How Fragile are Private Equity Firms?

Hrvoje Kurtović

HEC – University of Lausanne

Garen Markarian

HEC – University of Lausanne

Patrick Breuer

WHU – Otto Beisheim School of Management

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* Corresponding author, please, address all communication to garen.markarian@unil.ch, +41 21 692 33 12, Bâtiment Anthropole, 1015 Lausanne, Switzerland.

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Private Equity (PE) risk and performance is a black box for investors as information is quasi-private during a fund's life. To overcome this issue, we use the universe of listed PEs (LPEs) in U.S. exchanges, which permits the measurement of financial fundamentals based on audited quarterly reports, and the observation of share price performance and volatility on a real-time basis. We find that LPEs constantly exhibit leverage double to that of the broader market while showing no distinctive operational performance. Controlling for standard determinants of returns, PE firms do not outperform publicly traded peers. Using COVID-19 as an exogenous increase in risk, PE firms grossly underperform as markets penalize the riskiness and lack of transparency inherent in PE investments. The problems are likely greater in privately held PEs, where performance is self-reported and illiquidity periods last up to 10-12 years.

1. Introduction

From an unknown investment vehicle that saw its initial ascent in the roaring eighties, private equity today comprises a multi-trillion asset class. Blackstone alone is estimated to own companies with assets in excess of $550 billion, and employs around half a million employees, easily dwarfing Apple Inc., one of the most valuable publicly traded companies.[1] Private equity (PE thereafter) raised $2 trillion of capital on a global basis between 2006 and 2008 (Bernstein, Lerner, & Mezzanotti, 2019), where each dollar of capital is normally augmented by $2 of debt (Kaplan & Stromberg, 2009). In China, $60 billion was invested by local PE firms in 2019 alone.[2] PE commands a ubiquitous presence in today's society, from airports, train stations, water companies, malls, restaurant chains, airlines, and universities.[3] However, the private nature of transactions has not enabled academics, regulators, and the media at large to arrive at a firm understanding of neither the riskiness of PE firms nor their performance as an asset class. Information for performance measurement is held privately so performance is only observable ex-post (see Sorensen, Wang, & Yang, 2014 and Harris, Jenkinson, & Kaplan, 2014). PEs' self-reported values are often biased and understate their riskiness (Jenkinson, Landsman, & Rountree, 2020 and Jegadeesh, Kräussl, & Pollet, 2015). In this paper, we overcome this issue by examining the universe of publicly traded (or listed) private equity firms in the US (LPEs thereafter).

This approach is advantageous because prior research has not been able to reliably measure, neither the riskiness nor the returns of PE firms. In contrast, LPEs offer reliable audited financial reports in which performance is measured according to GAAP and standardized in the same asset class, which is directly comparable to non-PE firms in the public domain. Leverage-related decisions by LPE firms are readily observable as they show up in the balance sheet, while in the case of PE

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[1] https://www.blackstone.com/our-businesses/portfolio-operations/#:~:text=Blackstone's%20portfolio%20spans%20200%2B%20companies,facilitate%20practice%20sharing%20across%20companies

[2] https://www.mckinsey.com/industries/private-equity-and-principal-investors/our-insights/in-search-of-alpha-updating-the-playbook-for-private-equity-in-china#

[3] In one count, PE firms own in excess of 1,000 for-profit universities in the US: https://uncipc.org/wp-content/uploads/2018/12/Eaton-Howell-Yannelis_wp_PE-in-Higher-Ed.pdf

firms, transaction-level leverage is not. Similarly, the LPEs' Form 10-Ks contain extended disclosures on the nature of underlying investments, where market participants can simply evaluate the riskiness and performance outcomes of such investments on a daily basis using stock market data. Consequently, investors can better undertake capital allocation decisions, based on directly observable signals, across a wide range of asset classes including PE.

Spanning 2010 – 2019, our sample comprises 51 distinct US-based LPEs.[4] In these 10 years, the universe of LPEs has almost doubled to 44 firms in 2019, indicating that smaller-sized PEs have followed the trend set by the big and popular PEs such as Blackstone (IPO in 2007), KKR (in 2010), and Apollo Global (in 2010). The observed LPEs range in size from \$640 million to \$60.9bn, where the median LPE in 2019 is as large as \$1.2bn, hence, it compares well to non-listed PE firms which are typical of that range. Hence, the results of this study could potentially shed light on the PE universe as a whole.

We benchmark our LPE sample to all listed non-financial US-based firms in the same time period. As PEs hold a portfolio of different sizes and industries, we only exclude firms operating in finance, insurance, and real estate, yielding 4,191 distinct benchmark firms. Our study attempts to evaluate the performance of PE firms versus investments into public markets, hence, using a publicly held benchmark is appropriate, especially since our tests control for well-known determinants of returns such as size, market-to-book, leverage, ROA, etc.

We show that LPEs have median leverage of 36.1% that is almost double the leverage of the benchmark (19.3%) throughout our sample period. ROA (~4%) and ROE (~7.5%) are both similar across both groups, however, these metrics display a higher degree of volatility in the case of LPEs. On the other hand, idiosyncratic volatility is consistently lower for LPEs. This could be due to the LPEs' portfolio effect as they typically invest in a broad range of companies and industries, diversifying away idiosyncratic risk. Next, we investigate whether LPEs outperform benchmark firms in terms of

[4] On average 36 LPEs are listed in a single year. We allow firms to enter and leave the sample.

raw returns. Our results do not show evidence that this is the case. LPEs considerably outperform the benchmark only in 2010 and their returns mirror that of the benchmark thereafter.

Even after adjusting for widely utilized risk factors, we find that returns on LPEs and the benchmark as indistinguishable on average. We do so by computing Fama-French risk-adjusted returns, which indicate that the benchmark outperforms LPEs slightly (by 0.7%). Applying the method proposed by Daniel, Grinblatt, Titman, and Wermers (1997) confirms this result. Moreover, by comparing the Sharpe ratios (Sharpe, 1966) of both groups, we find that LPEs also do not significantly outperform the benchmark in this risk dimension.

Franzoni, Nowak, and Phalippou (2012) report that PE alphas diminish when a liquidity risk premium is considered. We argue that this finding also relates to LPEs. If LPE returns mimic the returns of PE firms as a whole, then, investors do not seem to get compensated for holding period illiquidity. Furthermore, if LPE returns are similar to benchmark returns, then controlling for illiquidity, it can be concluded that investments into PE are relatively unprofitable.

We next show that leverage, hence financial inflexibility, negatively influences the returns of LPEs. We examine returns during the 2020 COVID-19 crisis. Markets started to react gradually and negatively to this exogenous shock on March 4 and the S&P 500 reached its lowest point on March 23, 2020. We define this as the "fall" period. On June 5, 2020, the S&P 500 reached its pre-crash level "recovery" point of March 4. To investigate whether cumulative returns are different for LPEs and the benchmark, we conduct two-tailed t-tests. Our sample is comprised of 44 LPEs and 1,277 benchmark firms. We identify a highly statistically significant difference in means for both periods. The benchmark outperforms LPEs by 18.9% and 17.2% in the "fall" and "recovery" period, respectively. Thus, at least for a (strong) stock market crisis period, we reject the hypothesis that cumulative returns for LPEs are indistinguishable from the returns of the benchmark: the financial fragility of PE firms, coupled with a lack of transparency, leads to a larger fall and a more prolonged recovery.

The results on the t-tests are preliminary, as they do not control for a host of firm-level characteristics that could be driving the poor returns during the initial COVID-19 panic. For example, PE firms are highly leveraged as compared to their peers, hence, that could be a simple explanation for the differential returns. Therefore, we conduct multivariate tests with a large set of covariates to further confirm our univariate results. We regress cumulative returns on measures of financial flexibility as well as on stock and firm characteristics. After controlling for the standard determinants of returns, we note that LPE firms still underperform by -8.14% during the longer "fall" period, and by -14.12% during the longer "recovery" period. In fact, even if we control for FF-48 industry effects, we see that LPE firms still underperform. This indicates that the asset class as a whole underperformed relative to other industries. Given that these latter results that control for industry membership also control for firm performance, growth opportunities, size, leverage, and share price risk, perhaps the lack of transparency inherent in LPE investments magnifies the effects of distress.

In line with our previous results, we show that leverage is the financial metric that distinguishes LPEs statistically and economically from the benchmark. Leverage as a measure of financial flexibility is a highly statistically significant determinant for the LPE underperformance in returns.

Our paper contributes to two streams of the prior literature that has examined private equity firms, namely, the literature attempting to understand the riskiness, and performance, of private equity firms. Prior research indicates that relevant information for current performance measurement is privately held so that only the performance on fully realized deals is measurable (Sorensen et al., 2014 and Harris et al., 2014). PE's self-reported values are often biased (Jenkinson et al., 2020) and understate the true variation in the value of PE investments (Jegadeesh et al., 2015). The mechanisms inside a PE remain a black box for investors. However, we can observe sufficiently reliable numbers extracted from audited financial reports and, hence, also performance metrics even on a quarterly as well as stock prices on a daily level.

In addition to the dearth of transparency, the lack of transaction-based performance measures paired with the uniqueness of cash flows and fee structures of each PE prevents investors to assess risk on PE investments properly (Ang, Chen, Goetzmann, & Phalippou, 2018). As our approach is based on publicly available data, we are capable to compute correctly leverage, size, market-to-book, and the idiosyncratic volatility of LPEs - i.e., the main factors of firm risk.

The main contribution of our study is that previous research utilized aggregate fund-level data to observe cash-in at the time of fund inception and the cash-out upon liquidation, only. On the other hand, our study of LPEs offers the advantage that PE fund level characteristics and share price risk and return are observed annually / daily. Hence, our study extends prior work on the riskiness / performance characteristics of PE funds, where previous research considered these a black box and, thus, had to estimate them with an error.

This paper proceeds as follows: Section 2 presents the literature review. Section 3 describes the sample. Section 4 presents descriptive statistics and results. Section 5 reports results for regressions of cumulative returns on selected variables in the setting of the COVID-19 crisis. Section 6 concludes.

2. Literature Review on Private Equity Risk and Performance Characteristics

A variety of studies have attempted to pin down the exact risk and performance of PE firms, with mixed success. Below, we discuss several papers that have examined the characteristics of PE firms to illustrate both the contribution and limitations of prior research. We start first by discussing the unique institutional setting of PE firms.

With a slow growth starting in the 1950s, PE funds came to the mainstream in the 1980s with an explosion of leveraged buyouts made famous by KKR's acquisition of RJR Nabisco, making it the largest corporate acquisition of its decade. As of January 2020, PE funds number 3,524, and over 8,400 institutions invest in PE globally.[5] Although virtually everywhere, researchers and the media cannot agree on the risk and performance characteristics of PE funds. Part of the problem stems from the fact that much of private equity transactions are "private", and reporting is neither transparent nor timely by publicly traded firm standards.

PE funds are investment funds with normally a ten-year maturity, where after setting up of the fund and accumulation of investor capital, the PE fund manager(s) acquire a number of investments (i.e., other companies) to be sold at a profit prior to the 10-year fund maturity period. There is a

[5] https://docs.preqin.com/samples/2020-Preqin-Global-Alternatives-Reports-Sample-Pages.pdf

secondary market for PE positions that is opaque, complicating the re-balancing of PE investments for investors (i.e., LPs) (Sorensen et al., 2014). This leads to investors considering PE as illiquid, exclusive, and long-lasting (Goktan & Ucar, 2012). Measuring the performance of PEs is complicated as information is privately held. The mechanisms inside a PE are a black box for the investor and the issues with finding appropriate performance measurement intensify the obscurity investors find themselves in.

To shed light on this opacity, researchers and practitioners have proposed various approaches to deal with this topic. Methods utilized by researchers and by the PE industry itself include using appropriate comparables for valuation purposes, or some variant of the traditional internal rate of return (IRR) approach. Gompers, Kaplan, and Mukharlyamov (2016) interview 79 PE investors and conclude that only a few of them use Discounted Cash Flow (DCF) or Net Present Value (NPV) techniques but rather rely on comparables and IRR approaches. The latter approach is flawed as PE investors evaluate cash flows to leveraged equity in IRR calculations, which is in contrast with academic advice to evaluate and discount cash flows to an all-equity firm. Moreover, Gompers et al. (2016) reveal that target IRRs seem to be adjusted differently by different PE firms that make use of diverse factors. Therefore, different PE firms tend to also have different target IRRs for the same deal. This dilemma indicates that it is challenging to quantify PE performances even for the same investment, leading IRR to be categorized as a rather highly subjective approach.

