.306)
R^2	0.189
Observations	10000

t statistics in parentheses

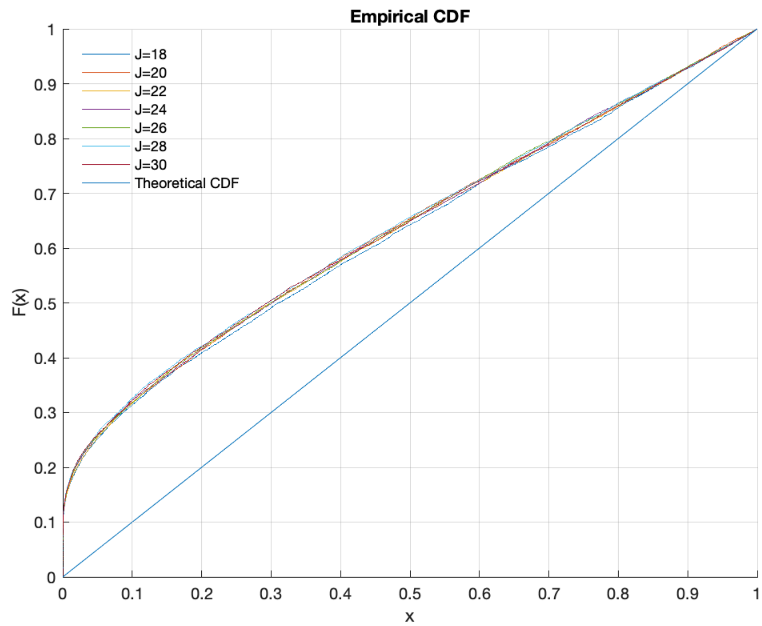
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.2 Simulation Results on Number of Cash Flows

In this section, we investigate, with the same return dynamics, whether varying the number of cash flows affects our result. We are interested in two specific issues: (i) whether the statistical power varies with the number of cash flows, i.e. whether more cash flows lead to more or less over-rejection of zero pricing error in PME and GPME; (ii) whether the PME-GPME wedge is more or less sensitive to β with increasing number of cash flows. If the wedge is more sensitive to β as the number of cash flows increases, the higher slope of VC than impact in the artificial leverage plots (e.g. Figure 8) may (partly) result from the fact that VC has more cash flow realizations, and not entirely from a true higher VC β.

We again use simulations to tackle the two issues. We follow the same simulation procedure as in Section C.1, but run 10,000 simulations for each number of cash flows $J = 18, 20, 22, 24, 26, 28, 30$. For over-rejection, we follow Korteweg and Nagel (2016) and plot the empirical cumulative distribution (CDF) of the p-values of the J-test based on the simulated data for each number of cash flow realizations. Under the asymptotic distribution, the p-values should have a uniform distribution and thus the empirical CDF should be a 45-degree line going through zero. Figure C.2 shows that the extent of over-rejection is very similar across different numbers of cash flows J, and thus the statistical power does not vary with the number of cash flow realizations.

Figure C.2: Actual and Nominal Size of J-test with # Cash Flows



For the PME-GPME wedge's sensitivity to β, we follow the same analysis as in Section C.1. In particular, for each cash flow realization J, we plot the best-fitted line of the PME-GPME wedge on true β for 10,000 simulations each with β randomly drawn from a uniform distribution between 0 and 3. Figure C.3 shows that the best-fitted line is similar for all different J's. Table C.2 confirms this by exhibiting that all coefficients are statistically significant and similar in economic magnitude (around 0.12).

Both over-rejection and sensitivity results affirm that the number of cash flows does not make a material difference to our main results, given the same underlying fund return dynamics. This implies that we can compare VC and impact results despite a difference in number of cash flow realizations. Also, in our main results, we collapse both VC and impact cash flows to the quarterly level before estimating abnormal performance. These simulation results also imply that collapsing the cash flows to different frequencies (for example annual) should not alter our conclusions.

Figure C.3: Simulated PME-GPME Wedge vs. True β with # Cash Flows

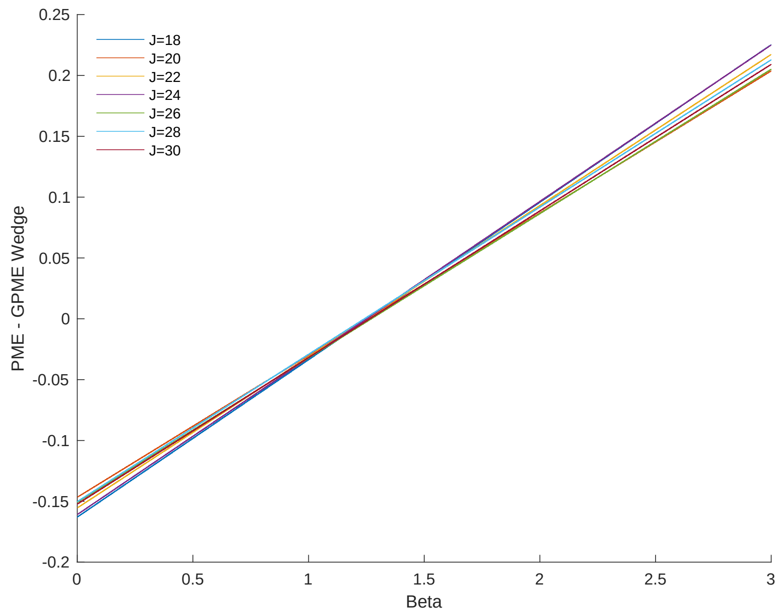


Table C.2: PME-GPME Wedge on β with # Cash Flows

J	18	20	22	24	26	28	30
Beta	0.1294***	0.1168***	0.1242***	0.1287***	0.1186***	0.1210***	0.1205***
	(38.724)	(36.940)	(35.430)	(36.244)	(36.257)	(35.346)	(36.499)
Constant	-0.1630***	-0.1467***	-0.1555***	-0.1609***	-0.1508***	-0.1503***	-0.1523***
	(-42.318)	(-38.442)	(-38.557)	(-39.041)	(-38.767)	(-37.545)	(-39.329)
R^2	0.200	0.184	0.173	0.182	0.181	0.175	0.176
Observations	9,999	9,995	9,999	9,998	10,000	9,999	9,997

