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Behind the Buyout: Private Equity and Corporate Default Risk

Evidence from panel data on Swedish firms using Survival and Difference-in-differences Models

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Abstract

This study investigates the relationship between private equity (PE) ownership and financial distress among Swedish firms from 1998 to 2022. Using complementary empirical strategies, including a Cox proportional hazards model coupled with a staggered difference-in-differences design, the analysis shows that PE-backed firms face a higher risk of financial distress compared to a control group matched on pre-treatment characteristics. We find that this effect is largely driven by increased leverage introduced at the time of acquisition, suggesting that the capital structure transformation associated with leveraged buyouts is the primary driver of elevated risk. No significant effect is found in the years following the end of private equity ownership. When distress is instead measured using the interest coverage ratio, the elevated default risk remains significant even after controlling for leverage. However, we find evidence that this is driven by ex-ante selection, reinforcing the importance of selection bias in interpreting the effects of PE ownership with this default measure.

JEL codes: G32, G33, L25, C41, C21
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Contents

1. Introduction

Over the past decades, private equity (PE) has become a central pillar of global capital markets (OECD, 2025). As part of this global expansion, Sweden stands out as the second-largest private equity market in Europe relative to the size of its economy. As a result, private equity and venture capital has contributed to a permanent increase in Sweden's GDP of approximately 4.7% since 2007 (Næss-Schmidt et al., 2022). While this has given rise to a comprehensive body of research focusing on value creation and firm performance among acquired firms, its association with financial distress remains relatively underexplored in the Swedish context. With rising interest rates, concerns have emerged that the highly leveraged ownership structures of PE-owned companies could have implications for firm-level financial distress as well as for the broader macroeconomy (Andersson et al., 2025).

In a broader context, private equity ownership is typically associated with improvements in firm performance among acquired companies. Næss-Schmidt et al. (2022) provides evidence of a 53% increase in operating profit and a 22% productivity enhancement in Swedish portfolio companies during the holding period. Despite these gains, previous research on private equity and its implications for financial distress presents mixed findings. Several studies examine the value creating mechanisms such as governance, operational and financial engineering, whereas the latter refers to value creation through substantial borrowing placed on the portfolio company's balance sheet (Kaplan & Strömberg, 2009; Jensen, 1989; Acharya et al., 2013). While some find an increased likelihood of default among PE-backed firms (Tykvová & Borel, 2022), this effect often diminishes when accounting for leverage (Hotchkiss et al., 2021). Other studies find no effect at all (Andersson et al., 2025). Moreover, evidence suggests that PE-owned firms manage financial risk more effectively due to access to additional capital from investors (Hotchkiss et al., 2021; Bernstein et al., 2019, Tykvová & Borel, 2022).

This study is motivated by the lack of research on private equity ownership in Sweden, despite its economic significance. While a recent Riksbank Staff Memo (Andersson et al., 2025) raises concerns about the financial vulnerabilities of PE-owned firms, it was published a few months after we began our analysis. The memo highlights that in a persistently high interest rate environment, the leveraged structures typical of PE ownership may increase bankruptcy risk. This emphasizes the relevance of our purpose and research questions followed.

This study aims to examine the relationship between private equity ownership and financial distress among Swedish private firms during the period 1998–2022. The analysis employs complementary methodological approaches, combining survival analysis techniques with time-varying PE-ownership status with a staggered difference-in-differences design. This allows us to estimate the instantaneous hazard rate, the dynamic average treatment effect, and the evolution of default risk over time, conditional on whether a firm is, or have been, backed by private equity.

Based on this framework, the study aims to address the following research questions:

1. How does private equity ownership affect a firm's risk of default, compared to similar firms not under PE ownership?
2. How does previous private equity ownership affect a firm's risk of default after exit, compared to similar firms with no prior PE ownership?

We utilize firm-level panel data collected from the Serrano database, Capital IQ Pro, and SVCA. We use transaction data from Capital IQ Pro and SVCA to identify firms involved in leveraged buyouts (LBOs), which are then matched to the Serrano database to access firm-level financials. The final panel dataset includes exit data, enabling a long-term analysis. This aligns with the future research priorities outlined in Andersson et al. (2025).

