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Does Private Equity Over-Lever Portfolio Companies? *

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Abstract

Detractors have warned that Private Equity (PE) funds tend to over-lever their portfolio companies because of an option-like payoff, building up default risk and debt overhang. This paper argues PE-ownership leads to substantially higher levels of *optimal* (value-maximizing) leverage, by reducing the expected cost of financial distress. Using data from a large sample of PE buyouts, I estimate a dynamic trade-off model where leverage is chosen by the PE investor. The model is able to explain both the level and change in leverage documented empirically following buyouts. The increase in optimal leverage is driven primarily by a reduction in the portfolio company's asset volatility and, to a lesser extent, an increase in asset return. Counterfactual analysis shows significant loss in firm value if PE sub-optimally chose lower leverage. Consistent with lower asset volatility, additional tests show PE-backed firms experience lower volatility of sales and receive greater equity injections for distress resolution, compared to non PE-backed firms. Overall, my findings broaden our understanding of factors that drive buyout leverage.

Keywords: Private Equity; Capital Structure; Default Risk; Trade-off Theory

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1 Introduction

It is well-known that Private Equity (PE) funds acquire companies in leveraged buyouts (LBO) using substantial amount of debt (Kaplan and Stromberg, 2009). The sharp increase in portfolio company leverage following a PE-sponsored buyout has generated conflicting views.[1] One well-known view is that PE fund managers over-leverage their portfolio companies (Kaplan and Stein, 1990; Andrade and Kaplan, 1998), and buyout capital structure is primarily driven by credit market conditions instead of debt capacity of a given firm (Axelson, Jenkinson, Strömberg, and Weisbach, 2013). The alternate view is that high leverage is efficient since PE leads to lower debt-equity conflicts for a given debt ratio relative to public firms (Malenko and Malenko, 2015), thereby allowing PE-backed firms to trade off the benefits of higher debt against potentially lower expected cost of financial distress. Which effect dominates is thus an empirical question.

In this paper, I examine if PE investors systematically over-lever portfolio companies and estimate the *optimal* (value-maximizing) leverage of PE-backed firms. If PE sponsors over-leverage and overpay for deals as suggested by Axelson et al. (2013) and Axelson, Strömberg, and Weisbach (2009), we would expect optimal leverage of portfolio firms to be meaningfully lower than what we see in the data, which can lead to significant aggregate costs (Faria-e Castro, Paul, and Sánchez, 2021).

Examining this mechanism is challenging since we do not readily observe optimal leverage. Existing papers empirically examining leverage in PE rely on standard regressions of leverage on a number of factors that proxy costs and benefits of debt.[2] However, this approach cannot detect if firms have too much debt or too little debt on average and implicitly assumes firms are always optimally levered (Korteweg, 2010). Moreover, it cannot incorporate the endogeneity of the bankruptcy decision, which is jointly determined with leverage. The alternate approach is to structurally estimate optimal leverage.

[1] Throughout the text, I use the terms PE-backed, PE-sponsored, and PE-owned interchangeably to refer to portfolio firms.

[2] See for example Axelson et al. (2013); Guo, Hotchkiss, and Song (2011); Kaplan and Stein (1993).

As Ivashina and Kovner (2011) suggest, PE managers are effectively shadow-borrowers since they control the borrower's equity, management, capital structure and strategic direction. Consistent with this observation, if we relabel the PE General Partner (GP) as a CEO who chooses capital structure to maximize equity value taking into consideration a potentially different expected cost of financial distress, then a standard trade-off model with endogenous leverage could explain high buyout debt. Consequently, I estimate a dynamic trade-off model using data from a large, international sample of PE-owned portfolio companies covering pre- (post-) buyout financial information. Since the data allows me to estimate optimal pre- (post-) buyout leverage ratios, I can identify the underlying mechanism that explains a change in the optimal leverage. Additionally, the model allows me to examine tax benefits of debt and default risk following PE-intervention.

Using the post-buyout sample, I begin with my benchmark case and estimate the Leland (1994) structural model that considers trade-off theory with endogenous debt and default. However, a key hurdle I encounter is the need for market prices of PE-backed firms since estimation of Leland-type models involves recovering a firm's unobserved asset value and volatility such that they deliver its empirically observed equity value and volatility (Elkamhi, Ericsson, and Parsons, 2012; Bharath and Shumway, 2008; Nagel and Purnanandam, 2020). Given the absence of equity prices of private companies, I design a similar yet even more conservative matching methodology relative to Bernstein, Lerner, and Mezzanotti (2019) to identify nearly-identical public companies. Specifically, I match each PE-backed firm in my sample to public companies in terms of profitability, leverage, total assets and volatility of return on assets in the same country-industry-year. These variables are chosen to condition on factors that typically differentiate PE-backed firms from public companies.

My key finding is that private equity leads to substantially higher levels of optimal leverage. The estimation predicts mean and median post-buyout leverage ratios of 47.7 and 52.6 percent respectively, which matches the data quite well. Specifically, mean and median leverage in the data is around 50 percent, consistent with previous studies (Brown, 2021;

Gornall, Gredil, Howell, Liu, and Sockin, 2021). Re-estimating the model with pre-buyout data generates much lower optimal leverage ratio of around 33 percent, which is also close to pre-buyout levels. The model thus explains both the level and *change* in post-buyout leverage. In a counterfactual exercise, I find that the median firm in my sample stands to lose approximately 4.0 percent of value if they chose to stay at debt levels close to what is observed pre-buyout. The model predicts substantial cross-sectional heterogeneity in the cost of sub-optimal leverage with an inter-quartile range of 2.4 to 5.7 percent of value.

Next, I inspect the channel driving the results. The primary reason for the increase in optimal leverage is a sizeable reduction in estimated asset volatility, and to a lesser extent, an increase in asset return. I find that mean asset volatility declines from 0.309 pre-buyout to 0.177 post-buyout. Lower asset volatility reduces the firm's time-weighted probability of default and, by extension, the expected present value of bankruptcy costs (for a given default cost), thus raising optimal leverage.[3] The benchmark finding is consistent with the theory proposed by Malenko and Malenko (2015), who argue risk-shifting incentives are lower under PE-ownership in a setting where debt brings the standard tax and agency benefits as well as bankruptcy costs.

To support this finding, I also provide reduced-form evidence consistent with lower asset risk. I provide evidence on two (not necessarily mutually exclusive) channels: operational engineering and financial distress resolution through equity injections (Gompers, Kaplan, and Mukharlyamov, 2022a; Gryglewicz and Mayer, 2020). Using a matched difference-in-differences strategy with firm and year fixed effects to alleviate concerns related to selection, unobserved firm-specific factors and aggregate credit conditions, I uncover two key empirical facts. First, PE-firms receive greater equity infusion when default risk is high, relative to matched public companies consistent with Bernstein et al. (2019), Hotchkiss, Smith, and Strömberg (2021) and Haque, Jang, and Mayer (2022). This capital infusion comes from

[3]Prior research shows that in endogenous default models, the higher volatility and resulting lower-coupon effect dominates the opposing effect of higher coupon due to the likelihood of a firm finding itself in a very good state when it raises risk. See for example, Strebulaev, Whited, et al. (2012).

sponsoring funds with so-called dry powder since committed capital is typically invested over a series of years, rather than all at once. The key implication is that equity injection reduces distress risk, hence diminishes incentives to shift risk to lenders. This is the distress resolution channel.

Second, I show that PE-sponsored firms experience a reduction in the volatility of sales following PE-takeover: the operational engineering channel. Lower volatility in sales is consistent with findings in Fracassi, Previtero, and Sheen (2022), who use granular store-level data to show firms diversify both their product basket as well as geographic product market after PE-takeover, thus lowering risk. One concern with this finding, may be that PE managers may be manipulating accounting data to maximize fund-level risk-adjusted return, consistent with findings from Brown, Gredil, and Kaplan (2019). To alleviate this concern I show that my results are unchanged with a restricted sample of just a few advanced European countries where firms are required to disclose their financial statements and have them regularly audited (unlike firms in the US).

For completeness and robustness purposes, I extend the standard model in three additional directions to capture issues often associated with PE. First, Hotchkiss et al. (2021) show that PE-backed firms tend to negotiate out-of-court with lenders more often that similar non-PE firms, if they are in distress. Following Strebulaev et al. (2012), I estimate a simple version of a trade-off model where firms issue private bank debt and can negotiate its coupon payments in low-profitability states of the world instead of filing for a relatively more traditional chapter 11 bankruptcy. Second, PE-backed firms have also been accused of so-called asset-stripping (e.g. Reuters, 2010; The Gaurdian, 2021). The Leland (1994) model can capture liquidation of assets to fund higher payouts, allowing me to compute optimal leverage at different liquidation rates as a share of asset value. Third, as Ivashina and Kovner (2011) suggest, close relationships between banks and PE funds may loosen covenant violation thresholds, allowing for higher leverage. I introduce an Interest Coverage covenant in a parsimonious manner into the Leland (1994) model to examine this channel. In general, I find that these extensions are not as successful in explaining post-buyout leverage ratios as the benchmark model, indicating these factors may not be the primary driver of higher optimal leverage.

Finally, one might worry that higher optimal leverage arises from PE sponsor reputation (Ivashina and Kovner, 2011). The benchmark model can capture this effect through changes in loss given default. For example, higher PE sponsor reputation could potentially reduce loss of customers or limit fire sales in highly levered firms or firms with high default risk. In a comparative static exercise, I show that changes in dead-weight default costs do not generate the substantial change in leverage as the change in asset volatility does, and thus cannot explain the observed change in the data.

Related Literature. This paper contributes to a large literature on debt and leverage in private equity-sponsored leveraged buyouts. The extant literature on capital structure in PE has primarily focused on the role of aggregate market conditions (Malenko and Malenko, 2015; Bernstein et al., 2019; Axelson et al., 2013), reputational concerns (Malenko and Malenko, 2015; Huang, Ritter, and Zhang, 2016), deal returns (Brown et al., 2019; Brown, 2021), mechanisms in the initial year of operation (Robb and Robinson, 2014), agency conflicts between general and limited partners (Axelson et al., 2009; Gryglewicz and Mayer, 2020), and PE sponsor-lender relationships (Ivashina and Kovner, 2011; Jang, 2022). My paper is conceptually closest to Hotchkiss et al. (2021) who argue the expected cost of financial distress under PE-ownership is lower, given the standard trade-offs associated with choosing leverage. My paper differs from these by proposing and directly estimating the *optimal* leverage in buyouts, while previous papers have primarily theorized that optimal leverage could be different under PE, such as Malenko and Malenko (2015). To the best of my knowledge, this is the first paper to quantitatively examine optimal leverage in PE taking into account the endogenous nature of default and corporate debt policy.

I also contribute to the large literature on the effects of private equity buyouts. As suggested by Kaplan and Stromberg (2009), recent theories (Malenko and Malenko, 2015;

Gryglewicz and Mayer, 2020) or survey evidence (Gompers et al., 2022a), PE owners affect firm value and outcomes through operational, governance, and financial engineering. In this context, several papers study whether and how PE owners affect firm outcomes, managerial incentives, stakeholders, and/or create value (see, among others, Boucly, Sraer, and Thesmar (2011); Cronqvist and Fahlenbrach (2013); Cohn, Mills, and Towery (2014); Bernstein and Sheen (2016); Antoni, Maug, and Obernberger (2019); Gupta, Howell, Yannelis, and Gupta (2021); Gornall et al. (2021); Cassel (2021); Ewens, Gupta, and Howell (2022); Fracassi et al. (2022); Cohn, Hotchkiss, and Towery (2022); Haque et al. (2022)).I complement these efforts by empirically examining the effect of PE-ownership on underlying asset volatility, default risk as well as the tax and incentive benefits of debt.