To mitigate the shortcoming in IRR based approaches, the public market equivalents (PME) approach developed by Kaplan and Schoar (2005) has been used widely in private equity research to measure PE performance (e.g., Harris et al. (2014), Buchner, Mohamed, & Schwienbacher (2016), Braun, Jenkinson, and Stoff (2017)). The PME is a ratio measuring fund performance by comparing the fund's return to a comparable market equivalent. This equivalent is a market index resembling similar risk in order to scale a fund's market value. For example, a PME of 1.2 indicates that investors in a certain PE fund end up with a return that is 20% higher than the return they would have got if they had invested in the benchmark public market index. Therefore, a PME > 1 reflects a PE investment that is outperforming the market. It is a systematic risk-adjusted performance measure, and hence, the idiosyncratic risk portion remains. When applying the PME approach, Harris et al. (2014) find that buyout funds' performance has consistently exceeded that of the public market. The authors test the computed PMEs across their sample and find that the average PMEs are robust to a range of public market benchmarks. To conduct their study, they use fund-level cash flows gathered from the Burgiss database. However, the structure of the study does not allow to directly measure the risk of the underlying portfolio companies, which represents the risk investors would face when investing in PE. Another limitation this study experiences is that the data for funds that are not fully realized (i.e., investments that have not been fully sold yet) have to be estimated, leading to potentially biased results.

More recently, Braun et al. (2017) using a sample spanning 1974-2013 examine the persistence in private equity performance. The increased sample size allows improvements upon the Harris et al. (2014) study, which only uses realized deals. The authors use an approach similar to the NPV, called the General Public Market Equivalent (GPME), where returns are added to a Fama-French three-factor model to estimate investment level stochastic discount factors. Although the GPME confirms the results derived with the PME methodology of earlier studies, it still is not an accurate measure of PE performance. First, GPME builds on the idea of PME and is consequently likely highly positively correlated with PME. Second, Sorensen et al. (2014) reflect on a shortcoming of the PME method since it implicitly assumes a (levered) beta of one. Their argumentation follows the path that the different cash flows a PE receives, which are the management fees and the shared profit when the fund gets liquidated, have different risk-profiles and should be discounted at a different rate. While management fees are risk-free and should be discounted at the risk-free rate, the shared profit is certainly riskier and should be discounted at a higher rate. Moreover, the PME method does not account for the cost of illiquidity arising from LPs not being able to assess their investment for a long period. Finally, they argue that the (levered) beta of PE investments may not be equal to one as initially assumed in the PME method, further biasing the estimates obtained by using this approach.

The limitations of the GPME, PME, comparables, and IRR approaches are obvious given that neither do they take the liquidity risk premium into account nor do they account for the leverage taken up by PE firms themselves. Franzoni et al. (2012) argue that due to the high levels of debt, PE investments are sensitive to the capital constraints faced by debt providers who are primarily banks and hedge funds. They construct two models to compute alphas resulting from PE investments and to exploit variation in returns across investments to estimate risk. Thus, they fit the four-factor model by Pástor and Stambaugh (2003) to their deal-level data. In the model with liquidity risk, the premia on the four factors entirely account for average PE returns, leading to alphas becoming zero, both economically and statistically. This inference is likely positively biased as their sample comprises the years (1975 – 2006) when the competition in the PE industry was not as intense as today. Braun et al. (2017), for example, argue that competition has clearly increased in recent years. PE, after all, likely mimics the pattern found in other asset classes where past performance is a poor indicator of the future.

To fill in the gap for a proper risk assessment, Buchner et al. (2016) approach this issue with a different and yet creative method. By computing the volatility of IRRs of different deals, the authors develop a metric that measures risk at the fund-level. Based on this metric, they consider upward and downward intra-fund volatility to examine the impact of upside and downside risk on fund performance. This approach has its shortcoming as IRR represents a profitability metric and is not meant to be set equal to the rate of return. Hence, using the volatility of IRR to proxy for a firm's true risk is not an adequate method to resolve this issue. Beyond that, Buchner et al. (2016) strongly and also wrongly assume that deal-level data can substitute fund-level data.

More recent approaches to estimate PE returns and risk involve a Bayesian Markov Chain Monte Carlo methodology (Ang et al., 2018). This methodology estimates a time-series of PE returns using cash flows accruing to LPs and factor returns from public capital markets. However, this method has several limitations which the authors themselves identify. First, the estimations degrade when underlying asset returns are not significantly correlated with the traded factors and when idiosyncratic volatility is extremely high. Second, existing PE returns time series exhibit smoothing biases likely since valuations of illiquid assets such as PE may only partially adjust to market prices. Paired with the findings from the above-discussed studies, these constraints show that there is a lack of transaction-based performance measures. Adding this point to the fact that each PE is unique in its cash flow and fee structure aggravates the search for finding an appropriate PE performance measure.

Finally, we conclude our literature review by discussing the inherent opacity found in the private equity industry as intermediary fund performance values lasting up to 10 years are unaudited and self-reported by PE firms themselves. In a recent study, Jenkinson et al. (2020) analyze whether fair value estimates of funds, the Net Asset Value (NAV), produced by PE managers are accurate and unbiased predictors of future DCFs. As PE funds have finite lives, the authors are able to track cash flow patterns over the entire fund life. Further, the authors need to assume a discount rate and set it equal to 11%, which is the average return from private equity investments documented in Kaplan and Schoar (2005). The study concludes that NAVs provided by GPs, on average, overestimate the returns in the form of DCFs to LPs. The authors themselves indicate a shortcoming of the DCF method as it is impossible to know which rate investors actually use. It is most likely higher than the 11% which slightly exceeds investment returns into public markets that do not have a 10-year illiquidity provision. Besides, investors do not have the information needed about the nature of the underlying investments made by the funds to construct a required rate based on all information needed for an adequate assessment. NAV estimates are only released infrequently, resulting in NAVs used for intermediate valuations understating the true variation in value for these investments (Jegadeesh et al., 2015), and infrequent performance reporting is negatively related to volatility (Botosan & Plumlee, 2002). Moreover, GPs, as any capital market agent, have the incentive to manipulate NAVs for their benefit (see Graham, Harvey, & Rajgopal (2005), and Burgstahler & Dichev, (1997), for a general discussion of earnings manipulations in agency settings).

In summary, and as Lopez-de-Silanes, Phalippou, and Gottschalg (2015) note, the use of aggregate fund-level data, which is the approach used by most PE studies, does not take into account the black box of PE operations. PE funds are not entities run by independent non-incentivized custodians. Absent transparency in regular financial reports and the lack of mandated audits coupled with the supercharged incentives of private equity fund managers make private equity firms highly opaque and susceptible to biases inherent in self-reported values. In this paper, we propose an alternate approach to overcome such shortcomings which uses publicly available data at the individual firm-level. Our study is based on data gathered from financial reports that are transparent in reporting performance and leverage. Finally, this data is also audited, hence, the reported numbers depict a sufficient level of reliability. Decisively, we can correctly calculate investor risk and return by observing stock market data. Our approach provides improved measures for the dimensions of performance, risk, and return that prior studies that examine PE firm performance lack.

3. Sample Selection and Variables

3.1 Sample Selection

To identify our sample of LPEs, we start with BlackRock's iShares listed private equity ETF, which includes LPEs from North America, Europe, and Asia. To eliminate cross-country heterogeneity and construct a homogenous sample we focus only on firms headquartered in the U.S., as this is the only country with a sizeable LPE sample suitable for statistical analyses. Using European or Asian LPEs would create a non-balanced sample, as there is only a handful of LPEs in each respective European or Asian exchange, rendering high country-specific variation to LPE firm characteristics and performance. To account for delisted LPEs and those not covered in the iShares ETF, we extend our sample by identifying other LPEs in the LPX index, the S&P globally listed private equity index, and in the listed private equity firms list of Cumming (2012). To further augment the sample with LPEs not present in any of these sources, we read the profiles of all listed firms available on Compustat to identify whether a listed financial firm is a private equity firm. Our U.S.-based sample starts in 2010 and ends in 2019, the latest year with available financial data. We start the collection in the year 2010 which is the first year with a sizeable sample of publicly traded private equity firms. For example, in the year 2007, there were only 25 LPEs, moreover, the years 2007-2009 coincide with the crisis rendering a large black swan event that potentially distorts the results in unknown dimensions. Our data collection methodology yields 51 distinct LPEs for the period 2010 – 2019. We allow firms to enter or leave the sample during the respective time period although using a constant sample of LPE firms yields inferences unchanged.

We use a number of databases to gather financial data. First, we obtain financial statement data from the Compustat annual database. We only observe firms with non-missing assets (at ≠.), non-missing sales (sale ≠ .), and non-missing fiscal year-end month dates. Moreover, we do not include firms that are already consolidated as part of another entity (hence, stko = 0). We merge this database, depending on the analysis, with the CRSP daily or monthly file to obtain returns data. Given that our analysis focuses on the performance of private equity firms, we require that LPEs are jointly present on both CRSP and Compustat. We further exclude all firms with negative book values of shareholder equity for any of the given years. Our core sample of LPEs is comprised of 384 firm-year observations over the years 2010-2019.

To conduct relevant benchmarking analyses, we prepare a sample of non-financial Compustat / CRSP firms, with non-missing assets, non-missing sales, and non-negative book values of shareholder equity, giving us 20,937 firm-years for the benchmark during the same sample period. It is difficult to ascertain what is an appropriate benchmark for a typical PE firm, as PEs hold a portfolio of investments of different sizes and industries. The publicly traded market value of a private equity firm is often estimated through the NAV, available only quarterly and defined as the expected yield from holding a portfolio of target firms for a *t* amount of years. As performance fees constitute a large portion of a private equity firm's revenue, the market value of an LPE which anticipates future cash flows to investors is a poor approximation of the underlying size of the portfolio firms. Hence, LPEs' market value could deviate from the current reality depicted by the NAV. This shortcoming is similar for using the book value of assets of the PE firm, as Jegadeesh et al. (2015) argue. Hence, for most of our analysis we do two types of analyses: first, a comparison with the universe of non-financial firms as PE firms typically operate in a variety of spaces except for financial services (although increasingly so, in the recent time period). Second, a risk-adjusted analysis that examines the performance of an LPE with respect to the benchmark while holding risk constant.

3.2 Variables

We compute several variables. We calculate compounded raw returns over the calendar year, *Return*, using CRSP monthly share price data. We require 12-months of consecutive observations otherwise we assign a missing value. We further calculate two more risk-adjusted share returns, *ReturnFF* and *ReturnDGTW*. We obtain daily Fama-French factors from Kenneth French's website. We calculate alpha as the intercept from regressions of daily raw returns on the market, size, book-to-market, and momentum factors. We multiply the intercept, alpha, by 252 for annualized returns. This methodology mimics that of Jagolinzer, Larcker, and Taylor (2011). Similarly, we mimic the methodology of Daniel et al. (1997), who use monthly returns in their calculations. *ReturnDGTW* is firm-level stock returns adjusted for a benchmark portfolio of similar size, book-to-market, and momentum. The latter variable needs two years of data for computation; hence, it is more restrictive than *ReturnFF* and has fewer observations.

As a measure of risk, we calculate the volatility of share returns using CRSP daily data. Specifically, we calculate the idiosyncratic volatility of each firm, *Idiosyncratic Volatility*, using the methodology devised by Shin & Stulz (2000) on a calendar year basis. For each firm, we regress firm daily returns on the CRSP value-weighted market returns, where idiosyncratic volatility is calculated as the variance of the residual over the calendar year. We calculate Sharpe ratios (Sharpe, 1966), *Sharpe*, as annualized returns minus the yearly Treasury rate, normalized by the annualized standard deviation.