We find that private equity ownership is associated with a higher risk of default for the portfolio companies when default is measured by the Zmijewski score. This elevated risk appears to be largely driven by the increased debt levels introduced through changes in capital structure at the time of acquisition. The effect does not persist after PE-exit, suggesting that the risk is concentrated during active ownership. In contrast, when default is measured using ICR, the elevated risk persists even after controlling for leverage and continues post-exit. However, this analysis may be subject to selection bias, as we show that PE firms tend to target companies that already exhibit elevated interest burdens, with financial risk intensifying after acquisition. It may also be an imperfect measure of default risk, given that debt can be serviced through means not captured by the coverage inputs (EBITA).

The structure of this thesis is as follows. Section 2 defines private equity and discusses its connection to financial distress. Section 3 provides a brief overview of previous research. Section 4 summarizes the data construction process and section 5 outlines the empirical strategy and econometric frameworks. Finally, Sections 6 and 7 presents the main results and relate them to previous research.

2. Background

In this chapter, we define private equity and examine the formal relationship between financial distress and private equity ownership to assess the potential implications of leveraged buyouts on a firm's financial health.

2.1 Defining Private Equity

While the term *private equity* is often used as an umbrella term for equity financing outside public stock markets, it is most commonly associated with the term *buyout* transactions (Andersson et al., 2025; Bergström and Englén, 2024; Kaplan and Strömberg, 2009). In such transactions, a private (unlisted) company is acquired by a private equity (PE) firm with the purpose of generating returns by developing and improving operational efficiency and thus creating value in the company. Eventually, the PE firm exits the investment by either selling the company privately (for instance, through a secondary buyout or acquisition by a larger corporation) or via an initial public offering (IPO) where the company is taken public. The acquired firm is referred to as a *portfolio company*, and a private equity firm typically manages several such companies.

In the case of a buyout, a significant portion of the acquisition is usually financed through leverage placed on the balance sheet of the portfolio company, thus resulting in a leveraged buyout. Typically, 60 to 90 percent of the transaction is financed through debt (Kaplan and Strömberg, 2009). The remaining part of the acquisition is typically financed through a pooled investment model, in which a private equity fund secures funding from institutional buyers (for instance pension funds or sovereign wealth funds). Together with the private equity firm (the 'general partner'), these institutional investors (the 'limited partner') inject and commit capital to the private equity fund, which in turn holds equity stakes in several different portfolio companies and is managed by the PE-firm. Accordingly, management and performance fees are charged to investors by the PE firm (Andersson et al., 2025). Moreover, these investments are often restricted to a certain time period (Bergström and Englén, 2024). Andersson et al. (2025) states that the average holding period is around 7 to 10 years, although this varies depending on each PE firm's investment strategy. While some private equity firms acquire highly profitable and financially stable companies, others engage in turnaround strategies aimed at resolving financial challenges in less profitable firms (Andersson et al., 2025).

Within the broader concept of private equity, venture capital (VC) and growth capital are also included. Venture capital refers to minority investments in early-stage or emerging companies, whereas growth capital involves minority or majority investments in growth companies. In contrast, an leverage buyout involves acquiring majority control of a mature firm, with the PE investor taking an active ownership role (Bergström and Englén, 2024; Kaplan and Strömberg, 2009).

2.2 Levereged buyouts and financial risk

In this study, we focus on leveraged buyouts and examine their connection to firm-level financial distress in portfolio companies. In Andersson et al. (2025), several key factors are highlighted regarding the relationship between private equity ownership and increased corporate default risk.

Most prominently, portfolio companies become highly leveraged following an LBO, since the debt burden is typically placed on the acquired company. This naturally increases the risk of financial distress, insolvency or even bankruptcy for the acquired firm. Another important factor is connected to the type of loan providers involved in the LBO. These may consist of either traditional banks or non-bank lenders, such as private credit institutions. In recent years, the presence of private credit institutions in LBO financing has increased. While loans from non-bank lenders usually come at a higher cost due to increased interest rates, they often provide portfolio companies with larger loan amounts. In addition, they are typically less restrictive in terms of loan conditions.

If the debt is financed through private credit institutions, portfolio companies are typically exposed to greater rollover risk. Private credit funds are dependent on continuous investor commitments and typically operate under a limited time horizon. As a result, portfolio companies may experience increased refinancing risk, especially during financial crises when the economic environment changes suddenly (e.g. due to rising interest rates). At the same time, PE funds may serve as important actors in resolving financial distress in portfolio companies, as they have the ability to inject additional capital when necessary. However, this ability depends on the fund's current position in its life cycle and typically decreases in later stages as capital becomes more constrained (Andersson et al., 2025). In Hotchkiss et al (2021), this relationship is examined. In the next section, we introduce their framework, among others, and present additional empirical evidence within this research area.