Finally, this paper also contributes to the structural corporate finance literature. Prior studies which estimated structural leverage models have focused on cost of default (Glover, 2016), pre-default costs (Elkamhi et al., 2012; Elkamhi and Salerno, 2020), the effect of changes in tax rates on small firms (Ivanov, Pettit, and Whited, 2020) and collateral (Li, Whited, and Wu, 2016). Unlike these papers, I provide an examination of the quantitative effect of changes in asset volatility on capital structure, as well as the (counterfactual) effect choosing lower leverage. Unlike papers which have typically calibrated Leland-type models, I structurally estimate the model for proper inference.

2 Structural Model of Optimal Leverage

The key assumption I make in this paper is that the PE manager behaves similar to a profit-maximizing equity-holder. This is a reasonable assumption as Jensen (1986), and more recently Ivashina and Kovner (2011) and Gompers, Kaplan, and Mukharlyamov (2022b) argue, PE managers usually own a majority of the equity in the companies within their portfolio, take active roles in governance and operations, and seek to maximize the value of their investments because they are usually compensated with a large share of the profits of these investments. In this section, I begin by outlining a model of the leveraged firm following Leland (1994). Since the model is well known, I do not repeat detailed theoretical derivations here and only present key equations.[4]

Consider a firm in a continuous-time infinite horizon framework, whose manager maximizes shareholder value. At all times in which the firm is operating, its assets in place produce cash flows at a rate of δ_t, implying cash flows of $\delta_t dt$ are produced in each time interval $[t, t+dt]$. Assume there exists a risk-neutral measure with risk-free rate r under which cash flow rate follows a geometric brownian motion

$$d\delta_t = \delta_t \mu dt + \delta_t \sigma dB_t \tag{1}$$

where $\mu < r$, $\sigma > 0$ are constants representing risk-neutral drift and volatility of δ_t. In Eq. (1), B_t is a standard Brownian motion, which we can think of as random shocks to a firm's fundamental value. Since all value is generated by assets in place in perpetuity, and assuming the firm's capital structure only consists of equity, we can write the value of the unlevered firm as:

$$E_U(\delta) = \mathbb{E}\Big(\int_t^{\infty} e^{-r(s-t)}\delta_s ds\Big) = \frac{(1-\tau)\delta_t}{r-\mu} \tag{2}$$

where τ represents a constant proportional corporate tax rate.[5]

Now suppose the firm issues debt to take advantage of tax shields. Debt takes the form of a consol bond with constant coupon rate C. I follow the literature in assuming a full loss offset provision, so the firm subsequently pays taxes $\tau(\delta_t - C)dt$ per unit in time.[6]

[4]Readers interested in the theory can also see Leland and Toft (1996), Leland (1998), He (2011), Strebulaev et al. (2012) and Glover (2016), among others.

[5]One concern could be that the model cannot capture time-varying macroeconomic risk. Recall that the goal of this paper is to explain leverage ratios in the cross-section pre-(post-) buyout, as opposed to the time-series. Thus time-varying credit conditions should be less of a concern, however, I also provide tests in Section 6 that tackle this issue directly.

[6]Strebulaev et al. (2012) argue taxes are asymmetric in the real world, so that profits are taxed at a higher rate than losses. While I abstract away from this for simplicity in the benchmark model, unreported results confirm carry-forward or carry-back provisions of tax code does not change the main result of this paper.

2.1 Equity Value and Endogenous Default

Now, I outline the value process for the equity-holder's payoffs. In the context of this paper, I assume the PE fund manager acts as the owner-manager or equivalently is the equity-holder following an LBO. Equity value can be computed through the following ordinary differential equation that equates the required rate of return for the equity-holder with the expected rate of return on equity, which is the sum of the terms on the right hand side.

$$rE(\delta) = \delta_t - (1-\tau)C + \mu\delta\frac{\partial E}{\partial \delta} + \frac{1}{2}\sigma^2\delta^2\frac{\partial^2 E(\delta,t)}{\partial \delta^2} \tag{3}$$

The left hand side is the required equity return. The first term on the right-hand side captures the cash flow generated by the firm per unit of time. The second term is the after-tax coupon payment per unit of time. The third and fourth term capture the expected change in equity value caused by a fluctuation in the firm's asset value. Following a series of unexpected negative shocks that deteriorates the firm's financial status, the equity-holder may choose to default. Standard smooth-pasting condition yields the endogenous default-triggering asset level

$$\delta_B = (1-\tau)C\frac{r-\mu}{r}\frac{\gamma}{1+\gamma} \tag{4}$$

where γ is the root of the fundamental quadratic equation, defined below.

$$\gamma = -\frac{\mu - 0.5\sigma + \sqrt{(0.5\sigma^2-\mu)^2 + 2\sigma r}}{\sigma^2} \tag{5}$$

2.2 Debt Value and Optimal Leverage

The value of debt is given by Eq. (6) below. The first term on the right-hand side is the constant coupon flow to debt-holders if the firm is solvent. The second term is equal to 0 since debt takes the form of a perpetual bond, thus time-independent. The last two terms on the right hand side are defined similar to the equity-holder's value.

$$rD(\delta) = c - \frac{\partial D(\delta)}{\partial t} + (\mu)\delta_t \frac{\partial D(\delta)}{\partial \delta} + \frac{1}{2}\sigma^2 \delta_t^2 \frac{\partial^2 D(\delta)}{\partial \delta^2} \tag{6}$$

The value of the leveraged firm is the sum of debt and equity values. Simplification yields the following standard equation which effectively is the sum of the value of the unlevered firm, the tax benefits of debt less bankruptcy costs, thus capturing trade-off theory.

$$V_L(\delta) = \frac{\delta_0}{r-\mu} + \frac{\tau C}{r}\big(1 - (\frac{\delta}{\delta_B})^{-\gamma}\big) - \frac{\alpha \delta_B}{r-\mu}(\frac{\delta}{\delta_B})^{-\gamma} \tag{7}$$

We obtain the optimal coupon C^* by maximizing the levered firm value in Eq. (7). This is then used to compute optimal leverage shown in Eq. (8).

$$L_i = \frac{D(\delta, \delta_B, C^*)}{D(\delta, \delta_B, C^*) + E(\delta, \delta_B, C^*)} \tag{8}$$

3 Estimation Method

To find out if a trade-off model of optimal leverage can, on average, explain leverage ratios we see in PE-backed firms, I now estimate the model with empirical data from a large sample of PE firms. In this section, I describe the empirical strategy and sample construction.

3.1 Estimation

To estimate the model, I first set some parameters to typical values seen in the literature. Specifically, I set the risk-free rate to 5 percent Strebulaev et al. (2012). Following Leland (1998), Strebulaev et al. (2012) and He (2011), I set the corporate tax rate to 20 percent, which is appropriate given the international nature of the sample, described subsequently. Bankruptcy cost is set to 23 percent following Andrade and Kaplan (1998).

Estimation strategy is standard. The advantage of the Leland (1994) model is that it provides closed-form solutions for debt value, equity values and volatilities. The two key inputs to the model - asset value (δ_t) and asset volatility (σ) - cannot be observed. Instead they are inferred by requiring the model to fit observable data. Specifically, I calibrate the model for each firm-quarter by simultaneously solving Eq. (9) and (10) for δ_t and σ that deliver the observed values of a firm's quarterly equity and stock return volatility. This procedure has been widely used in prior research (Nagel and Purnanandam, 2020; Elkamhi et al., 2012; Bharath and Shumway, 2008; Vassalou and Xing, 2004).

$$E_{mkt} = E_{mod}(\delta_t; \sigma) \tag{9}$$

$$\sigma_e = \frac{\delta_t}{E_{mod}(\delta_t; \sigma)} \frac{\partial E_{mod}(\delta_t; \sigma)}{\partial \delta_t} \sigma \tag{10}$$

In Eq. (9) and Eq. (10), *mod* and *mkt* denote model and market values respectively. I estimate δ and σ using straightforward numerical solution, and compute bootstrap standard errors using 5,000 replications.[7]

The necessity of market prices presents a challenge unique to this paper since we are examining private firms. In an ideal experiment, one would proxy for market prices using identical public companies. My empirical design follows similar thinking. I develop a more conservative matching procedure relative to Bernstein et al. (2019) and estimate the model using market price of this sample of matched public companies. As I will argue below, selection on unobservable dimensions is likely less of a concern given my choice of matching covariates and the conservative nature of my match.

3.2 Data

The data collection process is divided into three parts. First, I collect private equity deal-level data from Bureau Van Dijk's (BvD) Zephyr database. Zephyr has been increasingly

[7] I use Matlab's built-in Levenberg–Marquardt algorithm to iteratively solve the model, using a convergence tolerance criterion of 10^{-3}. Computation of bootstrapped standard errors is carried out through a Linux-based computing system, which substantially reduces estimation time.

utilized among PE researchers and has been verified as a comprehensive and representative sample of PE transactions compared with other PE databases (Jenkinson and Stucke, 2011; Bansraj, Smit, and Volosovych, 2020). Zephyr includes information on deal confirmation date, industry classification, country of the portfolio company and sponsoring fund.[8] I retrieve all Private Equity transactions labelled Institutional Buyout or deals where financing is labelled Leveraged Buyout or Private Equity from 2000 to 2019. In doing so, I exluded all Growth Capital and Venture Capital deals.

Second, I match target firms with their annual company-level accounting data from Orbis, which has also been used in previous studies such as Bernstein et al. (2019). One advantage of Orbis relative to other firm-level BvD datasets (e.g. Amadeus) is that Orbis does not remove firms from the sample after a few years of inactivity. This is important since it minimizes selection concerns arising from a substantial number of firms exiting after the financial crisis. I use information on deal-confirmation date from Zephyr to identify the pre-buyout and post-buyout years. I exclude firms in the utilities, financials and public sectors. I restrict the sample to firms with data on book assets, short-term debt, long-term debt, sales and cash and cash-like assets for the sample period. In addition, I require firms to have accounting data in at least the two years immediately preceding a buyout. Excluding firms that did not meet this minimum data criterion led to an initial sample of 1,383 PE-backed firms in the post-buyout sample. Next, I exclude firms that does not meet the requirements for the matching algorithm described below, leading to a final sample of 731 firms. As will be described below, variations in the matching criterion lead to higher or lower samples but does not change the main results of this paper.

All variables are defined in Table A1 in the Appendix. To minimize the effect of outliers, all variables are winsorized at the 1 and 99 percent level. Table A2 in the Appendix shows key moments such as asset value, net leverage and industry composition are quite comparable in the full and the matched sample. I focus on net leverage (henceforth, leverage) in this

[8] When sponsoring fund information is missing, Zephyr includes the name of the acquiring company which I use to pin down the sponsoring fund from public sources.

paper because PE buyout managers typically consider debt minus cash and cash-like assets when considering companies for leveraged buyout targets.

I also verify that key moments are comparable to other studies. For example, Brown (2021) report net leverage, measured as debt minus cash and cash-like assets over enterprise value, of 51 percent immediately following a buyout. First, as Table A2 shows, leverage ratio in my sample is quite similar and stands at 49.2 and 49.5 percent respectively in the full and matched samples respectively. Second, The sample is also consistent with the literature in the time series. Brown (2021) document that leverage nearly doubles following a buyout. As Figure 1 shows, leverage in this sample displays a similar pattern in the year following a buyout.

[Insert Figure 1 Here]

A key part of the empirical strategy relies on data of comparable (matched) public companies that have observable market prices. Hence in the third step, I retrieve financial data on non-PE backed public companies from Compustat (North America and Global). I restrict the Compustat data to the same sample period and data availability requirements mentioned above for the PE-backed firms. Since my PE-sample is at the firm-year level, I obtain accounting data for public companies at the annual frequency. However, for equity price and shares outstanding, I retrieve daily data. Further details on non-PE companies are provided below in section 3.3.