To understand firm fundamental characteristics, we calculate a variety of variables from accounting numbers. *Leverage* is calculated as long-term debt divided by total assets. *ROE* is calculated as net income before extraordinary items, normalized by the book value of equity. We calculate the book value of equity according to the method proposed by Davis, Fama, and French (2000) as the sum of shareholder equity, negative preferred stocks, deferred taxes, and investment tax credit. Given that private equity firms are heavily levered and, hence, riskier, *ROE* often paints a distorted picture of firm operating performance. Therefore, we also calculate return on assets, *ROA*, as net income before extraordinary items divided by total assets. We also compute the market-to-book ratio, *MB*, as the market value of the firm normalized by the book value of equity. The former variable is calculated by multiplying the share price by the total shares outstanding on the last trading day of the fiscal year to match its book value. To avoid micro-stocks, we set the condition that the market value for a firm in our benchmark must be ≥ $100m for any given year. To avoid unnecessary skewness, we set all values for *ROA* and *ROE* that are larger (or lower than) 100% (-100%) to exactly 100% (-100%), prior to winsorizing all financial metrics at the 1%-level. Finally, we define S*ize* as the book value of total assets. Appendix A gives an overview of all variables presented in this paper.

4. Descriptive Statistics and Results

4.1 Descriptive Statistics

We first start our analyses by presenting descriptive results on the characteristics of our sample of LPE firms. In all variables of interest, we also compare our results to the relevant benchmark, as explained in each respective section. Table 1 presents descriptive statistics on selected variables where Panel A shows results for our LPE sample and Panel B results for the benchmark firms. We see that the median LPE has total assets worth \$0.8bn, while the median benchmark company is worth \$1.2 billion. The standard deviation for *Size* is large for both groups, indicating that there is a large dispersion in the book value of assets across firms in each group. Given the bigger sample size, the dispersion is, as expected, bigger in the benchmark. *ROA* is qualitatively similar across both sets of companies where the median firm is successful with a yearly *ROA* of a bit less than 4%. Typical of non-value weighted means – in the case of the benchmark, the mean in *ROA* becomes negative (-0.2%) and indicates that the distribution of *ROA* is left-skewed. We observe the same trend in *ROE*. Both groups produce a median *ROE* of about 7.5% throughout our sample period, but the benchmark exhibits a more extreme left-skewness. Median *Leverage* is markedly higher for LPEs with 36.1% compared to 19.3% for the benchmark, and that is expected given the high financing rate of a typical private equity firm. Median *MB* is lower for LPE firms (1.0 vs. 2.4 for the benchmark) as is typical for PE firms as they have traditionally invested in lower-risk companies such as in entertainment, tourism, FMCG, leisure, and retail – and are not as active in high-risk 21st-century economy firms such as pharma, software, and high-tech (although this has been changing in the most recent time period). Moreover, the majority of LPEs report their investments, which represent a large of an LPE's equity, at fair value, thus, naturally preventing an extreme over- or undervaluation by the market. This trend is also observable in the 75th-percentiles of *MB* in both groups. While the value for benchmark *MB* goes up as high as 4.22, the value for LPEs being 1.11 only slightly deviates from its initial value of 1. The performance-related variables *ReturnFF*, *ReturnDGTW*, and *Sharpe*, which are the subject of this manuscript, will be examined more in detail in the next section. However, we give a brief overview here of the descriptive statistics for these variables. Over our sample period, LPEs earned, compared to the benchmark, a 0.9% higher risk-adjusted alpha, but 1.3% less excess return when measured with the method proposed by Daniel et al. (1997). Due to the bigger sample size and larger inherent variability of firm characteristics, standard deviations for *ReturnFF* and *ReturnDGTW* are both considerably larger for the benchmark. This itself is true by construction: LPE firms hold a portfolio of companies, and absent perfect correlations among them, risk is reduced. For *Sharpe*, we observe that LPEs have a Sharpe ratio larger by 1% and that the values for this variable are similarly spread out between the two groups. For illustrative purposes, we multiply the initial value of *Idiosyncratic Volatility* by 1,000, and we report the median value for *Idiosyncratic Volatility*. For the benchmark, a value of 38.3% is more than double the magnitude of the 16% volatility of LPEs. As discussed previously, as private equity firms invest across various industries, risk profiles within the LPE group should be widely spread out. Although LPEs are more highly levered, this is not reflected in *Idiosyncratic Volatility*. In further sections, we investigate why the *Idiosyncratic Volatility* standard deviation remains relatively low.

Overall, Table 1 shows that especially the distributions of the accounting variables are highly skewed. Thus, we decide to focus our analysis in the following sections on the median values of *leverage*, *ROA*, *ROE*, and *MB*. Our results remain mainly unchanged when considering instead mean values except in the highly skewed cases of *ROA* and *ROE*.

4.2 Time-Series Analysis

To observe how the selected variables change throughout the observed period, we present a graphical time-series analysis of each variable.

(Please insert Figure 1 over here)

We first look at firm leverage. PE firms have a long tradition of making full use of the leverage effect to boost returns (see Talmor & Vasvari, 2011), and we expect that our sample of LPE firms to be the same. We present median leverage ratios, *Leverage*, in Figure 1. Results clearly indicate that LPEs have a much higher leverage ratio over the full sample spanning 2010-2019. Leverage rates are roughly equal between LPE firms and our benchmark sample at the beginning of the time period 2010-2011 when financing was scarce and credit markets had frozen in the immediate period right after the great 2008 crisis (see Chodrow-Reich, 2014). However, with the easing of credit markets and the availability of capital, we see that LPE firms have taken full advantage of increasing their leverage ratios in order to boost shareholder returns, while industrial firms have not.[6] Starting from a low leverage rate of 12.6% in the early time period, it increases to 47.8% in 2019. Although there is also a corresponding increase in the leverage ratio of benchmark firms since credit markets eased for all firms, the increase from 14.1% to 24.7% appears small compared to LPEs' leverage. It is obvious that LPEs take full advantage of access to credit, but are also at the same time riskier.

(Please insert Figure 2 over here)

Next, we examine two accounting measures of performance, *ROA,* and *ROE*, in Figures 2 and 3. We present the median values of *ROA* in Figure 2. In the period spanning 2010-2011, *ROA* is roughly equal in both groups. Afterwards, LPE *ROA* rises so that it is consistently higher over the period 2011-2013, reaching its peak in 2012 at 5.7%. Meanwhile, benchmark *ROA* shows a declining trend throughout our sample period (from 4.1% to 2.6%). Though, LPE *ROA* is more volatile. That leads to LPE *ROA* being, compared to the benchmark, much lower in 2015, much higher in 2017, and roughly equal to it in the other years. LPE *ROA* experiences a major decline from 5.7% in 2012 to 2.2% in 2015. In the remaining four years of our sample period, *ROA* stays in a tight band of 3% to 4%. Looking at the operational aspect of firm performance, we see that LPEs yield neither consistently higher nor consistently lower *ROA*, as compared to benchmark firms.

(Please insert Figure 3 over here)

Next, we illustrate the development of the median Return on Equity, *ROE*. Because of the higher LPE leverage ratios and the trend towards more leverage in both groups throughout our sample

[6] The notion that industrial firms do not fully utilize the benefits of leverage is the subject of many studies (e.g. Molina (2005), Korteweg (2010))

period (although LPE leverage ratios increase more steeply, as observed in Figure 1), we expect *ROE* to be increasing overall for both groups, and a steeper increase for LPE firms in particular. Moreover, we expect LPE *ROE* to be much more volatile given the volatility of *ROA* in Figure 2. However, Figure 3 shows that our benchmark experiences a steady declining trend in *ROE* (from 8.3% to 6.4%) similar to the one we depict in Figure 2 for *ROA*. While we confirm here our claim of a more volatile *ROE* for LPEs, we also observe that LPE *ROE* is only higher than the benchmark's in 2013 and slightly higher in 2017 and 2019. For all other years, LPE *ROE* is either below or almost equal to benchmark *ROE*. LPE *ROE* follows an almost convex function by increasing from 5.3% to 9.4% in 2010-2013 and decreasing again to 4.9% from 2013 to 2015. For the remaining years, LPE *ROE* settles in a band between 5% and 8%. Overall, we do not observe the expected increase in overall *ROE* and a higher LPE *ROE*.

(Please insert Figure 4 over here)

Thereafter, we investigate the evolution of the median market-to-book ratio, *MB*, over our sample period in Figure 4. As LPE leverage experiences a constant increase while LPE *ROA* and *ROE* show a high degree of volatility over the same period of time, we do not anticipate the market to overvalue LPEs. Figure 4 verifies our claim, and surprisingly, investors value LPEs almost exactly at their book values throughout the entire sample period. We described this phenomenon in section 4.1 by pointing out the portfolio-based risk reduction of the PE industry paired with the fair value accounting practices. On the other hand, the benchmark *MB* always exceeds the value of 1. While *MB* starts with a value of 2 in the period 2010-2012, it undergoes a major increase of 0.4 in the period 2012-2013. In the subsequent years, benchmark *MB* stays roughly at the level of 2.5, including a spike at 2.8 in 2017, reflecting the period's economic boom.

(Please insert Figure 5 over here)

Figure 5 presents idiosyncratic volatility, where LPEs have consistently a lower median value for *Idiosyncratic Volatility* throughout our sample period. Both lines follow the same trend for most of the years. However, between 2010 and 2011 as well as between 2018 and 2019 LPE *Idiosyncratic Volatility* decreases whereas benchmark returns become more volatile. While the gap between the two groups is

12.1% in absolute terms in 2010, this gap increases to about 34% in 2019 given the booming market conditions. LPE volatility seems to be mostly driven in the same direction by the same factors that drive the benchmark volatility. Whereas LPEs experience the lowest value for *Idiosyncratic Volatility* in 2019 at 10.1%, the same value for the benchmark is at its peak in 2019 at 44%.

(Please insert Figure 6 over here)

To show whether LPE investors have to forfeit returns for the lower risk, we present median annualized returns in Figure 6. Returns for LPE are certainly higher at the beginning of our sample in 2010 (45.4% and 23.4% for the benchmark). In the following year, LPE returns decrease significantly to -8.1% and increase again sharply in 2012 to 27.8% when the benchmark yields considerably lower returns at 13.8%. In 2013, the benchmark outperforms LPEs by 20.81%. Thereafter, returns for LPEs are below the ones of the benchmark until 2015 when both groups start to follow a similar trend of the same magnitude. Only in 2017, LPE returns are smaller (4.5% and 15.3% for the benchmark). Throughout our observed period of time, LPE returns as well as benchmark returns deviate in wide spans of about 50%, making the returns for both groups very volatile. We do not observe that LPEs have either noticeably smaller or larger returns. Figure 6 further shows that the biggest differences in returns between both groups appear in three years: 2010, 2012, and 2013. We add the S&P 500 median annual returns to demonstrate how these returns relate to the overall market. The index follows a trend in returns that is aligned to the one of the benchmark's returns. LPEs outperform the benchmark in five out of nine years (not considering 2015) and the market in three of nine years. We do not consider the years 2015 in the former, and 2018 in the latter case, as the differences between the return values between LPE and the benchmark or market are too marginal in these years.

(Please insert Figure 7 and 8 over here)

Next, we elaborate on the figures that consider risk-adjusted returns and should be at the heart of understanding LPE performance. Figures 7 and 8 combine the findings of Figures 5 and 6 by showing risk-adjusted median excess returns, *ReturnFF,* and *ReturnDGTW*, respectively. To be able to validate our results we observe in Figure 7 for *ReturnFF*, we expect similar trends in Figure 8 for *ReturnDGTW*. However, as the method proposed by Daniel et al. (1997) applies more restrictions that favor the returns of the benchmark firms get compared to in their setting, we anticipate lower excess returns in Figure 8. Starting with Figure 7, we immediately see that the line for benchmark alphas can be smoothed at the intercept of about 3%. Benchmark *ReturnFF* is very stable and does not experience significant positive or negative jumps in our sample period except for the smaller ones between 2010 and 2012. This is expected as benchmark *ReturnFF* essentially approximates market returns and these are, once adjusted for risk, zero on average. Since we exclude financial and small-cap firms from the benchmark sample, this curve shifts up. On the other hand, LPE *ReturnFF* is highly volatile and ranges from -9.2% to 20.5%. Only in the years 2013 (-5.7%), 2014 (-9.2%), and 2017 (-1.7%) does investing in LPEs yield negative excess returns. However, the years 2010 (20.5%), 2012 (11%), 2016 (11.3%), and 2019 (13.5%) are highly profitable ones for LPE investors. This volatility is expected: LPE firms realize large fair-value-based returns when they exit investments, and such exits are particularly value-adding in boom years. On the other hand, industrial firms' accounting performance is more smoothed over time and is affected less by the business cycle.