3. Literature Review

In this section, we begin by focusing on the theoretical framework of mechanisms through which private equity ownership either creates value or amplifies financial risk. Next, we present the literature behind risk and bankruptcy predictors. Lastly, we present empirical evidence from similar studies, examining the short- and long-term effects of private equity on firm-level financial distress.

3.1 Value creation and risk mechanisms

As private equity is typically associated with active ownership and debt financing, it is important to understand the key mechanisms through which it affects firm performance and financial risk. In line with our research design, we primarily focus on those mechanisms related to leverage. Central to this discussion is Jensen (1989), who was among the first to outline the prominence of debt financing in value creation. By introducing fixed payment schemes, one forces managers to use free cash flows more efficiently and thus avoid wasteful spending (e.g. through unprofitable investments or unnecessary internal structures). Jensen (1989) further expresses that active control and strong governance are preferable to dispersed ownership structures.

Kaplan and Strömberg (2009) introduces the reasoning of *financial engineering*, which refers to the concept of generating returns by financing acquisitions largely with debt, thus creating value as long as the cost of debt is low relative to the risk-adjusted return of the investment. Increasing tax shields serves as an additional advantage. Moreover, Kaplan and Strömberg (2009) emphasize two additional mechanisms: *governance engineering* and *operational engineering*, with the latter having become more commonly used in later years. Whereas the first refers to value creation through active ownership and governance in acquired companies, the second describes a value-creating mechanism through which private equity firms specialize in certain industries and subsequently apply operational expertise. Acharya et al. (2013) support the view that private equity creates value by contributing operational skills and governance control, thus improving firm sales and margins. Hence, Acharya et al. (2013) propose that value creation is not solely driven by financial engineering.

However, high leverage has implications for financial distress. As stated by Kaplan and Strömberg (2009), the risk of financial distress increases when excessive leverage is combined with inflexible payment schemes. Kaplan and Stein (1993) complement this view by studying the LBO market in the early versus late 1980s. In the later period, when the LBO market was characterized by a low interest rate environment and generous loan amounts, they find higher debt levels and lower coverage ratios. They also observe a larger proportion of defaults in the later period. Hence, portfolio companies become more financially vulnerable than non-sponsored firms if market conditions deteriorate.

Andrade and Kaplan (1998) study a similar relationship using a sample of highly leveraged transactions (HLTs) where the target ended up in financial distress in the US during the late 1980s. Several key findings connected to the risk mechanism can be identified. First, they report that high leverage causes financial distress, not necessarily poor operational performance, which is also in line with the findings in Bergström et al. (2007). Considering operating margins, Andrade and Kaplan's (1998) sample even outperforms industry averages, and a large proportion recovers from the distress stage. This suggests that one should distinguish between financially and economically distressed firms. Lastly, by studying the entire life cycle of the sample firms, from before acquisition to post-distress, it is evident that these HLTs create value.

Moreover, Hotchkiss et al (2021) examine the relationship between PE ownership status and default risk, and analyze restructuring and recovery rates among previously PE-owned companies. They describe two contradictory mechanisms through which private equity can affect default risk. First, liquidity constraints may arise if PE firms focus solely on short-term activities, such as large dividend payouts, primarily to benefit themselves. The other mechanism refers to the possibility that private equity may help resolve financial distress in their portfolio companies by providing capital reserves when financial issues arise.

3.2 Bankrupcy predictors and default proxies

Overview of Bankruptcy Prediction Frameworks

To correctly asses firms in distress, our study builds on the extensive literature and theory on bankruptcy prediction. Typically, there are two main approaches to proxying bankruptcy risk and estimating default frequencies. One is the *market-based* approach using "distance to default" (DD) models as developed by Merton (1974). The second is the *accounting-based* approach using scores like the Altman's or Zmijewski's probit indices which estimate default risk using firm-level financial statement data.