3.3 Matching Procedure and Sample Characteristics

PE-backed companies are not a random sample of the population. For instance, they are like to be larger and more leveraged than the average firm. Following Bernstein et al. (2019), I find a suitable sample of comparable public companies using a matching algorithm. For each year a firm is under PE-ownership, I find at most 5 non-PE owned public companies, if available, in Compustat that (a) was in the same country, (b) belonged to the same

2-digit NAICS industry, (c) had return on asset (ROA), leverage, total book assets and volatility of ROA within a *10* percent bracket around a PE firm-year. The key difference from Bernstein et al. (2019) is that I include the volatility (standard deviation) of profits as a matching covariate and I require a much tighter match relative to their 30 percent bracket. Reasonable variations of this matching procedure with fewer or additional variables leads to moderate changes in matched sample size, but does not change the key result of the paper.[9]

The key concern with using market prices of the matched sample is selection of PE-backed firms based on dimensions we cannot observe in the data. For example, the traded price of a PE-backed company may be influenced by whether or not it is backed by a reputed private equity sponsor.[10] Demiroglu and James (2010) suggest reputation can be proxied by performance, which in this context is captured by ROA. Specifically, since performance is persistent in PE (Kaplan and Schoar, 2005), firms backed by more reputable sponsors are likely to be relatively more profitable. Similarly differences in risk-shifting or incentives due to PE-ownership is likely to be captured by matching on volatility of ROA.[11] Nevertheless, in section 6, I provide reduced-form evidence using PE-firm data consistent with the main mechanism that will drive the key result in my benchmark structural estimation.

[Insert Table 1 here]

Table 1 compares firms backed by PE and matched non-PE backed public firms. My matching algorithm leads to a match of 731 PE-owned firms with around 2,900 firm-year observations for key matching covariates in the post-buyout sample. The matched public firm sample has around 6,500 firm-year observations. We can see that the matching is quite effective in ensuring the two samples are very similar. There is no statistically significant difference in means across the two samples, and standardized percentage bias is less than or

[9] For instance, I introduced sales growth as a matching covariate which decreased our matched sample, but left our main results unchanged.

[10] In other words, investors may value a firm owned by Kohlberg Kravis Roberts Co. more highly than an identical firm owned by a less reputable sponsor.

[11] It is also plausible that any remaining confounding effect that is not captured by any of the four matching covariates are likely to have relatively smaller effect on equity prices since investors are likely to put more weight on observable financial data when determining market price.

equal to 5 percent for all matching covariates. Further inspection shows mean leverage ratio for the two samples is around 48 percent. This is also consistent with prior literature.[12]

We can also see both the median and standard deviations of matching covariates in the public company sample are quite similar. For example, median ROA volatility in the PE and matched samples are 0.055 and 0.054 respectively. Mean leverage ratios are quite close as well. Mean ROA is 3.4 and 3.2 percent for the PE and matched public sample, while the median ROA is somewhat higher for the matched public firms.

How does the matched PE sample used in the analysis compare with the unmatched full sample? Table A2 in the Appendix shows the samples are quite comparable both in terms of portfolio company characteristics and industry characteristics. For example both book assets and leverage ratios are quite similar. Manufacturing companies dominate both samples, although they are somewhat more frequent in the sample used in the analysis. Overall, the sectoral composition is qualitatively similar across both samples.

4 Benchmark Results

Because we are primarily interested in deriving an optimal leverage value consistent with trade-off theory, we need only two model inputs: market value and volatility of equity. Armed with the matched sample of public firms, I estimate the model for each firm-quarter by matching model-implied equity value and volatility with the observed market capitalization and historical equity volatility of the matched sample. Market capitalization is simply share price times number of shares outstanding while equity volatility is the standard deviation of daily (historical) price return. I set the drift rate, μ=1.78%, which is estimated directly from the data using mean historical equity return.

[12]For example, Gornall et al. (2021) use data from Stepstone SPI and Pitchbook respectively and find their sample has leverage ratio of approximately 50 percent, where leverage ratios are defined similarly.

4.1 Post-Buyout Optimal Leverage

Table 2 reports benchmark estimation results using over 32,000 firm-quarter observations. First, Panel A reports model inputs. The median equity value is USD 68.5 mn while the mean is USD 235 mn. Median equity volatility is estimated at 18.5 percent while the mean is higher at 26.2 percent.

[Place Table 2 Here]

Panel B reports my key results. I begin by tabulating the estimated mean, median, $25th$ and $75th$ percentile asset volatility, along with bootstrapped standard errors. The recovered asset volatility moments are marginally lower than their respective equity volatility. For example, mean asset volatility is 23.8 percent while the median is 18.4 percent. Using estimated asset volatility I derive model-implied optimal leverage using an initial asset value of 100. It is worth recalling the the Leland (1994) model is scale invariant so initial asset value choice does not affect leverage ratios.

Row 2 in Table 2 reports mean, median, $25th$ and $75th$ percentiles of optimal leverage. For example, using the median estimated asset volatility, the model predicts optimal leverage ratio of 50 percent. Similarly, using the $75th$ percentile estimated asset volatility, I find a much lower optimal leverage ratio of 32.2 percent. The $25th$ percentile asset volatility predicts a much higher optimal leverage ratio of 59.4 percent. The negative relationship between asset volatility and optimal leverage is well-known in the literature, but the key question is how these predicted leverage moments match with the real data. Row 3 tabulates mean, median, $25th$ and $75th$ percentiles of leverage ratios in the actual post-buyout sample. As can be seen, the model is quite consistent with the data. Median leverage ratio in the post-buyout data is 49.6 percent, while the mean is 47.8 percent. The model also is consistent with the first and third quartile predicted leverage ratios. For example, the $25th$ percentile leverage ratio in the data is 32.4 compared to 32.2 predicted by the model. Mean leverage in the data and the model are also quite comparable.

The next row reports the ratio of the default boundary to the cash flow generated in each time period, $\frac{\delta_B}{\delta_t}$. We can see the mean boundary to value ratio is 0.361, which is quite comparable to Elkamhi et al. (2012) who estimate the Leland and Toft (1996) model and find a mean ratio of 0.29. That being said, I find the median boundary to value ratio is much higher compared to their estimation, reflecting the skewed nature of the asset value distribution and higher leverage in PE-backed firms. Next, median and mean distance-to-default, computed following Bharath and Shumway (2008), is 2.2 and 2.5 respectively. A natural question is if distance-to-default is exceptionally low for firms closer to the tail of the distribution. To shed light on this question, I plot distance to default for the entire sample in Figure 3. I do not find evidence of a non-trivial share of firms with distance to default lower than 1.

[Insert Figure 3 Here]

Finally, I compute the tax benefit of debt scaled by the un-levered value of the firm as follows:

$$Tax\ Benefit = \frac{\frac{\tau C}{r}\left(1 - (\frac{\delta}{\delta_B})^{-\gamma}\right)}{\delta_t/(r-\mu)} \tag{11}$$

where the numerator is simply the variables which capture discounted tax benefits of the levered firm value from Eq. (6). The model predicts high leverage ratios do indeed generate significant tax benefits. Median and mean tax benefit of debt is approximately 20 percent of unlevered value.

As will be shown subsequently, changes in asset volatility and resulting optimal leverage effectively capture agency benefits of debt as well. While the Leland (1994) model does not explicitly model agency costs, subsequent analysis in this paper using the pre-buyout sample will reveal part of the value from debt is consistent with agency benefits Jensen (1986), in addition to tax benefits.

4.1.1 Parameter Sensitivity

One concern with the benchmark estimation is choice of value of calibrated parameters, which were set according to the literature. Since researchers have used a range of values in the past, it is worth examining how sensitive optimal leverage ratios are to the choice of r, τ, and α which were not estimated (unlike δ and σ). In addition, since the previous literature has used several proxies to approximate μ, I also check the robustness of the result with respect to changes in mean drift. In this section, I examine the change in optimal leverage ratio due to a 20 percent increase in one of these four parameters, while setting the remaining parameters to values used in the benchmark estimation. Since the effects on leverage could be asymmetric, given the highly non-linear nature of the model, I also repeat the exercise using a 20 percent decrease.

[Insert Table 3 Here]

Table 3 reports these results. Overall, the directional change is consistent with Leland (1994). Increase in risk-free rates raises the tax benefits of debt. However, if we examine the first row we can see that the effect of a 20 percent increase in risk-free rate on optimal leverage is quite small, given the estimated asset volatility and asset value. The median leverage in this case is 54.1 percent relative to 50 percent in the benchmark case. We note similar patterns in the first and third quartiles. Similarly, the effect of different choice of bankruptcy cost value is also relatively small. The model's predictions on asymmetric effect of an increase relative to a decrease in parameter value is also quite small. Change in μ also does not change optimal leverage drastically. A 20 percent increase in mean estimated drift leads to only a 1.5 percent point increase in leverage (at the median) as shown in row 3. In an additional exercise, I ask what level of drift would be required to lower model-implied leverage closer to standard public company debt levels, conditional on the estimated volatility level. Figure A1 in the Appendix reports results from this exercise through a scatter plot of asset return and leverage. We find at the estimated asset volatility level, drift would have to be significantly negative to match public company leverage ratio.

Relative to risk-free rates, tax rates tend to have a larger effect on optimal leverage. Median optimal leverage rises to 57.7 percent following a 20 percent increase in tax rate, and declines to 47.7 percent following an equivalent decrease in the tax rate, as presented in the last row of Table 3. Nevertheless, these changes are not significantly different from the benchmark model predictions and the overall takeaway from this exercise is that the choice of calibrated parameter values cannot explain the large change in leverage we observe in the data following buyouts.

4.2 Pre-Buyout Optimal Leverage

In this section, I investigate if the benchmark results documented thus far are due to selection effects, that is PE funds select companies with relatively higher levels of optimal leverage, or due to changes brought about by PE-ownership. Two key parameters can significantly shift optimal leverage when asset value follows the standard log-normal diffusion process: (i) asset return/drift, and (ii) asset volatility. On drift rate, there is extensive literature that shows PE-owned firms are more efficient and profitable given better management and more aligned incentives (Bernstein and Sheen, 2016; Davis, Haltiwanger, Handley, Jarmin, Lerner, and Miranda, 2014). On asset risk, Malenko and Malenko (2015) show that for a given leverage ratio, debt-equity conflicts could be less severe when a firm is owned by a PE sponsor relative to a non-PE owned public company with dispersed shareholders. They argue because PE-owned firms borrow against both its own assets and the sponsor's reputational capital, debt-equity conflicts stemming from risk-shifting are lower relative to non-PE or independent firms with similar leverage ratios. Their theory is consistent with Ivashina and Kovner (2011) who find PE investors have close relationships with banks and lenders. It follows that PE-backed firms experienced a reduction in asset volatility from risk-shifting activities following an LBO.

Using the benchmark model and pre-buyout financial data, I estimate asset volatility, drift and corresponding optimal leverage *before* companies in my sample are taken over by PE funds. My estimation strategy is the same as that described in the previous section. I find similar matched public companies and draw on equity value and volatility from the pre-buyout matched sample to estimate the model. I restrict the match to years $t-1$ and $t-2$ where t is the year that a company undergoes an LBO. Table A3 in the Appendix provides descriptive statistics of the PE-backed firms and their matched counterparts in the two years before buyout. First, as can be seen from examining the mean and median of the treated and control group, both samples are quite comparable. For instance, the mean leverage ratio in the PE-owned firms before the buyout is 29.9 percent and 28.7 percent in the matched group. The standard deviations are also quite comparable.

Crucially, we also note that median profitability and profit volatility are markedly differently in the pre-buyout sample. Comparing with corresponding moments in Table 1, we observe the median pre-buyout firm's ROA is approximately 2 percentage points lower than the median post-buyout firm, while volatility of ROA is higher. While, these univariate figures cannot be used to interpret any PE-effect, they are qualitatively both consistent with the literature on private equity's effect on value and risk as well as indicative of the underlying mechanism at play in the benchmark model.