In sum, we see that the benchmark constantly outperforms the market, whereby LPEs most of the time significantly out- or underperform the market with absolute excess returns larger than the benchmark's ones. *ReturnFF* is higher for LPEs in four and lower in six out of the ten years. This finding adds to the complexity of the LPE asset class: when reflecting on the findings illustrated in Figure 5 and Figure 6, we do not observe that the consistently lower idiosyncratic volatility and outperforming the benchmark in five out of nine years leads to consistently or at least to predominantly higher *ReturnFF* on the side of LPE. Moreover, we note that the line for LPE *ReturnFF* follows a pattern similar to the one for annual returns in Figure 6. As in Figure 6, LPEs have spikes in *ReturnFF* in 2010, 2012, 2016, and 2019. We confirm our main results in Figure 8. As expected, excess returns are in most cases smaller than in Figure 7, leading that *ReturnDGTW* for the benchmark can be smoothed at the zero intercept. However, LPE *ReturnDGTW* exceeds that of the benchmark in the same years as in Figure 7. Further, we see that the gap between the lines gets significantly bigger when LPEs show negative excess return, leading to LPEs performing worse in these years. This disparity bolsters our claim that the trends from Figures 5 and 6 do not automatically lead to consistently outperforming the benchmark if returns are risk-adjusted.

(Please insert Figure 9 and 10 over here)

To analyze the structure of *ReturnFF* and *ReturnDGTW* for LPEs and our benchmark, we divide our sample into terciles based on mean *ReturnFF* in Figure 9 and mean *ReturnDGTW* in Figure 10. In Figure 9, we demonstrate that the top LPE tercile consistently outperforms the model's benchmark but is itself outperformed by our benchmark throughout the entire sample period (2010 being an exception). On the other extreme, LPEs consistently underperform compared to the model's benchmark but outperform our benchmark in the bottom tercile. In the middle tercile, we observe that the line for benchmark alphas is consistently over the line intersecting zero while the line for LPEs moves around zero, thus, showing a higher degree of volatility. Overall, while all three lines for our benchmark are relatively flat, the ones for LPEs are generally volatile. We demonstrate that tercile *ReturnFF* across the benchmark is widely spread out moving in the range of approximately -40% to 40% whereas *ReturnFF* for LPEs are more centered around zero ranging in most years from approximately -20% to 20%. Given that we observe a rather homogenous group of firms within LPEs in terms of financial metrics and a heterogenous one within the benchmark, the disparity between those groups is unexpected. As already noted, private equity firms invest in different industries and it is not certain how the various industry risks affect risk-adjusted returns. This finding gives the first indication that LPE performance is more linked to certain financial characteristics such as leverage than to the industry risks of portfolio companies. Further, we show that the bottom tercile in both groups consistently underperforms.

Figure 10 confirms these findings. When observing *ReturnDGTW*, we see that the top benchmark tercile is much more volatile compares to the relatively flat middle and bottom benchmark terciles. Another difference to Figure 9 is that the line for the bottom LPE tercile moved closer to the line for the bottom benchmark tercile, which is only slightly lower aligned than in Figure 9. While the middle and bottom tercile *ReturnDGTW* for the benchmark are indistinguishable from the ones shown in Figure 9, its LPE counterpart performs now worse. In sum, we are able to show again that in both cases the bottom tercile underperforms and that the top tercile outperforms the model's benchmark.

(Please insert Figure 11 over here)

Finally, we depict another median excess return figure, *Sharpe*, which is returns scaled by the standard deviation to account for risk. At first glance, we note that *Sharpe* for LPEs and the benchmark move in eight out of the ten observed years in the same direction. In the period spanning 2014 – 2015, LPE *Sharpe* stays flat while benchmark Sharpe declines, and in the period 2016 – 2017, the opposite is the case. Moreover, we present that LPEs considerably outperform the benchmark in the years 2010 (1.4 and 0.7 for the benchmark), 2012 (1.2 and 0.4 for the benchmark), and most recently in 2019 (1.6 and 0.6 for the benchmark). While the benchmark outperforms LPEs in the period 2013 – 2015, none of the values of *Sharpe* is considerably larger than its LPE counterpart. In the case of LPEs, *Sharpe* is negative in four years and outperforms the benchmark in four years. Benchmark *Sharpe* is negative twice (2011 being too close to zero to consider it significantly negative). It is an interesting finding that if LPEs do outperform the benchmark they do so by a large margin. However, out of the ten observed years, the benchmark outperforms LPEs in six of them. Besides, Figure 11 follows most of the time the trends for annual returns in Figure 6. A major difference between the LPE trends in those figures is the large outperformance of LPEs in terms of *Sharpe* in 2019 which is not prevalent in that magnitude in Figure 6. We also discern that the difference between the two observed groups reached its peak. Given that the excess return is discounted by its standard deviation, we can explain this trend with a smaller discount rate in 2019 for LPEs if we take the trend for *Idiosyncratic Volatility* from Figure 5 for 2019 into account.

Our three risk-adjusted return figures, *ReturnFF*, *ReturnDGTW*, and *Sharpe* are not supportive of the claim that LPEs and, therefore, PEs generate abnormal returns that constantly outperform their peers (and in our case, our benchmark). In most years, our benchmark outperforms LPEs which is surprising as Figure 5 shows that LPEs exhibit consistently lower *Idiosyncratic Volatility* and Figure 6 does not show that LPEs perform considerably worse than the benchmark in terms of median annual returns. We assume that the lower LPE *Idiosyncratic Volatility* does not lead to a lower discounting of returns as previously thought. One explanation could be, given that volatility is a function of risk and information, the lower volatility of LPE firms is a consequence of their lower information environment: under-the-radar operations, investments into low-hype "value" industries, and their general lack of visibility in the media. It is not surprising, that although Blackstone, KKR, TPG, and Carlyle are all household names in finance, it is difficult that one can name a single company that they own. This lack of transparency / information is exacerbated when the subject is not a household private equity firm.

4.3 Differences in Means

So far, we have presented descriptive statistics and graphical analyses to introduce differences in share price and firm characteristics of LPEs and our benchmark firms. Next, we investigate whether our reported differences are statistically different. Table 2 presents the results of two-tailed t-tests on the selected variables between the two groups. The last two columns depict the difference in means for each variable and the respective t-statistic. Starting with the variable S*ize*, the difference in means of about $3.4 billion is statistically significant. Although we do not note a difference between the median values of *ROA* between the two groups, the skewness of the distribution of *ROA* leads to a highly statistically significant difference of 3.0% in absolute terms. Similarly, the difference in *ROE* is approximately equal to the one detected for *ROA* (3.5% in absolute terms) and is significant at the 5%-level. Further, we notice that LPEs have a considerably higher median value for *Leverage*. The difference in means for *Leverage* is highly statistically significant at 11.5% in absolute terms and reaches the highest t-statistic (|-12.14|) for all tests displayed in Table 2. Thus, this finding allows us to bolster our point that high financing rates that are typical in the PE industry, thus, also relate to LPEs. Next, we observe a highly statistically significant difference of 2.8 in *MB*. We assume that this difference is mostly driven by the fact that LPEs' accounting practices of valuing their investments at fair value allow for a closer approximation of the market to the book values of equity. This is not the case for the book equities of benchmark firms. Regarding *ReturnFF* and *ReturnDGTW,* the observation that the median values of these values between both groups only deviate by a small portion is also reflected in the difference of means. For *ReturnFF*, we compute a difference of 0.7% that is statistically insignificant. On the other hand, *ReturnDGTW* yields a much larger difference of 4.8%, but statistically indistinguishable from zero only at the 10%-level. Our third return metric, *Sharpe*, also indicates that its difference of 1.9% in absolute terms is statistically insignificant. Finally, our measure of risk demonstrates that there is a highly significant difference between LPEs and the benchmark in *Idiosyncratic Volatility*.

None of the differences in the risk-adjusted return measures between both groups is highly statistically significant. Although LPEs have higher *Sharpe* than the benchmark and *ReturnFF* as well as *ReturnDGTW* are considerably higher in terms of the mean values, we cannot confirm the anecdotal claim that LPEs as representatives for the PE industry yield higher returns and thus perform better. However, we can note significant differences in firm characteristics and in *MB* as well as in *Idiosyncratic Volatility* and *Leverage*.

5. Financial flexibility in the COVID-19 crisis

Gompers et al. (2016) show that PEs think that absolute performance measures such as IRR are more important to LPs than measures relative to the public market. However, the lack of transparency surrounding PE firms makes information arrival non-constant, self-selected by management, and regulatory 10-K and 10-Q filings are inadequate. In other words, PE firms suffer from a dearth of information and are inherently riskier. Given these arguments, we assume that investors either do not pay much attention to the fact that PEs are highly levered compared to the market, or they assume that PE firms have superior capabilities in managing financing, or, and finally, that PE firms' higher leverage is mitigated by the fact that a single LPE is a collection of potentially uncorrelated investments. In this section, we empirically show that leverage and financial flexibility influence the persistence of returns, especially in times of crisis: firms with weaker balance sheets are affected more by its negative effects (Kahle & Stulz, 2013). Based on our previous findings that LPEs are fundamentally different from our benchmark, we test the hypothesis that LPEs do not under- or outperform our benchmark in times of crisis. The COVID-19 crisis is an example of a financial crisis caused by an exogenous shock. The sudden stop in being able to operate businesses leads to a firm's reliance on its cash reserves. However, as firms experience lower or no revenues at all during these times, less financially flexible firms (i.e., firms with higher leverage and/or fewer cash reserves) should be perceived as riskier by investors.

5.1 Univariate T-Tests

First, we conduct two-tailed t-tests to determine if there is a significant difference between cumulative returns for LPEs and the benchmark during the COVID-19 crisis. We define the period "fall" which ranges from March 4 to March 23, 2020, which are the early and heavy stock market turbulence at the start of the crisis. Moreover, we define "recovery" which ranges from March 4 to June 5, 2020. We identify June 5 as the end of the observed period of time as the S&P 500 index recovers then fully to the initial level of March 4. Thus, period "recovery" contains 66 trading days. To reduce errors, we include observations only if returns for all 66 trading days are available. Moreover, we only include firms for which we have full financial data available for the end of the fiscal year 2019. We calculate returns for both the "fall" and "recovery" periods and utilize them in our tests.

Table 3 Panel A shows the t-test results for the period "fall" and "recovery". The sample is comprised of 44 LPE and 1,277 benchmark observations. Comparing the means for the period "fall", we see that LPEs are more strongly affected by this exogenous shock. The mean in cumulative returns is about -52.2% for LPEs compared to a mean of -33.3% for the benchmark, leading to a highly statistically significant difference in means of 18.9% (t-statistics = 6.90). Due to the bigger sample size, benchmark returns are more spread out (standard deviation: 17.9%) than LPE returns (standard deviation: 13.5%). We are not surprised that cumulative returns are negative and large in magnitude at the beginning of the COVID-19 crisis. The distribution of returns is almost symmetrical around the mean as we observe that the median values are almost equal to the means in both groups, the difference between these two statistics in absolute terms being 2.6% for LPEs and 0.4% for the benchmark.