Meanwhile, a large body of research compares the predictive power of the two approaches; the *market-based* vs.the *accounting-based*. Foundational studies by Beaver (1966), Altman (1968), Ohlson (1980), and Campbell et al. (2008) rely on static, accounting-based ratios (such as the Z-score, O-score, and Zmijewski score) to estimate the likelihood of corporate default. Shumway (2001) then develops a simple discrete-time proportional-hazard model that *combines* both *market* and *accounting* information to forecast bankruptcy. He benchmarks this hazard framework against several static, accounting-based indices and shows while the Zmijewski score is one of the stronger pure accounting predictors, incorporating market signals in a hazard model materially improves both in-sample and out-of-sample accuracy of default forecasts (Shumway, 2001). Hillegeist et al. (2004) similarly find that market-based DD measures offer greater predictive power than traditional accounting scores like Altman's or Zmijewski's, though the latter still contain incremental information.

A widely used measure of firm-level default risk is the Expected Default Frequency (EDF) model, based on Merton's (1974) model. It combines market and balance sheet data to compute distance to default, which is then converted into a default probability (Crosbie & Bohn, 2003). Building on this, Ampudia, Busetto, and Fornari (2022) introduce a new market-based measure of default risk called Distance to Insolvency (DI), which improves upon traditional models like the EDF, especially over short- to medium-term horizons (3–12 months).

Taken together, these studies suggest that default prediction is most effective when forward-looking market indicators are used alongside traditional financial ratios. Since our sample includes both listed and unlisted firms, we use the accounting-based Zmijewski score. Originally proposed by Zmijewski (1984), the model is based on a sample of U.S. firms from the 1970s and was designed to distinguish distressed firms, defined as those that went bankrupt, became insolvent, or reported negative net income, from non-distressed ones. The score embeds three key balance sheet ratios into a probit framework: Net Income to Total Assets (NI/TA), Total Liabilities to Total Assets (TL/TA), and Current Assets to Current Liabilities (CA/CL). These ratios are weighted by calibrated coefficients, reflecting their relative contribution to financial distress, and summed to construct the score. The interpretation of the ZM-score is straightforward: higher values indicate a greater likelihood of financial distress. In the model, a ZM-score of 0 implies a 50 percent probability of distress; any value above zero suggests a greater-than-even likelihood of financial failure (Zmijewski 1984). The Zmijewski score does however have its limitations worth to be mentioned. Being purely accounting-based compared to market-based, it is backward-looking and may lag rapidly evolving market perceptions; and its coefficients were calibrated on 1960s–70s U.S. data. Nonetheless, the Zmijewski score remains a practical and reliable tool for credit-risk screening, performing well compared to other accounting-based models (Ohlson, 1980; Shumway, 2001).

Alternative Measure of Financial Distress
A related line of research focuses on so-called zombie firms. These are older companies that cannot cover interest expenses with their operating income but continue to survive due to cheap credit and lenient lenders, a practice known as evergreening. Popularized after Japan's "lost decade," the term 'zombie firm' has regained relevance amid low interest rates and the COVID-19 crisis. The OECD defines zombies as firms at least 10 years old with an interest coverage ratio below 1 for three consecutive years (McGowan et al., 2017). Empirical research links zombie firms to a range of macroeconomic inefficiencies. These firms tend to underperform in terms of productivity and are associated with poor capital allocation, as they absorb resources that could otherwise support more dynamic and viable businesses (Caballero et al., 2008; Gouveia & Osterhold, 2018; Albuquerque & Iyer, 2023).

This literature becomes relevant when analyzing highly leveraged firms under PE ownership. Firms undergoing leveraged buyouts typically become highly indebted as a mechanical outcome of the PE acquisition. As a result, the overall impact of PE ownership on default risk is ambiguous and remains an empirical question. This trade-off is particularly relevant, yet unexplored: although PE-backed firms may experience short-term pressure on interest coverage, sustaining an ICR below 1 for three consecutive years is a severe outcome, making it a meaningful threshold for identifying prolonged financial distress, especially estimating the effect after the private equity firm has exited the investment.

3.3 Empirical evidence

Numerous studies have provided empirical evidence on whether private equity ownership creates value and/or causes financial distress, primarily utilizing firm-level data from the United States (US). Some studies find a significant effect of current PE ownership on firm-level financial distress (Tykvová and Borel, 2022). However, this effect tends to disappear once leverage (Hotchkiss et al., 2021) and other factors such as firm age and size (Wilson & Wright, 2013) are controlled for. While empirical evidence suggest that PE-ownership have its implications on financial distress, PE-backed firms also tend to manage these risks more efficiently than comparable non-buyout firms (Tykvová and Borel, 2022; Hotchkiss et al., 2021; Andrade and Kaplan, 1998). Moreover, some studies report long-term implications of PE ownership, with portfolio companies either strengthening their financial health and experiencing a lower probability of default (Hotchkiss et al., 2021), or exhibiting an increased likelihood of financial distress and bankruptcy (Ayash & Rastad, 2021).