4.2.1 Results and Discussion

The results of the pre-buyout estimation are reported in Table 4. Using over 9,000 firm-quarter observations, I estimate asset volatility and bootstrapped standard errors using 5,000 re-samplings.[13] I find the Leland (1994) model predicts substantially higher asset volatility distribution for the pre-buyout sample. For example, median and mean recovered asset volatility stands at 0.309 and 0.303, which is approximately 50 percent higher than the estimated σ_v post-buyout. Using these estimated asset volatilities, I again generate a distribution of optimal leverage ratio. The model predicts median optimal leverage of 33

[13]The pre-buyout estimation sample is relatively smaller since I match on only the two years before buyout.

percent, which is nearly identical to the data as can be seen in Panel B. Mean predicted leverage ratio is also quite similar at just under 30 percent. Counterfactual analysis, discussed in Section 4.3, will show much of the increase in optimal leverage is driven by lower asset volatility.

[Insert Table 4 Here]

Looking at the 25*th* and 75*th* percentile, we find the model struggles somewhat to explain the data. One interpretation is that firms for example in the first quartile are systematically under-leveraged pre-buyout. Alternatively, one might infer that the Leland (1994) model is particularly successful in explaining PE leverage ratios in the sample median (mean). Not surprisingly, we find the boundary-to-value ratio is much lower pre-buyout given less debt. On the other hand, the tax benefit of debt as a consequence of lower leverage is also lower: mean tax benefit to unlevered value is approximately half of what we observed in the post-buyout sample.

The reduction in asset volatility is consistent with the theory proposed by Malenko and Malenko (2015) and empirical evidence shown by Haque et al. (2022) on lower earnings volatility in a large sample of bank-dependant U.S. PE-backed firms. PE managers have lower incentive to shift risk to debt-holders relative to managers in a public firm due to repeated deals and, consequently, greater reliance on lenders for continued deal flow. Another, not necessarily mutually exclusive view is that higher risk pre-buyout is driven by inefficient management of free cash flows, first proposed by Jensen (1986). While the model is not intended to differentiate between these mechanisms, my estimation strategy uncovers a change in asset volatility consistent with these views. Moreover, Section 6 provides reduced-form empirical evidence consistent with the reduction in σ_v. A key implication is that, by reducing underlying risk, PE managers reduce the chances of bankruptcy which reduces the expected cost of financial distress consistent with trade-off theory.

4.3 Counterfactual Analysis

Since much of the criticism of PE centers around high leverage ratios, a natural counterfactual analysis is to quantify the difference in firm value if firms deviated from optimal leverage. In particular, I examine the cost of choosing sub-optimal leverage. Specifically, I examine the loss in leveraged firm value if a PE-backed firm chose lower leverage despite lower asset volatility and higher asset return post-buyout. Put differently, what is the cost to the firm if it does not behave according to the trade-off theory?

I proceed by re-running the model such that each PE firm chooses half the amount of the optimal model-implied coupon, given their estimated asset volatility and asset return. While at first pass this coupon choice may appear arbitrary, it mirrors the typical difference in leverage between PE-backed and public companies. For each firm, I estimate levered firm value V_L^{sub} corresponding to this sub-optimal leverage ratio. Letting, V_L^* denote levered firm value at the PE firm's optimal leverage ratio given the estimated asset volatility, I compute cost of deviating from optimal leverage as the difference between V_L^* and V_L^{sub}.

[Insert Figure 2 Here]

The results are plotted in Figure 2. The blue bar quantifies levered firm value when the firm chooses half the model predicted optimal coupon. The red bar reports levered firm value at the optimal coupon. All parameterizations are otherwise identical to the baseline post-buyout estimation. Thus, I interpret the difference as the cost of choosing optimal leverage. Not surprisingly, I find there is indeed a cost of deviating from optimal leverage. Beginning with the bars on the extreme left which reports the levered firm value given the $75th$ percentile asset volatility estimate post-buyout, we note firms stand to gain by reaching the higher optimal leverage. We also note that the cost of deviating from optimal leverage rises as asset volatility declines. For example, difference in levered firm value at the $75th$ percentile (estimated from asset volatility at the $25th$ percentile) is higher relative to the estimates at the median. While this is not particularly surprisingly given that Leland-type models predict higher value from lower volatility on average, the question worth examining is how large is this cost.

[Insert Table 5 Here]

Table 5 reports the difference in the two values as percentage of the sub-optimal leveraged firm value. We find the cost is non-trivial. For firms in the median of the cost distribution, deviating from optimal leverage can cost up to 4.0 percent of value, and can go upto 5.7 percent for those in the lower end of the risk distribution. In other words, for firms that achieve substantial reductions in risk, choosing lower leverage is much more costly than those with higher risk. It is interesting to note that the cost of deviation estimated from the model is quite comparable to the literature. Specifically, Korteweg (2010) finds that the net benefits to leverage is approximately 5.5 percent for a representative firm.

5 Model Extensions

Thus far, we have shown optimal leverage ratios estimated from a trade-off model is, on average, consistent with PE-firm leverage. In this section, I study simple extensions to the standard trade-off model to examine two issues often associated with PE-sponsored buyouts.

5.1 Debt Covenant

One alternate explanation behind high buyout leverage could be a weaker covenant setting due to close relationships between lenders and private equity sponsors (Ivashina and Kovner, 2011; Achleitner, Braun, Hinterramskogler, and Tappeiner, 2012; Demiroglu and James, 2010). For instance, it could be that banks set looser covenant violation thresholds for PE-sponsored deals, thus raising covenant slack relative to public firms and allowing higher leverage. We would thus expect a trade-off model with covenants to explain the data. To examine this possibility, I extend the Leland (1994) framework to incorporate covenants and re-estimate the model.

Specifically, I model an interest coverage threshold which the literature has shown is one of the most prevalent types of covenants (Greenwald et al., 2019). For parsimony, I follow Strebulaev et al. (2012) who propose simple extensions to the Leland (1994) model to capture an exogenous default threshold because the firm violates a net-worth covenant. The starting point is the observation that $\frac{\delta_t}{C}$ effectively captures a coverage ratio (EBITDA/Interest Expense) and thus replacing the optimal default barrier with a covenant violation threshold can incorporate coverage ratio covenants in a simple and parsimonious way.

$$\delta_t = \theta C \tag{12}$$

Setting $\theta C = \delta_B$, I derive the optimal coupon by maximizing Eq. (7). Details of the derivation are presented in Appendix A9. I re-estimate post-buyout asset volatility and leverage similar to the baseline. All calibrated parameters are the same as before except I need to set a value for the covenant violation threshold, θ. I set $\theta = 2.63$ following findings in Bräuning, Ivashina, and Ozdagli (2022), whose sample of 119 maintenance covenants require borrowers to maintain the coverage ratio at that level.

[Insert Table 6 Here]

Table 6 presents results from this estimation. The asset volatility estimates are largely unchanged in the post-buyout sample. To wit, compared to our benchmark estimation, this version of the model predicts median asset volatility of 0.192, marginally higher than the 0.177 estimate reported in Table 2. However, when I estimate optimal leverage with this new asset volatility, the model does a below par job of matching the data. Median leverage predicted by the model post-buyout is less than 10 percent, given the calibrated value of θ and other parameters.

Why is optimal leverage so low with interest coverage covenants? The key reason is that setting an exogenous default threshold which is equivalent to relaxing the deep-pockets assumption leads the agent to declare default much earlier and lowers optimal leverage. As long as $\theta < 1$, the agent can inject equity. The greater the default threshold in a covenant, the earlier an agent declares default. In this case, we set $\theta = 2.63$, thus forcing default much earlier.

In the context of the key hypothesis motivating this exercise - PE sponsorship can loosen covenant threshold - we can now use this version of the model to ask what level of violation threshold would lead to observed PE leverage, conditional on the estimated asset volatility levels? This question is plausible since the Bräuning et al. (2022) sample likely captures both sponsored and non-sponsored firms. In other words, would a much lower covenant violation threshold lead to observed PE buyout leverage?

[Insert Figure 4 Here]

We plot the sensitivity of optimal leverage to covenant violation threshold, θ, in Figure 4. We observe a highly non-linear relationship between θ and optimal leverage. θ close to 1 leads to leverage ratios around 20 percent, which is somewhat comparable to many public company leverage ratios. On the other hand, we note that it would require violation thresholds significantly lower than 1 to match observed PE leverage, given all other parameter values. This would imply equity issuance cost for PE-backed firms is lower than public firms, which is plausible given PE funds' deep-pockets (Bernstein et al., 2019; Hotchkiss et al., 2021). Crucially, at $\theta < 0.4$, this version of the trade-off model also does a reasonable job of matching buyout leverage, conditional on the estimated asset volatility parameter.

5.2 Renegotiable Bank Debt

Second, previous studies have shown that PE-backed firms tend to avoid bankruptcy court more often, and liquidate less often compared to non-PE backed, highly leveraged firms experiencing financial distress (Hotchkiss et al., 2021). One potential explanation for why higher leverage is optimal in PE-backed firms could be PE sponsors' ability to negotiate out-of-court with lenders. However, a standard property of the Leland (1994) model, as well as its variants such as Leland and Toft (1996) or Leland (1998), is that debt-holders take control of the company if equity-holders default and crucially, there is no scope for renegotiation. Put differently, debt in the benchmark model is defaultable public debt and does not take into account private debt contracts, such as bank debt. In this section, I estimate a simple extension of the standard trade-off model with bank debt to examine if post-buyout leverage can be explained by the ability of borrowers to renegotiate debt.

To keep my analysis parsimonious, I follow Strebulaev et al. (2012) and assume the firm only has bank debt outstanding and has full bargaining power with the lender. Since the model is well-known, I only discuss its key features in this section and refer readers to Appendix A8 for further details. In this model without defaultable debt, the firm simply negotiates its coupon payments in low-profitability states of the world. This negotiation occurs at an asset level which the equity holder chooses by maximizing equity-value payoff, similar conceptually to the endogenous default point discussed earlier. Crucially, due to the assumption that the firm has full bargaining power, the firm renegotiates to keep the value of bank debt at its reservation value. The value of the leveraged firm is the sum of the unleveraged value in perpetuity and the tax benefits of debt. Similar to Leland (1994), the firm chooses an optimal coupon by maximizing levered firm value.

I report mean and various percentiles of leverage, keeping all the parameter values fixed at their benchmark quantities. I report the results in Figure 6 for two bankruptcy cost values: the baseline case of 0.23 and a lower bankruptcy cost of 0.1. My results indicate that the extended model with bank debt produces much lower leverage ratios when bankruptcy cost is held at the benchmark value. As can be seen from the bottom four rows in Figure 6, mean and median optimal leverage is much lower relative to the baseline estimation, and by extension, the data. One interpretation is that this model predicts PE-backed firms are over-levered. On the other hand, when I lower default cost to 10 percent, not implausible given the arguments in Hotchkiss et al. (2021), optimal leverage is much closer to the baseline.

5.3 Asset Liquidation and Dividend Payout

Third, in the main analysis, net cash outflows associated with the leverage decisions must be financed by selling additional equity, consistent with bond covenants restricting firms from selling assets. In other words, there are no net cash outflows resulting from payments to debt or equity-holders. However, PE investors are often accused of asset stripping, to the point where the EU has implemented a directive to stop this type of activity (e.g. Reuters, 2010; The Gaurdian, 2021). Asset stripping typically involves selling off individual assets to generate dividend payouts for investors.

To capture liquidation of assets to fund higher payouts, I follow Leland (1994) and consider the case of cash outflows that are proportional to asset value. This leads to a lower effective drift rate of $\mu' = \mu - d$, where d is the payout rate as a share of asset value, δ. The only key change is that μ' replaces μ in the root of the fundamental quadratic equation, γ outlined in Eq. (5). I consider two cases where $d = 0.01$, similar to Leland (1994), as well as $d = 0.02$. These liquidation rates are equivalent to approximately 2 percent and 4 percent payout on equity value respectively, based on the median leverage ratio predicted in the baseline case.