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.3 Simulation Results on Fund Life

Another potential factor that could affect our results is fund life. Following Section C.2, we investigate whether varying fund life changes the degree of over-rejection and the PME-GPME wedge's sensitivity to β. The concern is also the same: the higher VC β we estimate may be partly explained by a longer fund life. Relatedly, Gredil, Sorensen, and Waller (2019) introduce the concept of "compounding error bias" when estimating NPV-like estimators, such as PME and GPME. This bias emerges from the fact that the sampling error is slow to decay because the estimated NPV compounds several periods of sampling error from estimated returns and is affected by fund duration.

We run the same set of simulations as in Section C.2, but instead of varying number of cash flows, we vary the fund life, h^{max}, from 6 to 11 years. Figure C.4 shows the results with over-rejection. Given the same fund return dynamics, the longer the fund life is, the more over-rejection we have. For the sensitivity, in Figure C.5 and Table C.3, we find that the estimated PME-GPME wedge increases more quickly with fund β when the funds have longer fund life. The coefficient on β increases from 0.09 when fund life is 6 years to 0.13 when fund life is 13 years (a 46% increase). As a result, there may be a concern that the higher VC slope in our main results is explained by a higher sensitivity to β from a longer fund life, rather than a higher true β. However, in Section B.3, we redo our analysis on a VC sample which matches the fund life distribution of impact sample and show that this is not the case. Our result is not driven by the potential compounding error from the longer VC fund life.

Figure C.4: Actual and Nominal Size of J-test with Fund Life

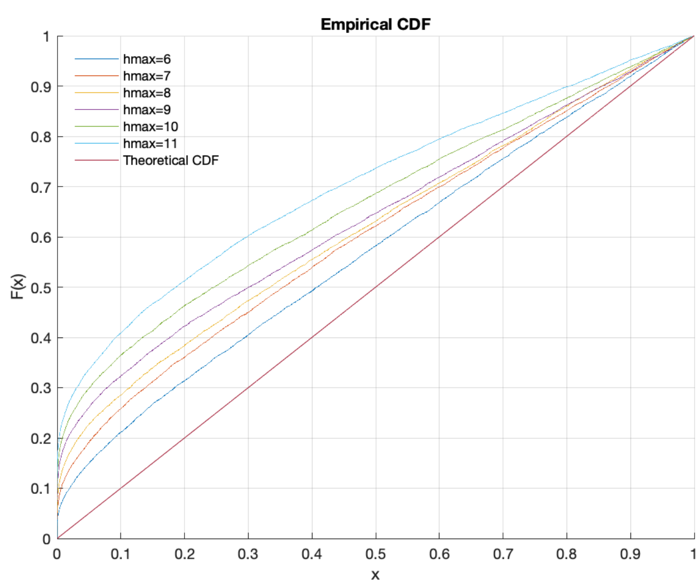


Figure C.5: Simulated PME-GPME Wedge vs. True β with Fund Life

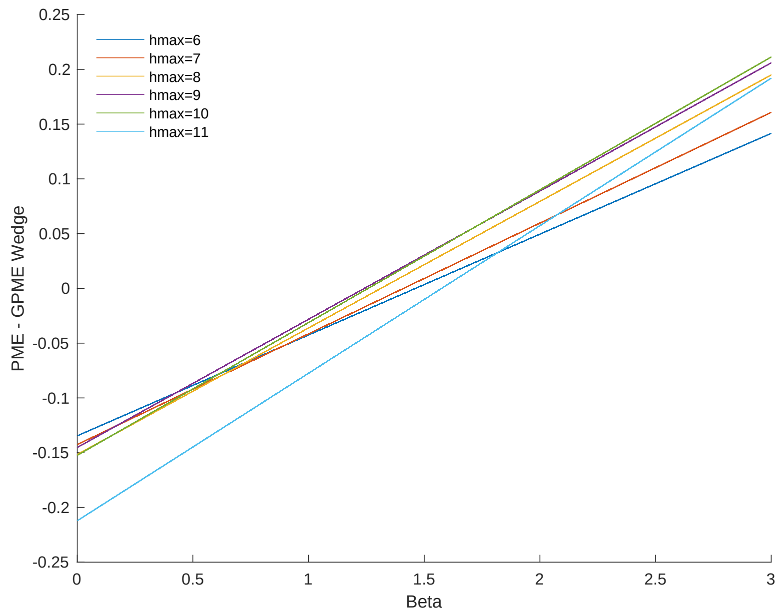


Table C.3: PME-GPME Wedge on β with Fund Life

hmax	6	7	8	9	10	11
Beta	0.0920***	0.1011***	0.1155***	0.1171***	0.1212***	0.1347***
	(39.306)	(40.448)	(37.644)	(36.871)	(34.296)	(20.022)
Constant	-0.1346***	-0.1426***	-0.1516***	-0.1453***	-0.1525***	-0.2122***
	(-41.470)	(-42.795)	(-41.280)	(-38.756)	(-35.644)	(-19.987)
R^2	0.199	0.206	0.195	0.178	0.151	0.023
Observations	10,000	9,999	9,999	9,999	10,000	9,998

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$