As a starting point, Hotchkiss et al. (2021) serves as a central inspiration in conducting this study. Using a large sample from the U.S. leveraged loan market from 1997 to 2010, they examine the short- and long-term relationship between PE ownership and financial distress, along with recovery rates and restructuring outcomes of defaulted firms. Compared to similar firms without PE funding, Hotchkiss et al. (2021) find no increased likelihood of default among PE-backed firms once controlling for leverage, suggesting that leverage is the key risk driver rather than PE ownership itself. In addition, PE funding is associated with more efficient management of financial distress, as PE-backed firms actually exhibit lower default frequencies at high levels of debt. In the second analysis, Hotchkiss et al. (2021) report a larger share of PE-backed firms (within the full sample) restructuring out of court or through agreements prior to bankruptcy filing. Once in default, PE-backed firms restructure more quickly and manage financial distress more efficiently, partly due to the availability of additional capital injections. Lastly, they find no evidence that PE firms leave their portfolio companies in poor financial condition post-exit. Instead, they previously PE-owned firms experience 50-60% lower risk of default.

Wilson & Wright (2013) use a large sample of UK firms during 1995-2010 and draw on a similar result. They reveal that once factors such as age, sector, and macroeconomic conditions are controlled for, the probability of insolvency is not higher for firms that have undergone a private equity acquisition, than for non-buyout companies. Further, Wilson & Wright (2013) report a significant effect of leverage on default risk in the full sample. A firms ability to handle high levels of debt, specifically its interest coverage, is highlighted as a key mechanism when studying the relationship between debt and default risk. Nonetheless, when restricting the sample to only buyouts, they find that debt levels do not explain which firms go into insolvency.

Using a large matched sample of European firms around the buyout event from 2000–2008, Tykvová and Borel (2022) examine whether private equity ownership increases the risk of financial distress and bankruptcy. They apply several accounting-based distress indicators (for instance ZM-score) alongside actual bankruptcy filings. The findings reveal that prior to the buyout, PE investors tend to acquire financially healthier firms than comparable non-buyout firms. After the acquisition, PE-backed firms show a higher risk of financial distress, as indicated by deteriorating financial indicators. Interestingly, this elevated risk does not lead to higher bankruptcy rates. In fact, no significant difference in bankruptcy likelihood is found between PE-backed and non-buyout firms.

Bernstein et al. (2019) find similar results as they were interested in PE and the resilience of PE-backed firms during the financial crisis of 2008. They examine whether private equity (PE) ownership increased firms' financial fragility during the crisis. Using a difference-in-differences (DiD) approach, where the firms are matched on key characteristics such as size, industry, and financial health as of 2007. The study finds that PE-backed firms were actually more resilient during the crisis: they maintained higher investment levels, accessed more external financing, and experienced stronger asset growth compared to their peers (Bernstein et al., 2019). This findings indicate that PE ownership can enhance firm robustness in downturns.

In contrast to this view, evidence from Ayash and Rastad (2021) on the long-term effects of PE ownership suggests that the 10-year default risk is significantly higher for previously PE-owned firms compared to firms without prior PE involvement. Unlike previous research results in this area, the authors succeed in confirming the prediction of Merton (1974), that PE funding and its aggressive implications for capital structure actually increase the risk of bankruptcy and thereby the cost of financial distress.

While most prior research focuses on the US and UK, Bergström et al. (2007) was among the first to study Swedish firms. Though not focused on financial distress, the study finds no significant effect of leverage on value creation but reports improved firm performance, suggesting PE adds value through other means than financial engineering.

3.4 Gaps and contributions

Building on the prior research outlined above, our study aims to address several important gaps in the literature. First, while many studies suggest that private equity ownership can provide capital, facilitate restructuring, and help firms avoid bankruptcy (even as these firms often face elevated financial distress) the overall evidence remains mixed and inconclusive. Also, given the significant size of the private equity market in Sweden, there are relatively few studies (almost none) examining the link between private equity ownership and financial distress. With rising interest rates following the pandemic, it is of great importance to understand how leveraged ownership structures affect financial stability, both at the firm level and from a broader macroeconomic perspective within the Swedish economy.