The rest of the estimation procedure is unchanged. I report the results in Figure 5 comparing optimal leverage ratios from the baseline post-buyout results with the extended version capturing asset liquidation in order to meet higher payouts. The top four moments capture the exercise where $d = 0.01$, and the bottom four moments are the ones with $d = 0.02$. Not surprisingly, we observe a decline in optimal leverage ratio in both cases and a higher decline when the asset liquidation rate is higher.

The key question is does asset liquidation substantially lower optimal leverage ratios? The answer appears to depend on what we consider as an appropriate liquidation rate. When the payout rate is 1 percent on asset value, consistent with Leland (1994), the change is quite small. For example, leverage ratios decline by approximately 2 percentage points at the mean and median. In fact, median leverage ratio of 50 percent with $d = 0.01$ is nearly identical to median leverage ratio in the data (49.8 percent) as reported in Table 1.

When I raise asset liquidation rate to 2 percent, median and mean optimal leverage ratio declines to 47.6 and 42.9 percent respectively. While the median is still quite close to the data, the mean optimal leverage is now much lower relative to mean leverage in the data. One interpretation of this result is that if PE investors exercise high asset liquidation rate in order to pay themselves dividend, then there is some moderate evidence of over-leveraging since actual mean leverage is higher. It is also worth observing that when $d = 0.02$, the disagreement between the baseline and the extended model appears to be more much pronounced at the first quartile, but is much smaller at the third quartile.

6 Reduced-form Evidence

The results so far are consistent with the idea that private equity can lower expected cost of financial distress by lowering underlying asset volatility of portfolio companies. Admittedly, one limitation of the benchmark model is that asset volatility is not endogenous.

In this section, I provide reduced-form evidence consistent with the idea that private equity can lower asset volatility. First, I show PE-ownership leads to a reduction in the volatility of sales consistent with an operational engineering channel (Gryglewicz and Mayer, 2020). Second, consistent with better distress resolution (Hotchkiss et al., 2021), I show PE-backed firms receive additional equity injection (relative to matched controls) whenever they are in financial distress. Equity injection during financial distress implies a reduction in incentives to engage in asset substitution or risk-shifting.

Operational Engineering Channel: Lower Sales Volatility. Fracassi et al. (2022) use store-level data to show PE-backed firms launch new products and expand their geographic reach relative to comparable controls. This diversification is consistent with a reduction in the volatility of sales and a reduction in volatility of the unlevered value of a firm in capital structure models. Thus, as a first exercise, I show the volatility of sales declines under PE-ownership relative to matched controls. I create a matched control group using the methodology described in Section 3.3, to address selection concerns, and run the following difference-in-differences regression specification.

$$Y_{it} = \alpha_i + \delta_t + Post_{it} + Post_t \times LBO_i + X_{it} + \epsilon_{it} \tag{13}$$

where the outcome variable is the *standard deviation* of a firm's Sales, scaled by Earnings Before and Interest Taxes, computed separately in the pre-(post-) buyout samples. LBO_i is a dummy taking value 1 if a company was ever owned by PE investors, and $Post$ is a dummy for the period following a PE-sponsored buyout. If the observation is a matched control firm, $Post_{it}$ equals 1 when the PE portfolio company matched to i has undergone an LBO, and 0 before. Furthermore I augment our specification with a set of firm covariates, firm (α_i) and year (δ_t) fixed effects. My estimation strategy thus controls for channels that have been documented as important drivers of buyout leverage: (i) economy-wide credit conditions (Axelson et al., 2013), the rise of structured credit (Shivdasani and Wang, 2011), (iii) fund managers non-randomly targeting specific firms and (iv) unobserved time-invariant factors.

[Insert Table 7a Here]

I report the results in Table 7a. We present results that iterate between various combinations of fixed effects and firm-controls. In column 1 for example, we include only firm fixed effects to capture time-invariant unobservable firm-level factors that can effect our outcome of interest. We observe a large and negative coefficient on the difference-in-differences estimator, $Post \times LBO$, indicating a reduction in sales volatility under PE-ownership. We also note that the $Post$ variable is positive and highly significant, suggesting these firms were on track to experience higher volatility but PE-ownership reduced this effect. In column (2) we drop firm fixed effects but include year fixed effects and immediately see a large drop in R^2, implying a lot of the variation does indeed come from time-invariant firm-level factors. Crucially, in column (3) we include both fixed effects and find that our coefficient of interest is still highly significant and negative. The estimate barely changes when we include time-varying firm-level controls including the natural log of total assets, leverage and ROA, signifying that the result is quite robust.

However, one concern with a reduction in sales volatility is a possibility that PE fund managers may manipulate accounting data to maximize risk-adjusted return at the fund-level, which in turn can lock-in greater capital from marginal investors in the future. Indeed, Brown et al. (2019) show PE fund managers can inflate fund returns during fund-raising, especially if the manager is under-performing. While my analysis is at the portfolio-company level, one could plausibly have similar concerns, since the location of private firms substantially affects its financial reporting environment. For example, private firms in the United States and Canada, are not required to make their financial reports public nor have them audited (Minnis and Shroff, 2017). On the other hand, most middle-market and larger European firms are required to both disclose their financial statements and have them regularly audited.

I thus repeat my analysis on sales volatility by restricting the estimation sample to the following European countries: Spain, Italy, France, Germany and UK. The rationale is that the need for auditing will lower systematic manipulation. Table A4a in the Appendix provides estimates with this sub-sample. As can be seen, although the estimates are somewhat smaller, they are still economically meaningful and highly significant. The only specification where the estimate is not significantly different from zero is where I do not include firm-level fixed effects or time fixed effects. Including firm and year FE, as well as firm-level time-varying control in column (4) yields an estimate of -0.308, which is significant at the 1 percent level.

Distress Resolution Channel: Equity Injection. One mechanism that can explain lower asset volatility and expected cost of financial distress is deployment of fresh capital into a distressed firm. Because PE groups raise funds that are drawn down and invested over multiple years—commitments that are very rarely abrogated—they may have "deep pockets" during downturns (Bernstein et al., 2019). These capital commitments may allow them to make equity investments in their firms when accessing other sources of equity, or financing in general, is challenging. Equity injection during financial distress can explain why debt overhang is less for a given leverage ratio, and reduces the equity-holder's incentive to shift risk to debt-holders when in financial distress. Put differently, capital infusion resolves financial distress more quickly and thus reduces a classic asset substitution problem at high leverage ratios.[14]

Following prior studies, I show that PE-backed firms in my sample receive greater capital injection relative to comparable non-PE companies. I proceed as follows. I define an indicator variable $Distress$ as follows:

$$Distress = \begin{cases} 1 & \text{if Altman Z-Score} < x \\ 0 & \text{otherwise} \end{cases}$$

where the Altman Z-score is computed at the *company-year* level and x is a positive constant.[15] Using this $Distress$ variable, I estimate Eq. (14) below where the dependant variable is Net Equity Contribution/Asset at the firm-year level. Equity Contribution is defined as the difference in total Book Equity over the past year, minus profit following Bernstein et al. (2019).[16] I introduce a triple interaction between LBO, $Post$ and $Distress$. All second-order interactions are also included, unless they are absorbed by fixed effects. A positive coefficient is indicative of PE-backed firms receiving additional equity contribution compared to a matched control group when they are in financial distress. To summarize, I

[14] The literature argues the motivation to inject fresh equity comes from PE sponsors being repeat players in the buyout market; recurrent episodes of costly financial distress could harm reputations with lenders, fund investors, and other stakeholders

[15] Since I do not observe data on Retained Earnings, I proxy with Cash flows which Orbis (2007) defines as Profit for the Period plus Depreciation.

[16] For profit I proxy with Cash Flows in period t. I also verify that my results are not affected if I used other measures of Profit such as Profit Before Taxes. These are available upon request.

estimate variants of the following triple-interaction equation:

$$Y_{it} = \beta_1 Post_{it} + \beta_1 LBO_i \times Post_{it} + \beta_2 LBO_i \times Post_{it} \times Distress_{it} + \gamma^{'} \mathbf{X}_{it} + \alpha_i + \delta_t + \epsilon_{it} \quad (14)$$

[Insert Table 8a Here]

I report the results in Table 8a. The sample size is somewhat smaller relative to the regressions in Table 7a since our outcome variable is measured in changes. The key coefficient of interest is that on the triple interaction term $LBO \times Post \times Distress$. x is set to 1 in columns (1) and (2) and 1.5 in columns (3) and (4). In column (1) we include both firm and year fixed effects, thus our estimated coefficient is identified from within-firm variation over time.

We observe that the triple interaction coefficient is positive and highly significant. The estimate implies PE-backed firms receive 94.4 percent greater capital infusion relative to matched non-PE firms, conditional on severe financial distress. The estimate rises to 1.13 if we drop time fixed effects, as shown in column (2). In column (3) we use a higher threshold, which intuitively captures a relatively lower severity of financial distress. We find that our coefficient of interest is significant at the 10 percent level, and the point estimate is much smaller at 0.461. This is consistent with the idea that relatively greater financial distress leads to higher equity injection by sponsoring funds.

7 Conclusion

Private Equity is often accused of over-leveraging their investments. Prior studies argue PE sponsors primarily look at credit market conditions when choosing buyout debt, and buyout capital structure is unrelated with cross-sectional factors. This standard view implicitly assumes optimal leverage does not change post-buyout. However, we do not know whether higher buyout leverage is optimal without a structural model that endogenizes default, leverage and the key benefits and costs of debt. This paper argues a PE-manager behaves much like a standard equity-holder and chooses capital structure by balancing the benefits of debt with the expected cost of financial distress. The model's key result is that PE managers are able to achieve a higher level of optimal leverage, which are on average, consistent with the data. The model also predicts higher optimal leverage results from a significant reduction in asset risk, and to some extent, an increase in asset return. Consistent with higher optimal leverage, I show that PE's contribution to corporate distress and financial fragility is lower than previously argued.

To support results from the structural estimation, I provide additional empirical evidence consistent with key factors that drive higher optimal leverage. Specifically, using a set of matched difference-in-differences regressions, I show that PE backed firms reduce sales volatility and also receive greater equity injections when in financial distress relative to comparable non PE-backed companies. These mechanisms support the notion of lower agency costs and reduced incentives to shift risk to debt-holders, which reduces the expected present value of bankruptcy costs and raises the optimal level of leverage.

How can we reconcile the empirical evidence on credit market conditions and initial buyout structure, in prior studies? One possible explanation is prior studies primarily examine firm characteristics at deal entry, while my empirical strategy internalized the effects of post-buyout changes in the portfolio company's characteristics. Overall, this paper broadens our understanding of what drives buyout leverage, and highlights the need to examine the value-maximizing leverage ratio when firms are backed by financial sponsors.