To account for the possibility that our results occur due to our arbitrary definition of the period length, we run the same t-tests again in Panel B but extend the length of the period. The period "fall" starts now on February 19, 2020, when the S&P 500 reached its peak in 2020 right before the outbreak of the crisis started to impact US markets. The index fully recovered on August 21, 2020. In this new and extended period, the number of trading days we observe increases from 66 to 130. To be able to confirm our results from Panel A, we expect no change in our earlier inferences. Our benchmark sample size decreases in Table 3 Panel B by 14 observations to 1,263 while our LPE sample size stays the same (N=44). Due to the longer fall period, the means for cumulative returns decrease even sharper to -57.1% for LPEs and -40.1% for the benchmark. However, the difference in means gets smaller by approximately 2% (the difference being 16.9%) but remains highly statistically significant (t-statistics: 3.97). Returns for the benchmark are even more spread out in the longer period (standard deviation: 28.2%) while LPE returns become slightly more concentrated around the mean (standard deviation: 12.2%). As in Panel A, the distribution of cumulative returns stays relatively centered around the mean. Overall, we are able to demonstrate that during the outbreak of the COVID-19 crisis investors expected LPEs to perform worse compared to the benchmark. The results obtained in Panel A and Panel B show that the difference between these expectations is highly statistically significant and irresistible to a subjective choice about the start of the crisis.

Next, we perform two-tailed t-tests on the entire period "recovery" to examine if there is a significant difference in means even when taking the longer recovery phase into account. If it were the case that LPEs recover much quicker than the benchmark, we would expect the difference between means to decrease by a high magnitude in comparison to the differences obtained for the period "fall". Panel A shows that the mean of cumulative returns for LPEs still stays negative (-14.5%) while the benchmark is able to achieve positive returns (2.7%) on average over the same time period. This difference is highly statistically significant (t-statistics: 4.68) and with 17.2% only slightly lower than the difference in means for the period "fall" (18.9%). As the number of observed trading days increases, we also see an increase in standard deviation for both groups (LPE: 17.6%, benchmark: 24.2%). Both distributions become more positively skewed compared to the distribution observed in period "fall". We assume that this is the result of a marginal number of stocks experiencing an intensive recovery phase compared to the rest of the group.

Panel B presents the results for the extended period. We apply the same rationale as previously, namely to account for selection bias. As the longer "fall" period weighs in more, returns for LPEs drop to -24.8% while benchmark returns become again negative to -3.9%. Yet, we observe that the difference of 20.9% between those returns is higher than the comparable difference for the shorter period (16.9%). The difference remains statistically significant at the 5%-level (t-statistics: 2.27). Further, we notice a vice-versa effect as opposed to the one in the "fall" period. While the difference in means dropped by ~2% when extending the "fall" period, the difference observed for the period "recovery" increases by more than 3% when extending the period. Hence, LPEs must have recovered faster than the benchmark in the shorter period compared to the longer period. However, this recovery advantage is only marginal as the benchmark overall performs significantly better in the entire period. Returns for the benchmark become more widely spread out (standard deviation: 61%) whereas returns for LPEs only get marginally more spread out (Standard deviation: 18.9%). Even after observing more trading days, the distribution of cumulative returns stays slightly positively skewed. In sum, we do not observe the huge decrease in the difference of returns between groups in Table 3 to be able to prove the claim that LPEs recover much quicker.

Ultimately, we reject the hypothesis that cumulative returns for LPEs are indistinguishable from the returns of the benchmark. Our t-tests show that we can do so for both periods and our results are robust to the choice of period length.

5.2 Multivariate Regression Analyses

In Table 4, we estimate regressions of cumulative returns on measures of financial flexibility as well as on stock and firm characteristics. To proxy for financial flexibility, we compute cash over assets, short-term debt over assets as well as long-term debt over assets, hereafter *Leverage*. Firm characteristics include a metric for firm size (computed as the natural logarithm of *Size*) and *ROA*. Stock characteristics consist of market-to-book, *MB*, and *Idiosyncratic Volatility*. All characteristics relate to the fiscal year 2019. To account for the concerns that large share repurchase programs and dividend payments decrease financial flexibility through less retention of cash flow (DeAngelo, Goncalves, and Stulz, 2018), we also control for payout over assets, which we define as the sum of total dividend and share repurchases divided by total assets. Next, we include an LPE-dummy that is set equal to one if the respective observation is an LPE and zero otherwise. The sample we use to construct Table 4 consists of all LPEs and benchmark firms with full financial data available for 2019, the last reporting date before the crisis. We run the regression for each of our predefined periods "fall" and "recovery" adapted from section 5.1 twice for the shorter and longer periods. We report all results as clustered on an industry-level. Industry classifications are implemented from Fama and French (1997). To not mix the effects of within industry variation with the one solely attributed to LPEs, we exclude LPEs from their initially assigned industries by creating a new industry code that covers only LPEs. Finally, we re-run the regressions for both periods including industry fixed effects in which we exclude the newly created LPE industry. Estimation results without industry fixed effects are displayed in columns (1) and (2) while results including industry fixed effects are shown in columns (3) and (4).

Panel A shows coefficient estimates for all presented covariates for the shorter periods "fall" and "recovery" as described in Table 3 Panel A. We find that the coefficient for the dummy for LPE is negative and highly statistically significant for "fall" (-5.4%). After accounting for time-invariant industry effects, the dummy experiences an increase in absolute terms for "fall" (-9.6%). This indicates that LPEs after controlling for financial flexibility, stock and firm characteristics undergo a sharper decline in returns compared to the benchmark in the "fall" period. Considering industry-fixed effects within the benchmark, the negative effect of being an LPE on cumulative returns gets bolstered. We do not observe a statistically significant effect of the LPE-dummy regarding the "recovery" period. Results show that LPEs are more vulnerable to the initial exogenous shock caused by COVID-19.

Considering the cash metric, the coefficient for cash over assets is positive and significant in both periods (16.4% in column (1) and 13.2% in column (2)), indicating that higher cash reserves lead to higher cumulative returns. Yet, the coefficient is only significant at the 10%-level in the "recovery" period. When including industry-fixed effects, we observe in columns (3) and (4) that the coefficients decrease by approximately half (6.9% and 7.3% respectively) and become statistically insignificant. Results denote that a firm with more cash holdings related to its assets does not perform better due to its holdings but because the industry it operates in holds usually more cash.

Next, we analyze the coefficients on the two debt metrics, short-term debt over assets and *Leverage*. The coefficients for short-term debt over assets are statistically not different from zero before and also after accounting for industry-fixed effects. Conversely, we see that the coefficients for *Leverage* are negative and highly statistically significant even after including industry fixed effects. They are similar for both regressions on "fall" in which an increase of one unit in *Leverage* leads to a decrease in cumulative returns of -26.7% and -27% in (1) and (3). Examining the entire time horizon, the effects drop in absolute terms to -13% and -10.8% respectively, but still highly significant in column (2) and at least significant at the 5%-level in column (4). In our previous analyses, we observe that LPEs differ from the benchmark, especially in *Leverage*. Here, we also show that *Leverage* remains a highly statistically significant determinant of returns in both periods and in a setting with and without fixed effects. Hence, we include the interaction between the LPE-dummy and L*everage* as a further independent variable to determine the effect of *Leverage* within LPEs. We find that within LPEs, the firms with higher *Leverage* also yield lower returns. The interaction variable is highly statistically significant in all four regressions and the effect for the "fall" period is -20.5% in (1) and -23.7% in (3) as well as -34.7% in (2) and -38.7% in (4) for the "recovery" period. Our results exhibit that *Leverage* as a measure of financial flexibility is a highly statistically significant determinant for the LPE underperformance in returns.

As discussed, we incorporate payout over assets to account for the claim that repurchase programs and dividends could have led firms into a situation of financial constraints. However, we do not observe an effect that is distinguishable from zero in any of the four estimations. We cannot provide evidence that is supportive of this claim.

Interestingly, the firm characteristics that we take account of, namely *ROA* and the natural logarithm of *Size*, have significant effects on cumulative returns, but only either in the "fall" or "recovery" period. *Size* has a significant positive effect when observing the entire period until full recovery, its coefficients being 1.3% in both (2) and (4), respectively. In contrast, *ROA* only has a significant positive effect in the "fall" period. A one-unit increase in *ROA* leads to a 9.7% and 11% increase in cumulative returns in (1) and (3). This indicates that the 2019 profitability measure in the form of *ROA* leads to the perception by investors that a firm would be less affected by the exogenous shock regardless of its size. In the recovery phase and with the lowered anxiety about the COVID-19 virus, both profitable and unprofitable firms recovered equally. The main variable that affected share price returns in both phases is firm size, which perhaps reflects bankruptcy risk.

To control for risk, we include 2019 *Idiosyncratic Volatility* (here, not multiplied by 1,000) in our regressions. We do not observe that volatility has a significant effect on returns in the "fall" period. Though this effect becomes highly significant when considering the entire period, and the signs of the coefficients switch from being negative with -1.8 and -1.4 in (1) and (3) to being positive. A one-unit increase in volatility leads to an 18.4 and 17.3 increase in cumulative returns in (2) and (4) for "recovery". *MB* as the second stock characteristic has no impact on cumulative returns that is different from zero.

Overall, the results in Panel A of Table 4 show that cumulative returns depend mainly on three covariates in our setting which are not affected by time-invariant effects. One of them is the LPE-dummy in the "fall" period and another is *Leverage* as one of the measures of financial flexibility. Nevertheless, it seems that LPEs and, thus, firm and financial characteristics that appear mostly within the LPE industry are more important determinants of cumulative returns during the COVID-19 crisis as shown by the interaction of the LPE-Dummy and *Leverage*.

To account for the possibility that our choice of the period length affects our results, we run the same regressions again, but for a longer period of time. We expect our results to be independent of the arbitrary choice of period lengths. The periods resemble those we also use to construct Table 3 Panel B. Table 4 Panel B confirms our results that the LPE-dummy and *Leverage* are the most important determinants of cumulative returns even when considering additional trading days before and after the shorter period.

The coefficient for the LPE-dummy is negative and highly statistically significant in all four regressions. However, we observe that the effects are of much larger magnitude and now also highly significant in the "recovery" period in comparison to the same regressions run in Panel A. The coefficients for the "recovery" period are -14.1% and -13.4% in (2) and (4) (1.5% and -0.3% in Panel A). Hence, extending the period shows that LPEs recover much slower from an exogenous shock such as COVID-19 since we observe an increasing disparity between LPEs and non-LPEs in the coefficient of the LPE-dummy.

Leverage remains an important and highly statistically significant predictor of cumulative returns in all four regressions. Compared to the results reported in Panel A, the negative effect of having more *Leverage* gets intensified. Without accounting for industry-fixed effects, the coefficients increase in absolute terms to -30.8% (from -26.7%) in (1) and to -20.2% (from -13.0%) in (2). As in Panel A, the effect increases in magnitude in period "recovery" after including industry fixed effects. The coefficients increase in absolute terms to -30.8% (from -27%) in (3) and to -16% (from -10.8%) in (4). Interestingly, the interaction between the LPE-dummy and *Leverage* is not significant anymore when excluding fixed-effects. Hence, when comparing LPEs as a group to the entire benchmark, *Leverage* does not seem to affect returns within LPEs. However, as soon as we include industry fixed effects and, therefore, compare LPEs to other industries, we observe a similar negative effect (-14.3% in (3) and -18% in (4)) of the interaction variable on returns (although smaller in magnitude) as noted in Panel A.

As shown in Panel A, *Size* stays highly statistically significant only in the period "recovery". Remarkably, the coefficients for *Size* are the only significant ones in the entire Panel B where the direction of the effect reverses. While we report positive effects in Panel A, we show negative ones of the same magnitude in Panel B. These are -1.4% in (2) and -1.8% in (4). Apparently, investors attribute higher growth perspectives to smaller firms throughout the crisis. As most of the days we add to this longer period are after the last day of the shorter period, we assume that the market needs time to adjust their perceptions about the growth perspectives and hence about the resilience to the crisis of bigger sized firms. On the other hand, *ROA* only stays highly statistically significant in (3).

At this point, we point out that the coefficients for the LPE-dummy and *Leverage* are the only statistically significant ones in (1) in the longer "fall" period. We are able to confirm the main identified predictors of cumulative returns in the COVID-19 crisis, which show that financial flexibility in the form of *Leverage* is highly valued by investors in times of crisis. As illustrated in Figure 1, LPEs are highly levered and show a long-term debt to assets ratio that is double that of the benchmark.