Another gap we identify is that most existing studies focus primarily on short-term outcomes during the private equity holding period. In contrast, our study examines default risk up to five years post-exit, offering a longer-term perspective that is largely overlooked in the current literature. This is mainly because that requires exit-data, which is difficult to access. Andersson et al. (2025), representing the Swedish Riksbank, explicitly suggest this analysis as a key direction for future research. This brings relevance to our study, by providing valuable insights for both policymakers concerned with financial stability and investors seeking to understand the lasting impact of private equity ownership.

Finally, though there is rich literature on zombie firms (Caballero et al., 2008; McGowan et al., 2017), no study has systematically linked ICR-defined distress to PE ownership dynamics. Our inclusion of ICR < 1 for three consecutive years as an alternative proxy contributes to this underexplored connection between leveraged PE structures and persistent interest coverage problems.

4. Data

In this section, we provide a detailed overview of our data collection process, as well as the identification of the treatment group and the construction of the control group. We also outline the delimitations of this study and present descriptive statistics.

4.1 Data construction

4.1.1 Identifying the treatment group

To identify all private equity-sponsored companies in Sweden, we have integrated transaction data from **S&P Capital IQ Pro** (CIQ) together with transaction data from the **Swedish Private Equity & Venture Capital Association** (SVCA). After these datasets are merged to one complete set of private equity-backed companies these firms are identified in the **Serrano Dataset** provided by the Swedish House of Finance.

The dataset from S&P Capital IQ Pro provides detailed M&A transaction data, which we filter by target geography, deal type, completion status, and transaction date. Specifically, we restrict the sample to include only LBOs and secondary LBOs, enabling us to trace the full ownership history of portfolio companies. S&P defines an LBO as "*a transaction in which an investor acquires a controlling interest in a company's equity and in which a significant portion of the purchase price is financed through leverage (borrowing)*" (S&P Capital IQ, 2024).

After applying our selection criteria, the final dataset includes 1,305 transactions, filtered to fulfill the following critera:

(i) The target or issuer is located in Sweden

(ii) The transaction is classified as a Leveraged Buyout, including secondary LBOs

(iii) The transaction has been completed

(iv) The transaction was completed between 1998 and 2022.

In addition, we also use transaction data from the Swedish Private Equity & Venture Capital Association (SVCA), covering 524 Swedish portfolio companies between 1998 and 2022. For each company, the dataset includes the year of acquisition and exit, where exits may occur through IPOs, trade sales, bankruptcies, or other divestments. Unlike the CIQ dataset, SVCA provides detailed ownership periods, including both entry and exit years. Transactions are classified as "Buyouts," reflecting majority-stake investments in mature firms based on the investor's strategy. Using data from CIQ and SVCA, we conducted a comprehensive matching process to identify overlapping portfolio companies. To ensure consistency, we applied quality checks on holding periods, targets, buyers, and majority ownership. For transactions lacking exit data, a 7-year holding period was assumed, following Andersson, Kärnä & Myers (2025). We also included additional SVCA transactions not found in CIQ, which contain both entry and exit years.

This results in a complete sample of 749 company transactions, with 481 unique PE-backed companies, including the entry and exit years of the investments.