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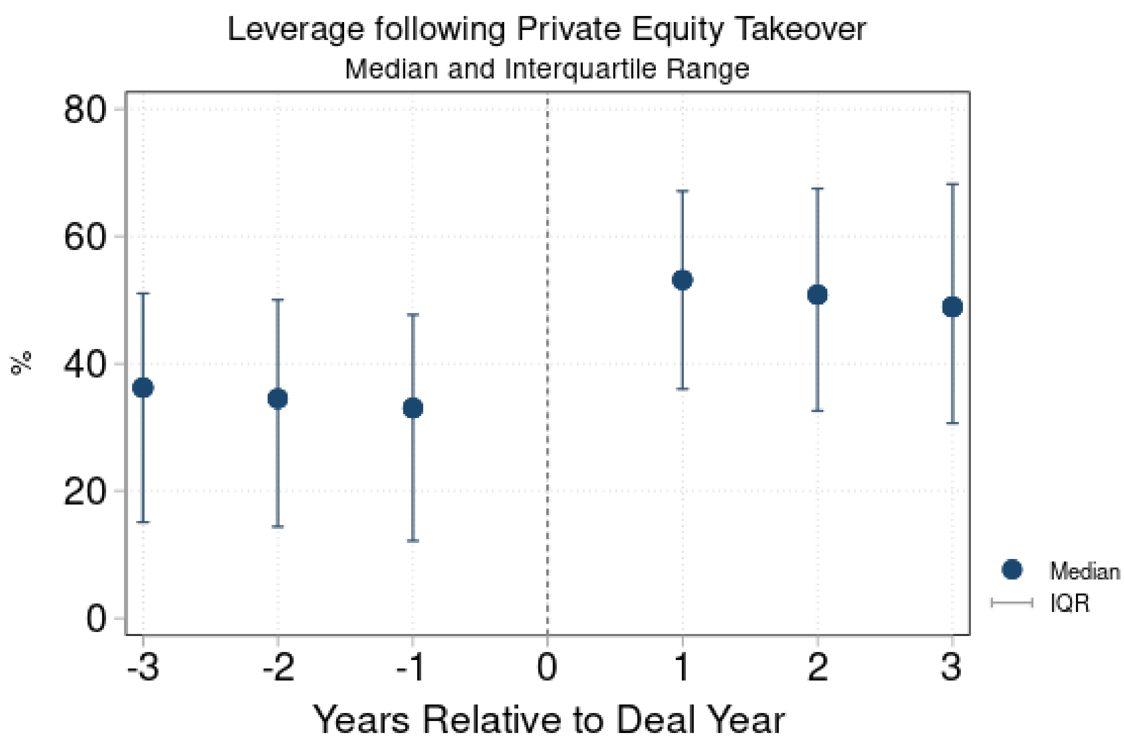
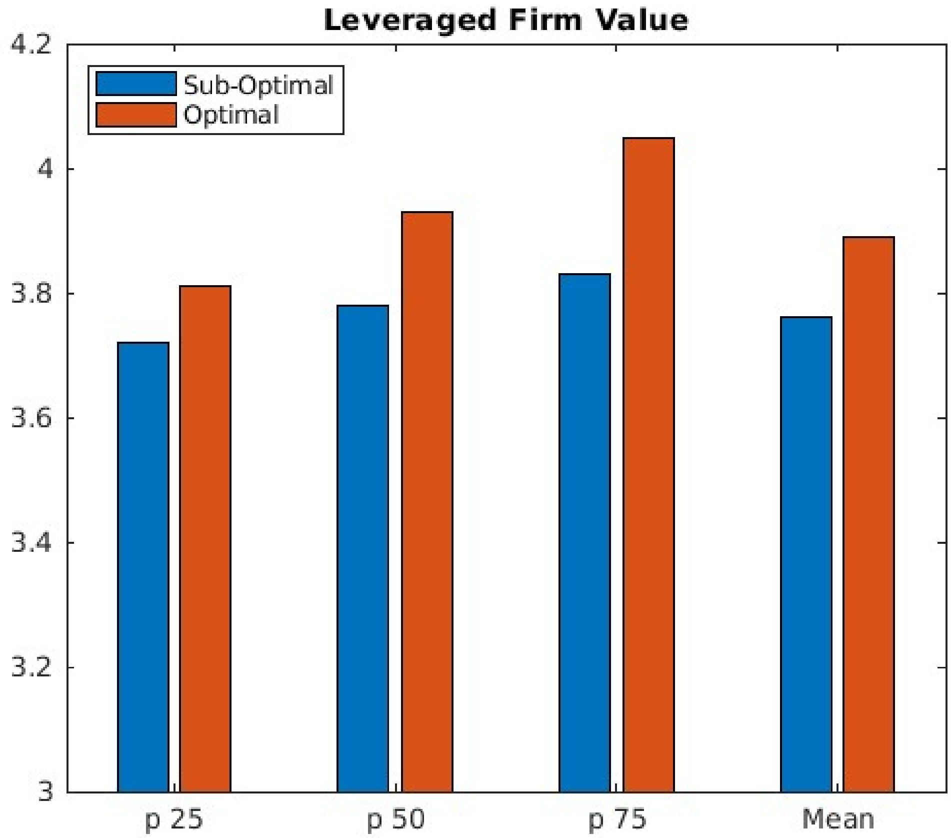
Figure 1: Leverage Dynamics



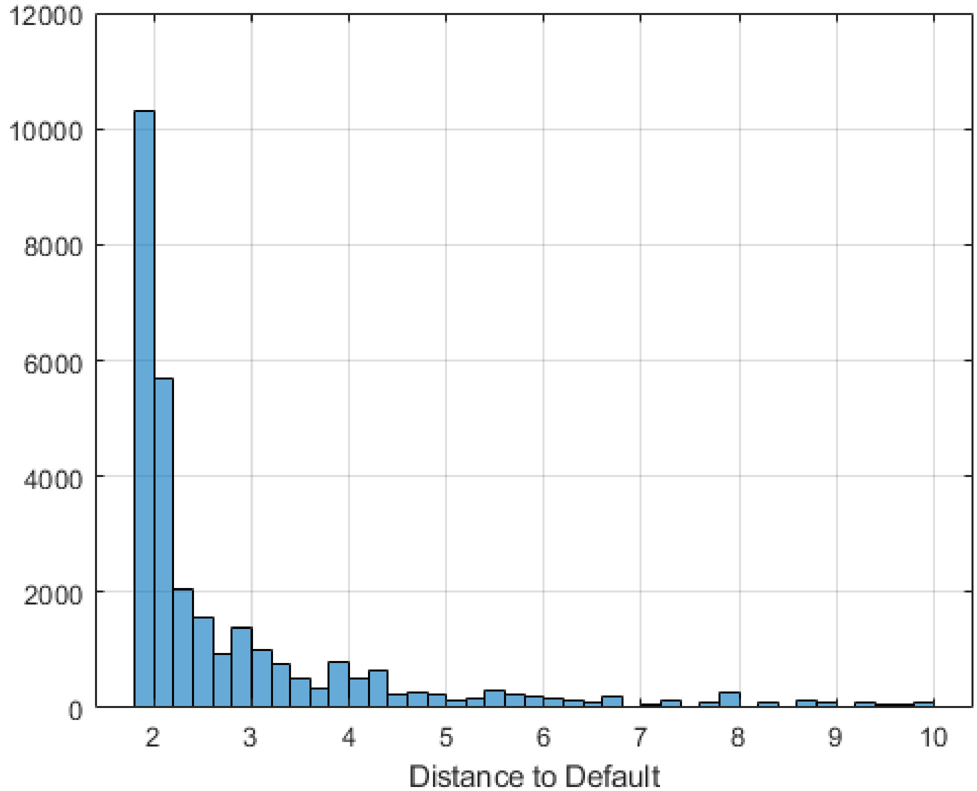
(a) *This chart plots leverage (Net Debt/Asset) in PE-backed firms in the pre-(post-) buyout periods. The x-axis plots years relative to the PE deal-year. The dot plots the median quantity, and the bands plot the interquartile range (IQR).*

Figure 2: Counterfactual Policy: Cost of Choosing Lower (sub-optimal) Leverage



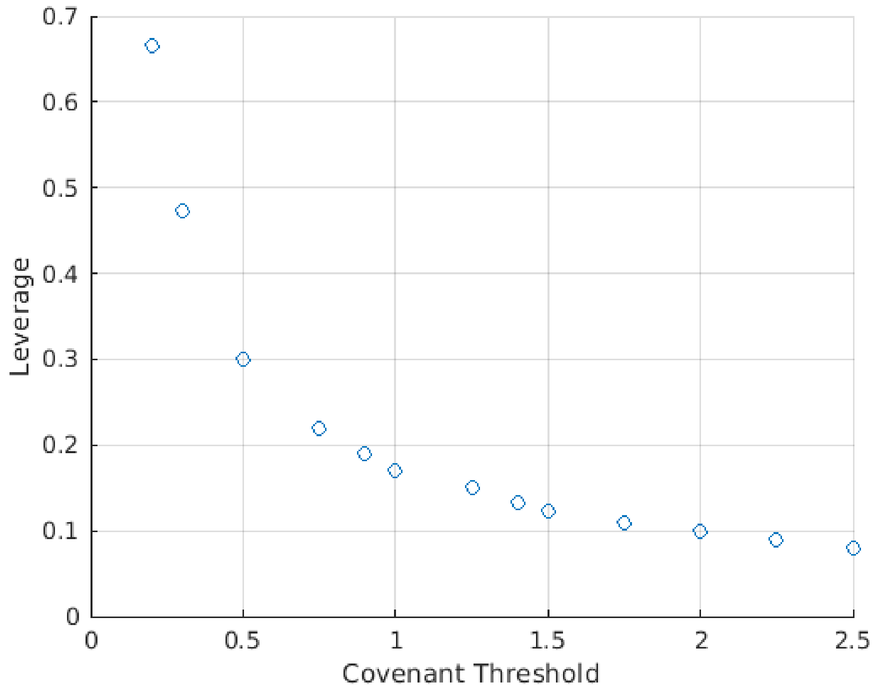
(a) *Notes: The chart above reports results from a counterfactual analysis on the cost of deviating from optimal leverage for a PE-backed company. The y-axis plots leveraged firm value and the difference between the two bars captures the cost of choosing sub-optimal leverage. Both charts plots the difference in firm value at the optimal* C^* *and a sub-optimal* C_{sub}*, where* $C_{sub} = 0.5 * C^*$*. This particular formulation of sub-optimal capital structure was chosen to match leverage ratios of standard non-PE companies.* δ_0 *value was set to 100. All values were multiplied by 0.001 to simplify visual exposition.*

Figure 3: Distance to Default Post-Buyout



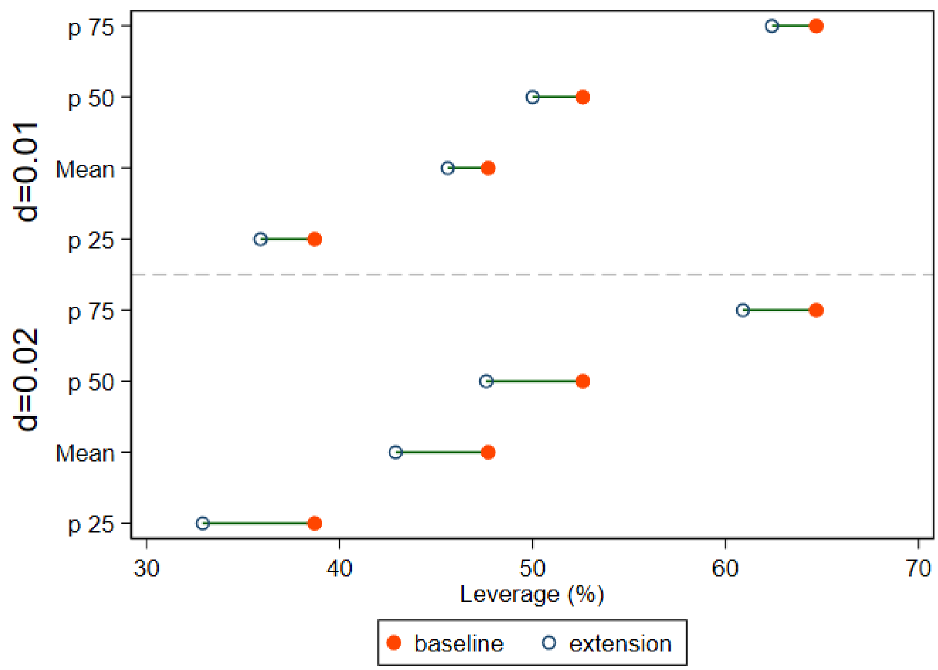
(a) *Notes: The chart above reports distance to default estimates from the benchmark Leland (1994) estimation. The model is estimated by solving for unobserved asset value and volatility that matches observed equity value and volatility. Market equity is computed as outlined in Section 3.3 and Equity volatility is computed as the standard deviation of (historical) daily stock price return for each firm and aggregated to the quarterly level to facilitate model calibration at the firm-quarter level. To calibrate the model, we set the risk-free rate to the drift rate,* $T = 1$ *and we approximate the default barrier with* V_B *which is derived endogenously.*