Combining these two findings, it becomes reasonable to assume that leverage is the financial metric that mostly distinguishes LPEs from the benchmark, leading to a highly statistically negative effect of being an LPE in almost all regression in Table 4. Even within the LPE group itself, higher leveraged LPEs are significantly worse off. The remainder of the control variables, cash over assets, short-term debt, *MB*, and *Idiosyncratic Volatility* either exhibit similar effects to the ones shown in Panel A or have no statistically significant effect at all.

6. Conclusion

In this paper, we examine the riskiness and performance of US-based PEs by using a novel approach discussing LPEs as a proxy for the PE universe. We are able to observe PE fund level characteristics and share price risk as well as return frequently, whereas information is typically held privately in the PE industry during a fund's life. LPEs are compared in the period 2010-2019 to a benchmark comprising all non-financial US-based firms. We find that there is no difference in the performance metrics *ROA*, and *ROE*, across both groups. However, LPEs exhibit *Leverage* almost double that of the benchmark but also lower *Idiosyncratic Volatility*. In terms of raw returns, we do not find evidence that LPEs outperform the benchmark. Even after introducing risk-adjusted returns, this result holds. When considering that investors in PE do not have access to their invested amount for a longer period of 7-12 years, the liquidity risk premium reveals investments in PE as highly unprofitable.

We empirically discover that a firm's stock is more negatively affected if the firm is less financially flexible in terms of leverage in times of crisis. As LPEs are heavily leveraged in comparison to the benchmark, we observe more negative cumulative returns for LPEs in the setting of the COVID-19 crisis. The benchmark outperforms LPEs by 18.9% and 17.2% in the market's downturn and recovery, respectively. In our multivariate analyses, both the LPE-dummy and leverage as well as the interaction between these two variables are the covariates that are highly statistically significant across most regressions and robustness tests. We conclude that investors value leverage as a measure of financial flexibility in times of crisis and, hence, punish LPEs for their high leverage, which is seen as one of the primary reasons for LPEs' underperformance in cumulative returns.

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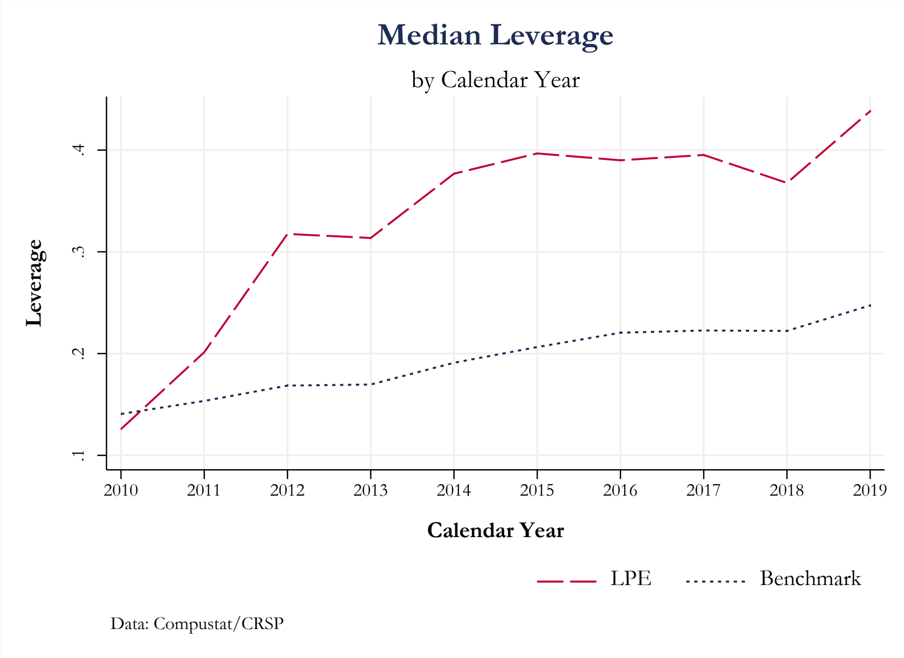

Figure 1. Evolution of leverage

The figure shows yearly median leverage for both groups, LPE (dashed line) and all non-financial firms (dotted line) in our sample with available financial and stock market data for the period 2010 – 2019.

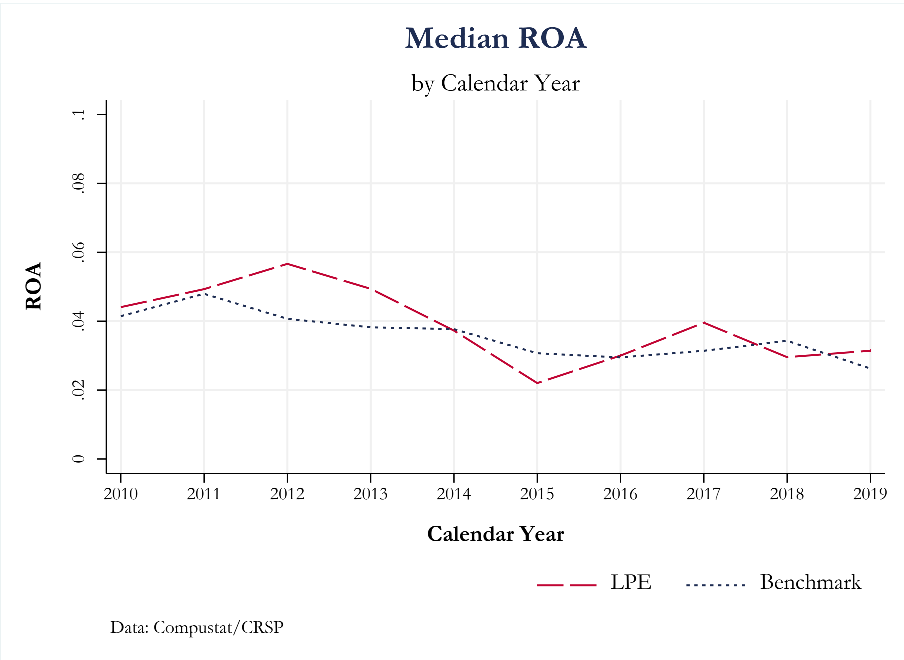

Figure 2. Evolution of return on assets (ROA)

The figure shows the yearly median return on assets for both groups, LPE (dashed line) and all non-financial firms (dotted line) in our sample with available financial and stock market data for the period 2010 – 2019.

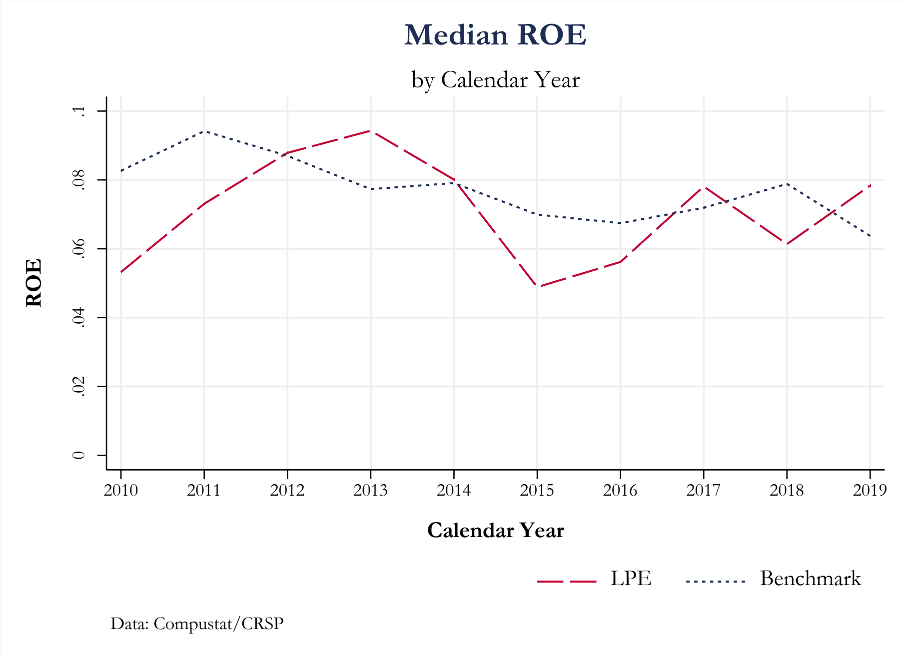

Figure 3. Evolution of return on equity (ROE)

The figure shows the yearly median return on equity for both groups, LPE (dashed line) and all non-financial firms (dotted line) in our sample with available financial and stock market data for the period 2010 – 2019.

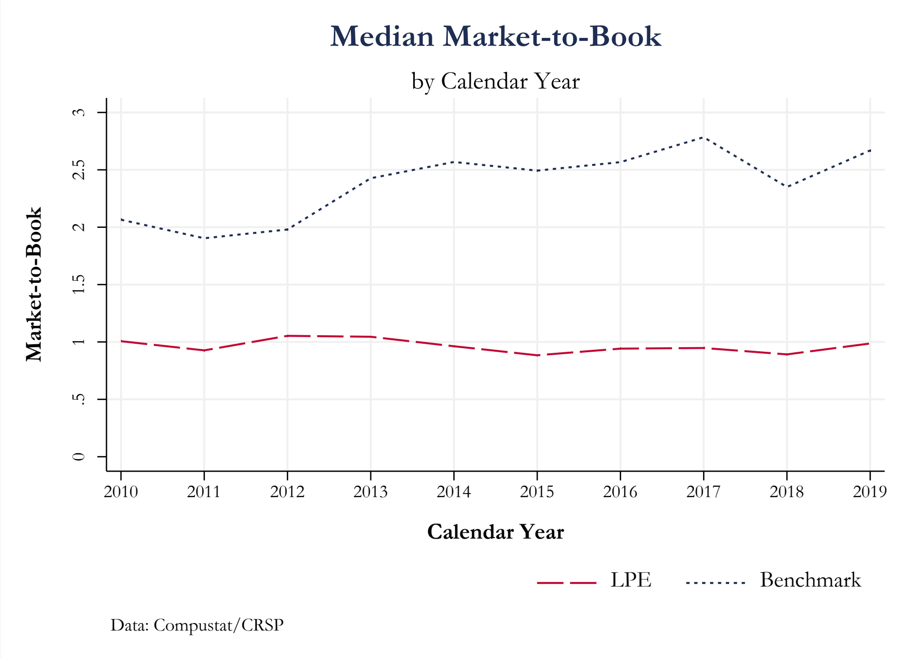

Figure 4. Evolution of market-to-book

The figure shows yearly median market-to-book for both groups, LPE (dashed line) and all non-financial firms (dotted line) in our sample with available financial and stock market data for the period 2010 – 2019.

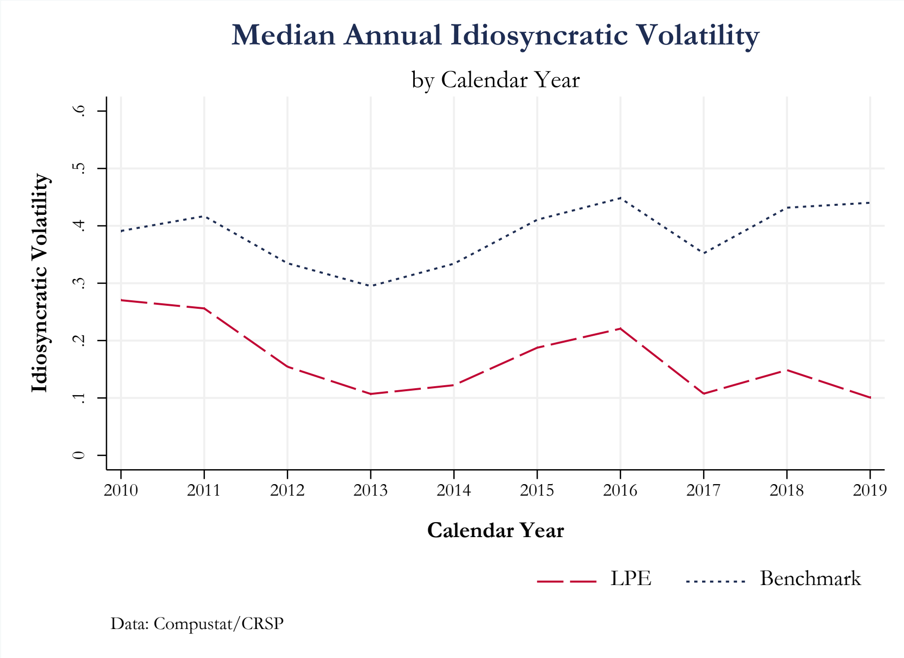

Figure 5. Evolution of idiosyncratic volatility

The figure shows the yearly idiosyncratic value for both groups, LPE (dashed line) and all non-financial firms (dotted line) in our sample with available financial and stock market data for the period 2010 – 2019. For better illustration, the values displayed here are multiplied by 1,000.