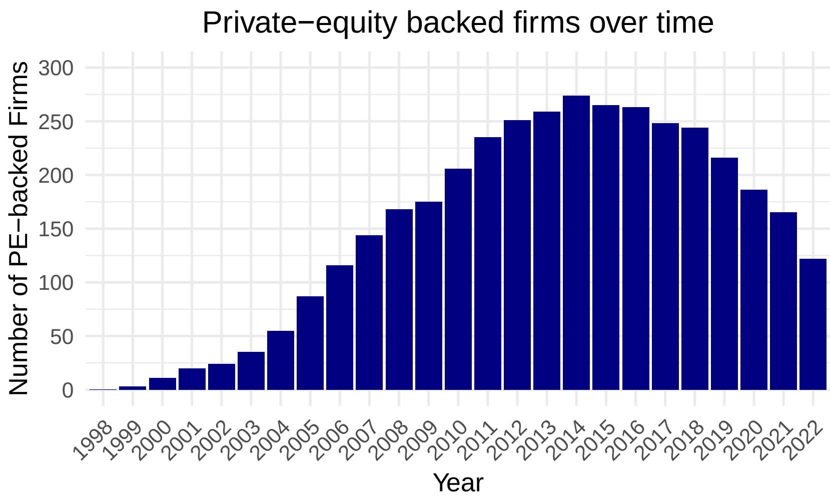

Figure 4.1: Number of PE-backed firms over sample years

Having obtained and identified the PE-backed firms, we then retrieved their financial history. We use the Serrano dataset provided by the Swedish House of Finance. The data contains firm year observations on detailed financial statement information for all Swedish companies that have reported to the Swedish Companies Registration Agency (Bolagsverket) each year since registration until the most recent year and report. The data covers the period from 1998 until 2022 and comprises approximately 17 million observations. Before we retrieve the PE-backed companies we clean the data, keeping firms classified as Limited Liability Companies which constitute the vast majority of our sample, along with Joint Stock Banks and Insurance Companies. We exclude firm-years with missing data on total assets, employees, operating revenue/loss, debt-to-equity ratio, or industry code (sni2007). We also remove entries with negative sales, which we consider implausible. After cleaning, 9,046,707 firm-year observations remain.

We then link the PE-backed firms to the Serrano dataset by matching company names to organization numbers. Since many firms belong to complex group structures, where holding companies own several subsidiaries, we identify the entity that best reflects the group's core activities. This is done using ownership data from *Allabolag.se*, annual reports, and firm-level employment and sales figures. While this approach involves some subjectivity, we believe it to be the most effective way to handle the complexities of group structures. Firms are then classified by their two-digit sni2007 code (primary industry), yielding 21 distinct industry sectors.

Following this approach, we identify all 481 Swedish firms financed by private equity in the Serrano data by assigning them binary variables.

4.1.2 Constructing the control group

In order to analyze the impact of PE-investment, we compare the set of targets of such transactions to similar companies that did not go undergo a PE-investment. However, since PE-backed companies are surely not a random sample of the population, constructing a control group is inherently challenging. Although observable factors related to selection into PE-investment can be controlled for, unobservable factors remain a concern.

Following the methodology of Boucly, Sraer, and Thesmar (2011), we identify the set of control firms that operated in the same industry and year as the treatment firm one year prior to the PE-investment in the treatment group. We then construct a matched control group for each PE-backed firm in our sample using a nearest neighbor matching procedure. While the Boucly, Sraer, and Thesmar (2011) method is multivariate and matches on two variables, employment and return on asset (ROA), we use a univariate approach and match based on one variable, net sales. Matching on net sales to construct control groups in studies involving private equity (PE)–backed firms is a recognized approach in the literature. Net sales proxy the scale of a firm's operations, helping ensure PE-backed and non-PE firms are comparable in size and market presence. Paglia and Harjoto (2014), for example, highlight net sales as a central metric when assessing how private-equity and venture-capital financing affect business growth.

While there are different perspectives regarding the optimal choice of matching variables, we believe net sales is the most informative measure for identifying a comparable firm, as it effectively captures the overall scale of a company's operations, ensuring that treatment and control groups are comparable in size and market presence.

In our sample, a matching company meets the following criteria:

1. It operates within the same two-digit industry and year as the treatment firm, one year prior to the investment.

2. By calculating the absolute difference in net sales between each PE-backed firm and non-PE firms, the five closest matches for each target firm are selected based on this metric.

This matching methodology results in 1,328 control firms, firms that have never been PE-backed, in our sample. Coupled with now 475 treatment firms, the resulting unadjusted sample comprises 1,803 unique firms and a total of 36,458 firm-year observations. This will be our unadjusted sample used in further analysis.

To further balance the sample and check for robustness in our control group we also use Propensity Score Matching (PSM) creating a sample adjusted for covariate imbalances. Propensity score methods are particularly suitable for this setting, as they allow for the design of observational studies that approximate randomized controlled trials by balancing covariates between treated and control groups. Following recommendations by Austin (2014), we assess covariate balance using standardized mean differences (SMDs), which offer a transparent and interpretable measure of covariate imbalance before and after matching. A standardized difference below 0.1 in absolute value is typically interpreted as evidence of negligible imbalance, thus providing reassurance that treatment and control groups are comparable in terms of observed covariates (Austin, 2014).