Figure 4: Model Extension: Optimal Leverage with Binding Covenant Threshold



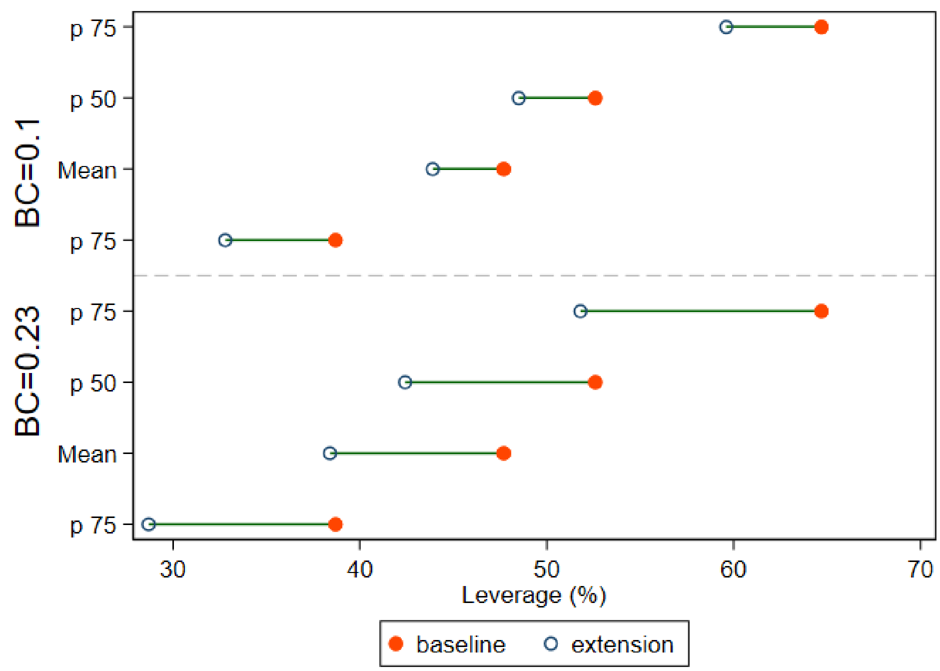
(a) *Notes: This chart reports leverage estimates from a trade-off model extended to capture an interest coverage covenant. The key difference of the model relative to the standard Leland (1994) model is explained in Section 5. Estimation methodology is described in Section 3.3. The x-axis plots θ, the covenant violation threshold, that links firm earnings to interest expenses and the y axis plots model predicted optimal leverage.*

Figure 5: Model Extension: Optimal Leverage under Asset Liquidation



(a) *Notes: This chart reports leverage estimates from a trade-off model extended to capture asset liquiditation. The key difference of the model relative to the standard Leland (1994) model is explained in Section 5. I use asset volatility quantities and all other calibrations from the benchmark estimation.*

Figure 6: Model Extension: Optimal Leverage under Bank Debt



(a) *Notes: This chart reports leverage estimates from a trade-off model extended to capture bank debt. The key difference of the model relative to the standard Leland (1994) model is explained in Section 5. I use asset volatility quantities and all other calibrations from the benchmark estimation. BC is abbreviation for bankruptcy cost. I use both the baseline bankruptcy cost as well as an alternative value of 0.1, presented in the top 4 rows.*

Table 1: Covariate Balance

Variable	PE Sample				Matched Sample					
	N	Mean	Median	SD	N	Mean	Median	SD	Mean diff.	%bias
Log Size	3020	18.2	17.89	1.57	6706	18.3	18.7	1.72	-0.1	-5.0
Leverage (%)	2875	48.8	49.8	28.9	6580	48.1	44.1	26.9	0.7	2.6
ROA (%)	3012	3.4	3.3	0.179	6585	3.2	4.2	0.07	0.2	1.7
Volatility	3028	0.091	0.055	0.34	6715	0.102	0.0539	0.32	-0.01	-3.0

(a) *Notes: This table reports summary statistics of sample firms across PE-backed and non-PE backed comparable public companies. The last column reports mean difference across the two groups.*

Table 2: Benchmark Results: Post-Buyout Leverage

A. Model Input	N	Q1	Q2	Q3	Mean
Market Equity ($ Mn)	32229	19.2	69.9	237	348
Equity Volatility	32229	0.135	0.191	0.357	0.242

B: Results	Q1	Q2 (Median)	Q3	Mean
Asset Volatility	0.122	0.177	0.277	0.203
	(0.054)	(0.046)	(0.032)	(0.058)
Leverage (Model)	38.7	52.6	64.7	47.7
Leverage (Data)	32.3	49.8	65.6	49.5
Boundary to Value ($\frac{\delta_B}{\delta_t}$)	0.188	0.331	0.475	0.361
Distance-to-Default	1.956	2.207	3.603	2.588
Tax/Unlevered Value	0.137	0.197	0.252	0.205

(a) *Notes: The columns are ordered by quartiles, after which the mean is reported.* δ_t *is recovered asset value in a firm-quarter,* δ_B *is the model-predicted endogenous default barrier. For the estimation, I set* r*=0.05,* τ*=0.2 and* α*=0.23.* μ*=0.0178, which is estimated directly from mean historical equity return data. See Appendix Table A5 for a summary of calibrated parameters and their sources. The formula for Tax Benefit to unlevered value is provided in Eq.* (10)*. Bootstrapped standard errors are reported in parenthesis computed from 5,000 re-samplings with replacement.*

Table 3: Sensitivity of Optimal Leverage to Calibrated Parameters

	Q2 (Median)	Q1	Q3
Benchmark Estimation	52.6	38.7	64.7
A. 20 % increase in calibrated parameter			
Risk-free rate, r	54.1	40.7	65.3
Bankruptcy cost, ρ	51.8	38.6	63.7
Drift, μ	54.1	39.6	66.0
Tax rate, τ	57.7	32.4	67.4
B. 20 % decrease in calibrated parameter			
Risk-free rate, r	50.7	36.4	62.9
Bankruptcy cost, ρ	53.4	38.9	64.8
Drift, μ	51.1	37.9	62.3
Tax rate, τ	47.7	44.5	60.3

(a) *Notes: This table reports sensitivity tests of model-implied optimal leverage with respect to the calibrated parameters, which were set according to previous studies. The benchmark estimation reports the same results from Table 2 as reference where leverage ratios are derived from estimated asset volatilities. For example, 'Q2 Median' in the first row reports the optimal leverage ratio at the median estimated asset volatility using the benchmark calibration. For each of the three calibrated parameters, Panel A reports optimal leverage from a 20 percent increase in the value of one calibrated parameter, while keeping the others at their benchmark value. Panel B reports the same for a 20 percent decrease.*

Table 4: Model Predicted Pre-Buyout Leverage

	N	Q1	Q2 (Median)	Q3	Mean
A. Model Inputs					
Market Equity ($ Mn)	9312	8.65	28.8	104	289
Equity Volatility	9312	0.329	0.424	0.924	1.3
B. Estimation Results					
Asset Volatility		0.272	0.331	0.406	0.320
		(0.003)	(0.01)	(0.006)	(0.002)
Leverage (Model)		25.3	29.1	33.0	22.2
Leverage (Data)		5.90	27.5	46.8	24.6
Boundary to Value		0.09	0.11	0.14	0.14
Distance-to-Default		2.22	2.57	2.91	2.56
Tax/Unlevered Value		0.04	0.04	0.051	0.049

(a) *Notes: The columns are ordered by quartiles, after which the mean is reported.* δ_t *is recovered asset value in a firm-quarter,* δ_B *is the model-predicted endogenous default barrier. For the estimation, I set* r*=0.05,* τ*=0.2 and* α*=0.23.* μ*=-0.013, which is estimated directly from mean historical equity return data for the pre-buyout sample. The formula for Tax Benefit to unlevered value is provided in Eq. (10). Bootstrapped standard errors are reported in parenthesis obtained from 5,000 re-samplings with replacement.*

Table 5: How Large is the Cost of Deviating from Optimal Leverage?

	p25	p50	p75	Mean
Levered Value: Sub-optimal	3.72	3.78	3.83	3.76
Levered Value: Optimal	3.81	3.93	4.05	3.89
Difference	0.09	0.15	0.22	0.13
Cost of Sub-Optimal Leverage	2.4%	4.0%	5.7%	3.5%

(a) *Notes: This table reports simulated cost of deviating from optimal leverage as outlined in Section 4.3. The columns are ordered by quartiles, after which the mean is reported. The first two rows report levered firm value (divded by 1000), given the estimated optimal leverage at different percentiles. All parameterizations are the same as the benchmark post-buyout. Sub-optimal firm value is estimated by setting optimal coupon to half of that predicted by the benchmark model. The last row reports the difference in two values as a percentage of the sub-optimal value, quantifying the cost of deviating from optimal leverage.*

Table 6: Extended Model with Debt Covenants

Results	Q1	Q2 (Median)	Q3	Mean
Asset Volatility	0.136***	0.192***	0.358***	0.244***
Leverage - Model (%)	11.68	8.3	2.61	6.1
Leverage - Data (%)	32.3	49.8	65.6	49.5
Boundary to Value ($\frac{\delta_B}{\delta_t}$)	0.074	0.296	0.443	0.28
Distance-to-Default	2.249	2.700	3.660	2.860
Tax/Unlevered Value	0.005	0.020	0.031	0.019

(a) *Notes: This table reports results of the benchmark model that incorporates coverage ratio covenant described in Section 5. The columns are ordered by quartiles, after which the mean is reported. δ_t is recovered asset value in a firm-quarter, δ_B is the model-predicted endogenous default barrier. For the estimation, I set r=0.05, τ=0.2 and α=0.23. μ=0.0178, which is estimated directly from mean historical equity return data. See Appendix Table A5 for a summary of calibrated parameters and their sources. The formula for Tax Benefit to unlevered value is provided in Eq. (10). For each asset volatility quartile estimate, bootstrapped standard errors are computed from 5,000 re-samplings with replacement.*

Table 7: Reduced Sales Volatility under PE-ownership

Y_{jt} : *Sales Volatility*	(1)	(2)	(3)	(4)
Post × *LBO*	-0.713***	-1.074***	-0.835***	-0.825***
	(0.182)	(0.405)	(0.191)	(0.202)
Post	0.682***	0.179	0.709***	0.710***
	(0.131)	(0.303)	(0.132)	(0.134)
R^2	0.931	0.010	0.932	0.929
Firm FE	Y	N	Y	Y
Year FE	N	Y	Y	Y
Controls	N	N	N	Y
N	2,538	2,537	2,537	2,465

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

(a) *Notes: This table reports difference-in-differences regression estimates at the firm-year level. The dependant variable is each firm's standard deviation of Sales, scaled by the firm's Earnings Before Interest and Taxes. Post takes value 1 for each year after a buyout, defined similarly for matched controls. LBO takes value 1 if a firm was actually acquired by a PE-sponsored leveraged buyout, 0 for matched controls. Controls include the log of book assets, leverage and return on assets. All variables are defined in Table A1 in the Appendix.*

Table 8: Equity Injection during Financial Distress

$Y:$ *Equity Injection*	*Altman* < 1		*Altman* < 1.5	
	(1)	(2)	(3)	(4)
Post $\times$ *Distress* $\times$ *LBO*	0.944***	1.130**	0.461*	0.926***
	(0.211)	(0.462)	(0.229)	(0.207)
Post $\times$ *Distress*	-1.241***	-1.207***	-0.622*	-0.803***
	(0.395)	(0.262)	(0.298)	(0.186)
R-squared	0.320	0.313	0.320	0.314
Firm FE	Y	Y	Y	Y
Year FE	Y	N	Y	N
Controls	Y	Y	Y	Y
N	1,965	1,965	1,965	1,965