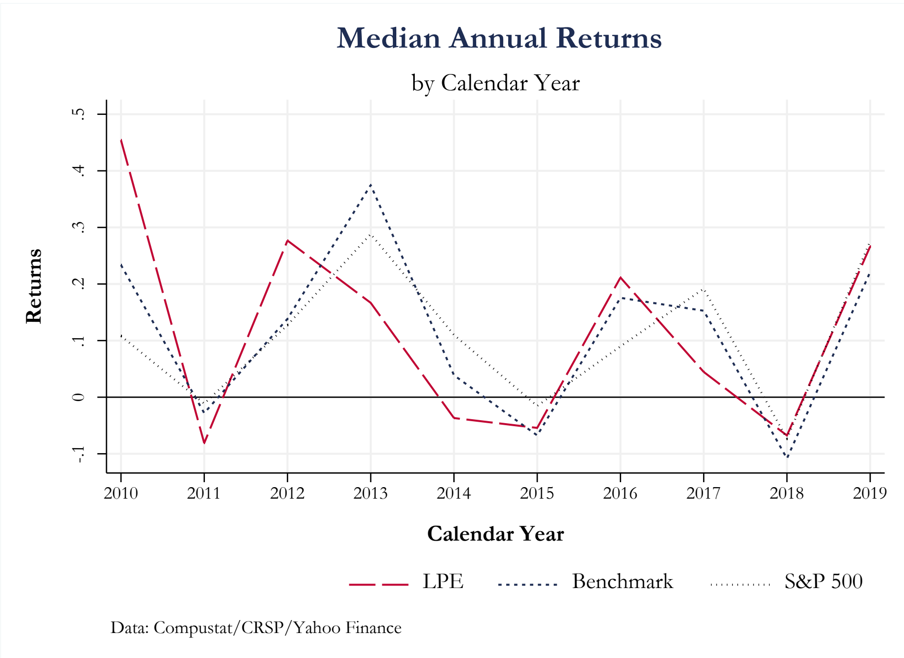

Figure 6. Evolution of annualized returns

The figure shows yearly median annualized returns for both groups, LPE (dashed line) and all non-financial firms (dotted line) in our sample with available financial and stock market data and the S&P 500 (light dotted line) for the period 2010 – 2019.

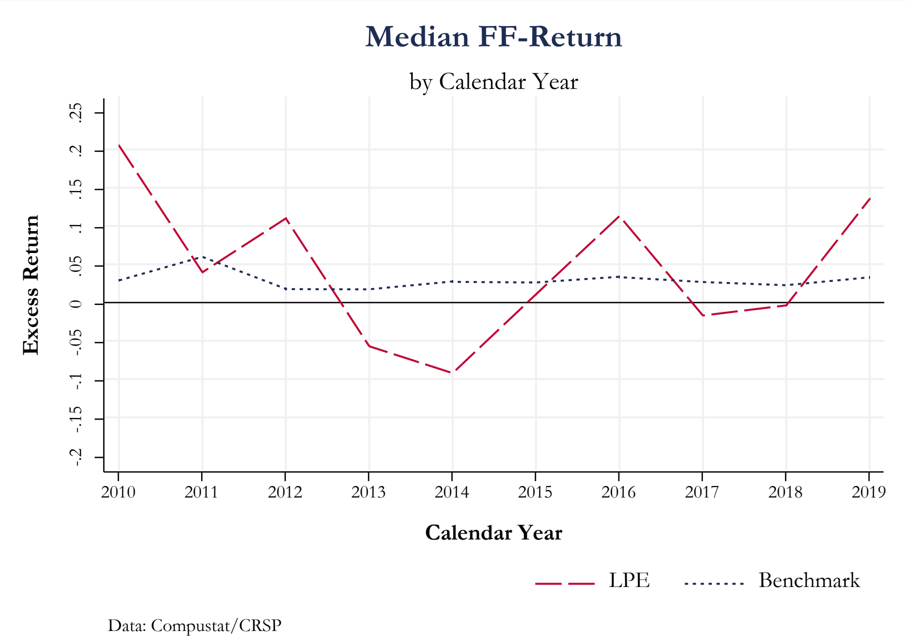

Figure 7. Evolution of Fama-French (FF) risk-adjusted returns

The figure shows yearly median risk-adjusted alpha returns for both groups, LPE (dashed line) and all non-financial firms (dotted line) in our sample with available financial and stock market data for the period 2010 – 2019. Excess returns are computed as Fama-French risk-adjusted returns.

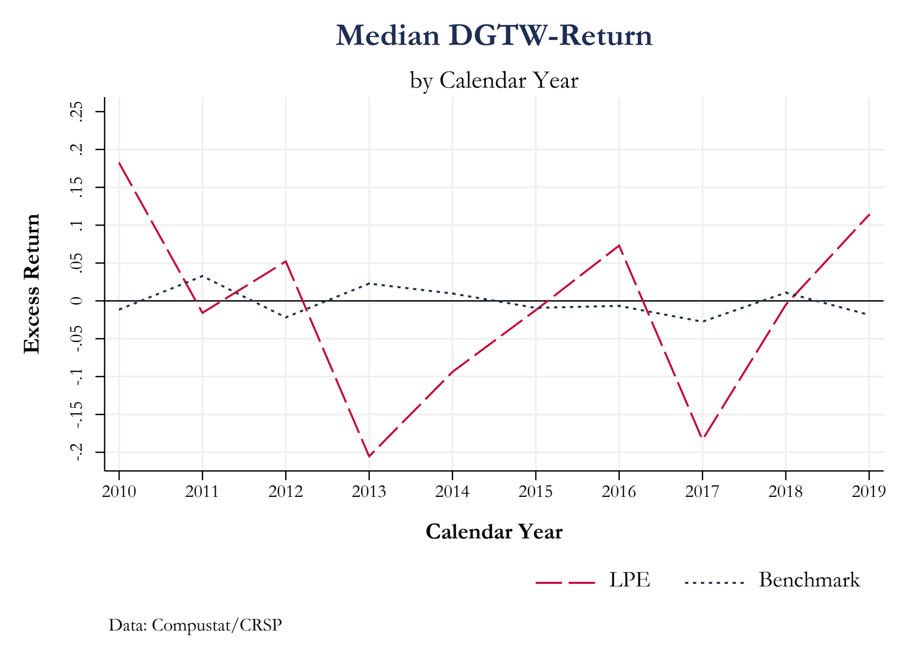

Figure 8. Evolution of excess returns according to DGTW

The figure shows yearly median excess returns for both groups, LPE (dashed line) and all non-financial firms (dotted line) in our sample with available financial and stock market data for the period 2010 – 2019. Excess returns are computed by the method proposed by Daniel et al. (1997).

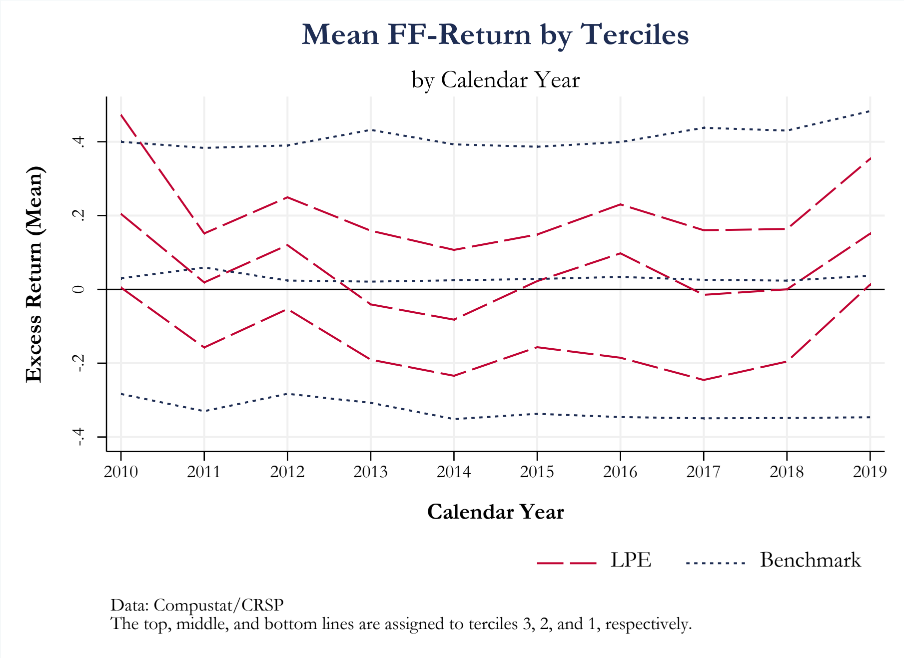

Figure 9. Evolution of Fama-French (FF) risk-adjusted returns divided into terciles

The figure shows yearly mean risk-adjusted alphas for both groups, LPE (dashed line) and all non-financial firms (dotted line) in our sample with available financial and stock market data for the period 2010 – 2019. Each group is divided into terciles according to its alpha return for a given year. Excess returns are computed as Fama-French risk-adjusted returns.

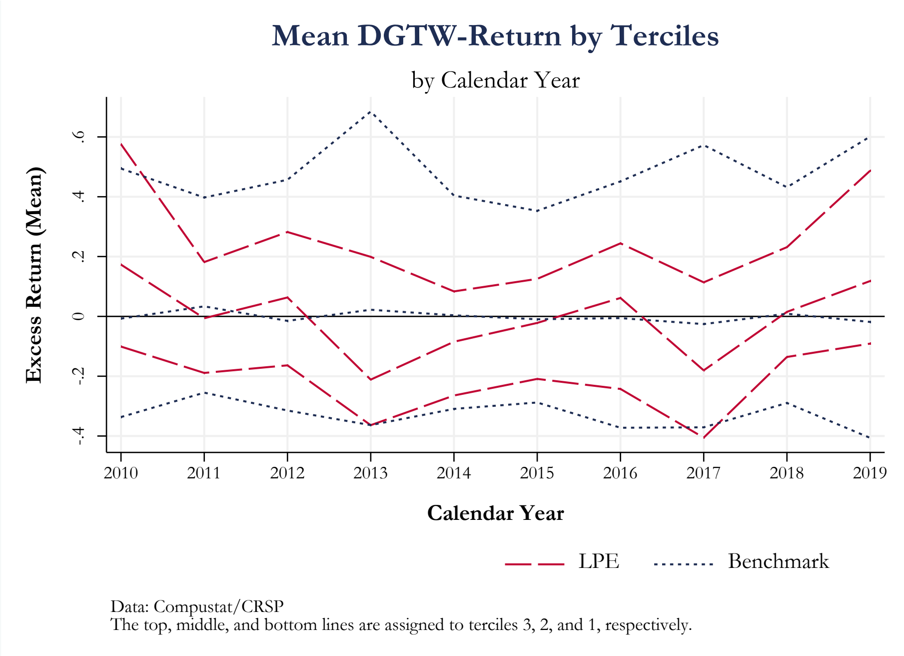

Figure 10. Evolution of excess returns according to DGTW divided into terciles

The figure shows yearly median excess returns for both groups, LPE (dashed line) and all non-financial firms (dotted line) in our sample with available financial and stock market data for the period 2010 – 2019. Each group is divided into terciles according to its excess return for a given year. Excess returns are computed by the method proposed by Daniel et al. (1997).