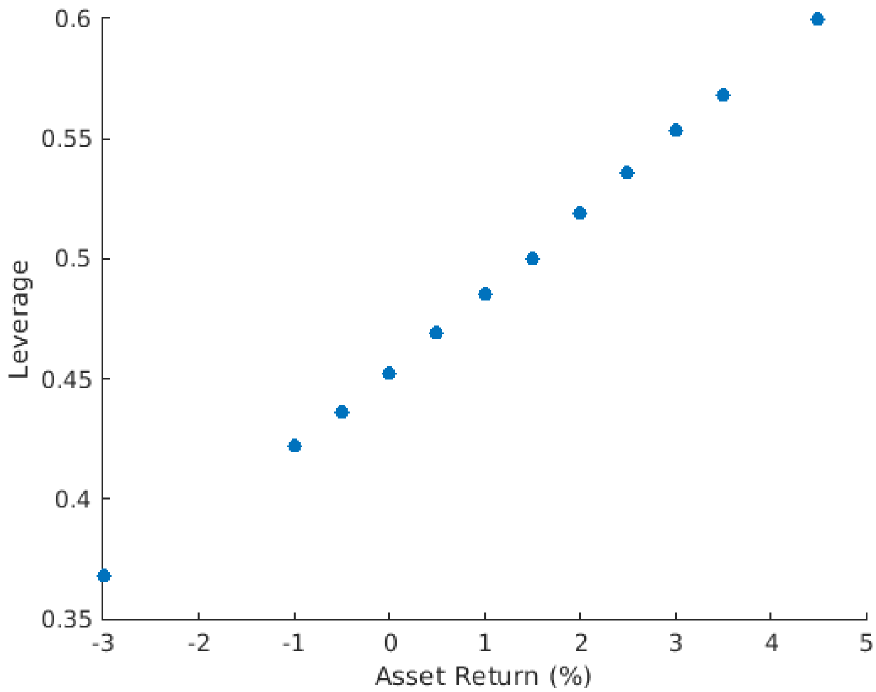
Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

(a) *Notes: This table reports results of matched difference-in-differences regressions of outcomes of PE-backed companies relative to public controls. Following Bernstein et al. (2019),* Y_{jt} *is Net Equity Contribution/Asset. Equity Contribution is measured as the difference in total equity (shareholder value) over the past year, minus profit. Specifications vary by fixed effects and definition of Distress. Post takes value 1 in years after a buyout. Distress takes value 1 if the computed Altman Z-score is less than 1 in a given company-year in Columns (1) and (2) and less than 1.5 in columns (3) and (4). I also control for confounding pairwise interactions if they are not absorbed by firm fixed effects.*

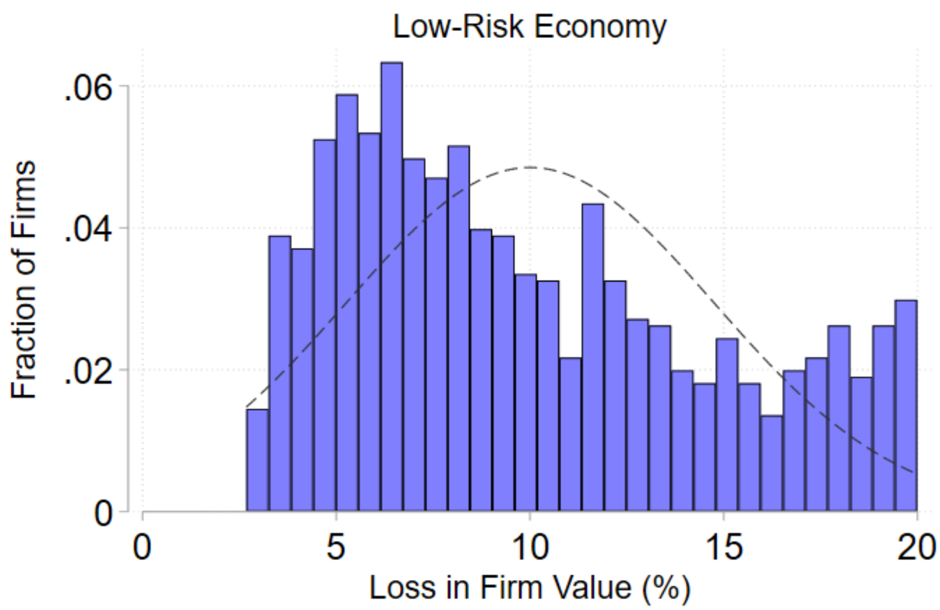
Internet Appendix

Figure A1: Sensitivity: Asset Return and Optimal Leverage



(a) *Notes: This chart reports leverage estimates from a trade-off model at different values of asset return, μ. σ_v is set to the value estimated from the benchmark analysis. All other parameter values are set to their benchmark calibrations.*

Figure A2: Counterfactual Policy: Sub-optimal Leverage and Low-risk economy



(a) *Notes: This chart reports the cost of choosing sub-optimal leverage in a low-risk economy using the benchmark estimation. To simulate a low-risk economy, I introduce a common (negative) shock of* $\sigma = 0.1$ *to the distribution of estimated firm risk.*

Table A1: Variable Definition

Variable	Description
Sales	Net Sales. BvD Code (TURN)
Size	Total Book Assets. BvD Code (TOAS)/Compustat Code (AT)
Debt	Total Book Debt. BvD Code (CULI -OCLI + LTDB); Compustat Code(dlc+dltt)
Cash and Cash Equivalents	Total Cash and Cash-like assets. BvD Code (Cash); Compustat Code (che)
Leverage	(Debt- Cash and Cash Equivalents)/Size
EBIT	Earnings Before Interest and Taxes. BvD Code (OPPL); Compustat ()
Return on Asset	EBIT/Size
Profit Volatility (Volatility)	Standard Deviation of EBIT
Sales Volatility	Standard deviation of (Sales/EBIT)
Shares Outstanding	Compustat (cshod)
Market Price	Compustat (prccd)
Net Equity Injection	Change in Book Equity (BvD Code SHFD)- Profit (PL)

Table A2: Sample Comparison

	All PE-backed Firms			PE Sample Used in Analysis		
	N	Mean	SD	N	Mean	SD
A. By Firm Characteristics						
Asset Size ($ Mn)	6576	18.3	1.6	3020	18.2	1.6
Leverage	6576	49.2	31.7	2875	49.5	28.9
		Share of Sample			Share of Sample	
B. By 1-digit NAICS Industry						
Agricultural, Forestry and Fisheries		0.8%			0.5%	
Mining, Utilities and Construction		6.1%			3.8%	
Manufacturing		42.8%			55.7%	
Wholesale and Retail Trade		13.1%			10.9%	
Information, Financials, Admins		32.9%			26.3%	
Other		4.2%			2.8%	

(a) *Notes: This table compares the PE sample retrieved from Orbis after standard cleaning procedures with the PE sample used in the analysis. The PE sample used in the analysis are those that could be matched to one or more comparable public companies using the methodology described in 3.3.*

Table A3: Matched Pre-Buyout Sample

A. Covariate Balance	PE Sample				Matched Sample				
	N	Mean	Median	SD	N	Mean	Median	SD	Mean diff.
Log Size	1551	18.79	18.6	1.586	9439	18.73	18.96	1.39	0.06
Leverage	1535	0.299	0.34	0.25	9389	0.287	0.25	0.25	0.012
Profitability	1552	0.011	0.01	0.6	9447	0.031	0.015	0.32	-0.02
Volatility	1539	0.31	0.29	0.13	9400	0..26	0..33	0.08	0.05

(a) *Notes: This table reports summary statistics of sample firms across PE-backed and non-PE backed comparable public companies using the pre-buyout sample only. The last column reports mean difference across the two groups.*

Table A4: Reduced Sales Volatility under PE-ownership: Restricted Sample

Y_{jt} : *Sales Volatility*	(1)	(2)	(3)	(4)
Post × *LBO*	-0.297***	-0.523	-0.316***	-0.308***
	(0.085)	(0.597)	(0.091)	(0.095)
Post	0.242***	-0.134	0.240***	0.242***
	(0.067)	(0.513)	(0.068)	(0.070)
R-squared	0.991	0.024	0.992	0.992
Firm FE	Y	N	Y	Y
Year FE	N	Y	Y	Y
Controls	N	N	N	Y
N	872	870	870	849

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

(a) *Notes: This table reports difference-in-differences regression estimates at the firm-year level; the estimation is restricted to 5 large european economies: UK, France, Italy, Spain and Germany. The dependant variable is each firm's standard deviation of Sales, scaled by the firm's Earnings Before Interest and Taxes and computed separately in the pre-(post-) buyout samples. Post takes value 1 for each year after a buyout, defined similarly for matched controls. LBO takes value 1 if a firm was actually acquired by a PE-sponsored leveraged buyout, 0 for matched controls. Controls include the log of book assets, leverage and return on assets. All variables are defined in Table A1 in the Appendix.*

Table A5: Model Parameters

Parameter	Value	Source
Risk-free rate	0.05	He (2011); Strebulaev and Whited (2012)
Tax Rate	0.2	Leland (1998); He (2011)
Bankruptcy Cost	0.23	Andrade and Kaplan (1998)
Drift, Post	0.017	Estimated
Drift, Pre	0.05	Estimated

(a) *Notes: This table reports key parameters required to initialize the benchmark model, and tabulates their sources. Drift is computed directly from historical (daily) equity return and aggregated to the quarterly level to facilitate the estimation.*

A8 Trade-off Model with Bank Debt

Trade-off model with Bank debt follows Strebulaev et al. (2012). I only outline the key equations and refer readers to the original paper for further details. The firm has only bank debt D_B outstanding, with a strong bargaining position with the bank. Thus, the firm can make a take-it-or-leave-it offer which the bank can reject. In that case the firm is liquidated. The bank's payoff can be denoted by:

$$R_B(\delta) = min\big[c_{bank}/r, (1-\alpha)(1-\tau)\frac{\delta}{r-\mu}\big] \tag{15}$$

where $\frac{c_{bank}}{r}$ is the promised coupon if the firm is solvent. Due to the firm's bargaining power, it will keep the bank debt at its reservation value if renegotiation were to occur, which we can denote as:

$$R_B(\delta) = (1-\alpha)(1-\tau)\frac{\delta}{r-\mu} \tag{16}$$

Importantly, total levered firm value is now the sum of only the un-levered value post-tax and tax benefits of (bank) debt, and can be given by the equation below.

$$V_L(\delta) = (1-\tau)\frac{\delta}{r-\mu} + \tau D_B(\delta) \tag{17}$$

The renegotiation point is conceptually similar to the default point in the standard model. Equity-holders maximize their payoff by choosing the renegotiation point. The mathematical derivations related to an optimal coupon are outlined in Strebulaev et al. (2012) and follow the same value-pasting strategy as Leland (1994).

A9 Optimal Coupon in Trade-off Model with Debt Covenant

As outlined in Section 5, I set the default barrier to a multiple of required coupon payment to capture an interest coverage covenant in a parsimonious manner. Thus, the borrower is forced to relinquish control to creditors if asset value falls to this exogenously specified level. Taking a derivative of the value of the levered firm in Eq. (7) with respect to C with $V_B = \theta C$ and setting the derivative equal to 0 yields the following expression:

$$\frac{\tau}{r} - (1+\gamma)\frac{\tau}{r}\theta C^{\gamma}\delta^{-\gamma} - (1+\gamma)\frac{\alpha}{r-\mu}\theta C^{\gamma}\delta^{\gamma} = 0 \tag{18}$$

Define:

$$X = (1+\gamma)\delta^{-\gamma}\big(\frac{\tau}{r} + \frac{\alpha}{r-\mu}\big) \tag{19}$$

Simplifying Eq. (18) using the definition in Eq. (19) yields:

$$C^{*} = \big(\frac{\tau}{r}\frac{1}{X}\big) * \frac{1}{\gamma} * \frac{1}{\theta} \tag{20}$$