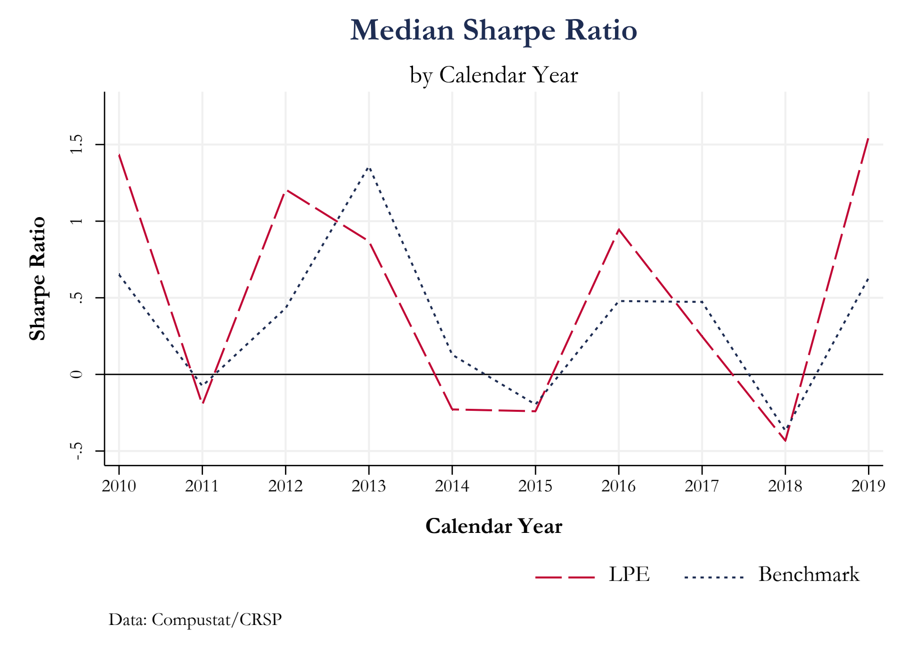

Figure 11. Evolution of the Sharpe ratio

The figure shows the yearly median Sharpe ratio for both groups, LPE (dashed line) and all non-financial firms (dotted line) in our sample with available financial and stock market data for the period 2010 – 2019. The 1-year Treasury bill return for each respective year is used to proxy for the risk-free rate.

Table 1: Descriptive Statistics

This table presents descriptive statistics for firm and stock characteristics on which we evaluate LPEs and the benchmark. The sample for Panel A consists of all US-based LPEs. Panel B shows statistics for all non-financial firms (SIC 6000 – 6799). All firms in the sample have positive book values of shareholder equity and financial and stock market data available for any of the years between 2010 and 2019. Variable definitions are provided in Appendix A. The values for *Idiosyncratic Volatility* are multiplied by 1,000.

Panel A: LPE	N	Mean	P25	P50	P75	SD
Size in $bn	384	4.142	0.380	0.792	2.211	9.784
ROA	384	0.029	0.007	0.037	0.059	0.069
ROE	384	0.057	0.018	0.075	0.112	0.146
Leverage	384	0.326	0.213	0.361	0.437	0.161
MB	384	1.199	0.806	0.952	1.113	1.060
ReturnFF	384	0.032	-0.081	0.039	0.146	0.194
ReturnDGTW	346	0.002	-0.168	-0.015	0.153	0.269
Sharpe	384	0.505	-0.245	0.317	1.221	1.094
Idiosyncratic Volatility	384	0.208	0.098	0.160	0.246	0.201

Panel B: Benchmark	N	Mean	P25	P50	P75	SD
Size in $bn	20,937	7.570	0.364	1.233	4.406	28.704
ROA	20,937	-0.002	-0.008	0.036	0.074	0.167
ROE	20,937	0.022	-0.018	0.078	0.153	0.318
Leverage	20,839	0.211	0.016	0.193	0.336	0.185
MB	20,933	4.043	1.431	2.364	4.218	5.488
ReturnFF	20,936	0.038	-0.153	0.030	0.215	0.414
ReturnDGTW	18,640	0.051	-0.197	-0.002	0.206	0.530
Sharpe	20,936	0.486	-0.321	0.307	1.100	1.116
Idiosyncratic Volatility	20,936	0.684	0.194	0.383	0.749	2.509

Table 2: Differences in means for selected variables

The table shows results from two-tailed t-tests on selected variables for the entire LPE and benchmark sample. Variable definitions are provided in Appendix A. The values for *Idiosyncratic Volatility* are multiplied by 1,000. A positive difference in mean indicates that the benchmark mean is larger than the respective LPE mean and vice-versa. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	LPE		**Benchmark**			
	N	Mean	N	Mean	Difference in Means	t-statistic
Size in $bn	384	4.142	20,937	7.570	3.428**	(2.338)
ROA	384	0.029	20,937	-0.002	-0.030***	(-3.576)
ROE	384	0.057	20,937	0.022	-0.035**	(-2.155)
Leverage	384	0.326	20,839	0.211	-0.115***	(-12.142)
MB	384	1.199	20,933	4.043	2.845***	(10.155)
ReturnFF	384	0.032	20,936	0.038	0.007	(0.322)
ReturnDGTW	346	0.002	18,640	0.051	0.048*	(1.690)
Sharpe	384	0.505	20,936	0.486	-0.019	(-0.336)
Idiosyncratic Volatility	384	0.208	20,936	0.684	0.476***	(3.717)

Table 3: Differences in means for cumulative returns

The table shows results from two-tailed t-tests on cumulative returns for the entire LPE and benchmark sample. Period "fall" is defined in Panel A as the period ranging from March 4 to March 23, 2020. Period "recovery" ranges from March 4 to June 5, 2020. In Panel B, period "fall" ranges from February 19 to March 23, 2020, while "recovery ranges from February 19 to August 21, 2020. A positive difference in mean indicates that the benchmark mean is larger than the respective LPE mean and vice-versa. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A	**LPE**			**Benchmark**				
	Mean	P50	SD	Mean	P50	SD	Difference in Means	t-statistic
Fall	-0.522	-0.548	0.135	-0.333	-0.329	0.179	0.189***	(6.902)
Recovery	-0.145	-0.180	0.176	0.027	0.016	0.242	0.172***	(4.680)
N	44			1,277			1,321	

Panel B	**LPE**			**Benchmark**				
	Mean	P50	SD	Mean	P50	SD	Difference in Means	t-statistic
Fall	-0.571	-0.589	0.122	-0.401	-0.407	0.282	0.169***	(3.974)
Recovery	-0.248	-0.265	0.189	-0.039	-0.102	0.610	0.209**	(2.272)
N	44			1,263			1,307	

Table 4: Cumulative stock returns, financial flexibility measures, and stock characteristics

The table shows results from cross-sectional regressions of cumulative raw returns on the LPE-dummy, firm and stock characteristics. Columns (1) and (3) show results for the period "fall" while columns (2) and (4) show results for the period "recovery". Period "fall" is defined in Panel A as the period ranging from March 4 to March 23, 2020. Period "recovery" ranges from March 4 to June 5, 2020. In Panel B, period "fall" ranges from February 19 to March 23, 2020, while "recovery ranges from February 19 to August 21, 2020. Variable definitions are provided in Appendix A. The LPE-dummy equals 1 if the observation comes from an LPE and zero otherwise. Regressions (3) and (4) include industry-fixed effects. Industries are defined as Fama-French 49 industries. Numbers in brackets are t-statistics and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Standard errors are robust to clustering at the industry level.

Panel A Mar 4 – Jun 5	(1) Fall	(2) Recovery	(3) Fall	(4) Recovery
LPE-Dummy	-0.0540***	0.0154	-0.0964***	-0.0035
	[-3.08]	[0.70]	[-6.42]	[-0.17]
Leverage	-0.2667***	-0.1300***	-0.2702***	-0.1075**
	[-6.55]	[-3.42]	[-7.71]	[-2.54]
*LPE-Dummy*Leverage*	-0.2049***	-0.3469***	-0.2373***	-0.3868***
	[-3.78]	[-6.28]	[-5.33]	[-6.35]
Cash / assets	0.1643***	0.1323*	0.0687	0.0727
	[4.03]	[1.84]	[1.34]	[1.00]
St-debt / assets	0.0499	0.0781	-0.0105	0.0687
	[0.37]	[0.43]	[-0.10]	[0.36]
Payout / assets	0.0233	0.1274	0.0410	0.1386
	[0.26]	[1.34]	[0.42]	[1.32]
Size	0.0061	0.0134***	0.0028	0.0126***
	[1.50]	[3.27]	[0.79]	[3.33]
ROA	0.0973***	0.0390	0.1096***	0.0680
	[3.52]	[0.51]	[3.06]	[0.82]
MB	-0.0001	0.0000	-0.0001	-0.0000
	[-0.28]	[0.02]	[-0.49]	[-0.52]
Idiosyncratic Volatility	-1.7625	18.4353***	-1.4451	17.3157**
	[-1.07]	[2.77]	[-1.12]	[2.38]
Constant	-0.3336***	-0.0805**	-0.2450***	-0.0452
	[-11.98]	[-2.12]	[-8.89]	[-1.47]
Industry Fixed Effects	No	No	Yes	Yes
N	1,316	1,316	1,316	1,316
R^2	0.148	0.069	0.308	0.127

Panel B Feb 19 – Aug 21	(1) Fall	(2) Recovery	(3) Fall	(4) Recovery
LPE-Dummy	-0.0814*** [-3.71]	-0.1412*** [-3.59]	-0.1097*** [-7.16]	-0.1344*** [-4.51]
Leverage	-0.3077*** [-4.72]	-0.2022** [-2.66]	-0.3080*** [-5.33]	-0.1595** [-2.04]
*LPE-Dummy*Leverage*	-0.0930 [-1.46]	-0.0129 [-0.14]	-0.1429*** [-3.37]	-0.1808** [-2.44]
Cash / assets	0.0998 [0.93]	0.4021* [1.79]	-0.0552 [-0.41]	0.1147 [0.70]
St-debt / assets	-0.0018 [-0.01]	0.3875 [1.33]	-0.0820 [-0.57]	0.2013 [0.72]
Payout / assets	0.0221 [0.24]	-0.0147 [-0.08]	0.0582 [0.56]	-0.0669 [-0.32]
Size	-0.0035 [-0.44]	-0.0141** [-2.13]	-0.0079 [-0.99]	-0.0179** [-2.65]
ROA	0.0601 [1.36]	-0.0229 [-0.18]	0.1097*** [3.84]	0.0537 [0.51]
MB	-0.0000 [-0.16]	0.0001 [0.28]	-0.0001 [-0.50]	-0.0000 [-0.30]
Idiosyncratic Volatility	-2.2447 [-1.39]	23.1759*** [2.87]	-1.3172 [-1.09]	22.5025*** [3.01]
Constant	-0.3082*** [-3.49]	0.0419 [0.59]	-0.2168** [-2.65]	0.1418** [2.46]
Industry Fixed Effects	No	No	Yes	Yes
N	1,302	1,302	1,302	1,302
R^2	0.070	0.051	0.174	0.103

Appendix A: Variable definitions

This appendix contains definitions of all variables presented in this paper. Compustat data items are in capitalized letters.

Variable name	Description
Size	The book value of total assets; AT
ROA	The ratio of net income to assets; IB / AT
ROE	The ratio of net income to the book value of equity; IB / (SEQ + TXDB + ITCB - PSTKRV). If PSTKRV missing, we substitute by PSTKL or PSTK.
Leverage	The ratio of long-term debt to assets; DLTT/AT
MB	The ratio of market value to book value of equity; (PRCC_F * CSHO) / (SEQ + TXDB + ITCB – PSTKRV). If PSTKRV missing, we substitute by PSTKL or PSTK.
ReturnFF	The risk-adjusted return yielded from a Fama-French three-factor model.
ReturnDGTW	The excess return from applying the method proposed by Daniel et al. (1997).
Sharpe	The ratio of excess returns divided by the annualized standard deviation. Excess returns are computed by proxying Treasury Bill rates as the risk-free rate.
Idiosyncratic Volatility	The idiosyncratic volatility derived from Shin and Stulz (2000).
LPE-Dummy	A dummy variable that equals one if the observation is an LPE and zero otherwise.
Cash / assets	The ratio of cash to assets; CHE / AT
St-debt / assets	The ratio of short-term debt to assets; DLC / AT
Payout / assets	The ratio of total dividends and share repurchases to total assets; (DVC + DVP + PRSTKC) / AT. Missing DVC, DVP, and PRSTKC are set to zero.
Ln(Assets)	The natural logarithm of book value of total assets (AT)