From the longitudinal panel we derive three key pre-treatment (lagged) covariates; employee count, return on assets (ROA) and debt-to-asset ratio, ensuring each variable is measured one year before treatment (i.e., private-equity backing). The matching variables were chosen based on established metrics in previous research as proxies for firm size, profitability, and leverage. In particular, following Boucly, Sraer, and Thesmar (2011), the number of employees serves as an indicator of firm size. Profitability is measured using ROA, consistent with Bernstein, Lerner, and Mezzanotti (2019), who utilize similar pre-crisis performance metrics. While the debt-to-assets ratio is included to capture differences in capital structure, as suggested by Bernstein and Strömberg (2009).

The table below shows sample sizes at key stages of the propensity score matching process. Here, All is the full sample; Matched (ESS) is the effective sample after matching for balance and statistical power. Matched is the final sample, with the treated group unchanged and controls adjusted for optimal balance. Unmatched includes observations without suitable matches, and "Discarded" refers to extreme values (none here).

Table 4.1: Sample Sizes for Control and Treated groups (adjusted).

	Control	Treated
All	34180	475
Matched (ESS)	1785	455
Matched	2083	455
Unmatched	32097	20
Discarded	0	0

From this procedure, we then retain the full panel for all matched firms. By employing this last step we end up with 461 firms in the treatment group. These extra six firms arise because, while only 455 firms enter treatment at their first PE-backed year (and are matched), six of those initially matched controls go on to become PE-backed later. Number of control firms are 1356. We plot the covariate balance of standardized mean differences below to displays the propensity score and the three lagged covariates before (red) and after (blue) weighting shows all adjusted differences clustered essentially at zero, confirming excellent baseline balance between treated and control groups after the matching procedure. In our plot, the 0.1 treshold is marked with the dashed grey line.

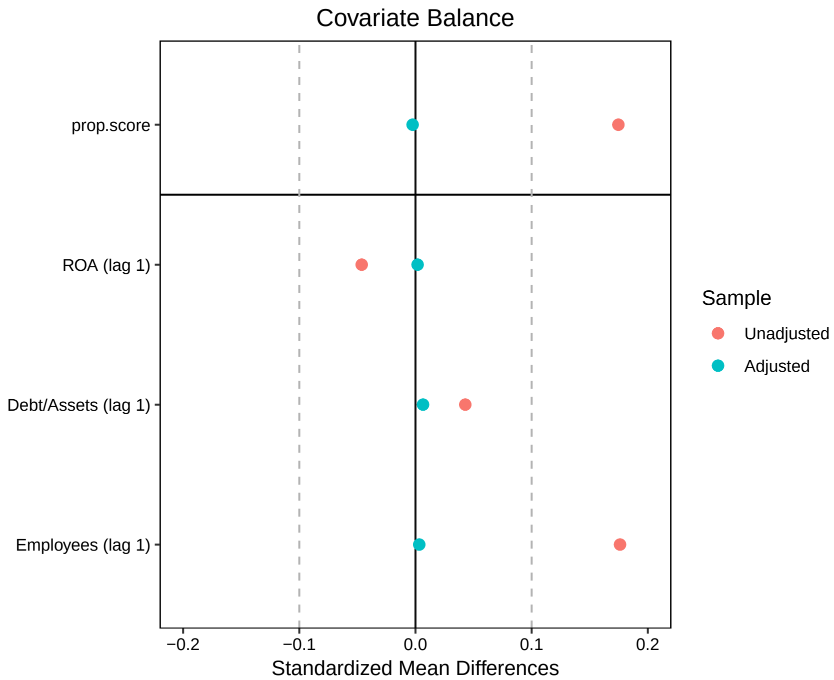

Figure 4.2: Covariate balance pre- and post-matching measured by standardized mean differences

The plot in Figure 4.2 reveals that even the unadjusted data, before propensity score matching, displayed relatively good balance with the standardized mean differences already indicating satisfactory comparability in the variables ROA and Debt to assets where both fell well under the 0.1 threshold in SMD even before the propensity score matching.

However, the matching process have enhanced the credibility of our comparisons by reducing any residual imbalance further. Table 9.1 (which can be found in the Appendix) shows the same results in a table and indicates that covariate balance improves after matching, with all adjusted differences moving closer to zero compared to the unmatched sample. To further illustrate the impact of our matching procedure, Figure 4.3 plots average net sales, our primary matching variable, for firms that will eventually receive PE-backing versus those that never do, before propensity-score matching. Figure 4.4 then shows the adjusted sample after matching. Although both panels exhibit a similar upward trajectory, we know that the PSM-sample substantially reduces bias arising from pre-existing differences in firm size, profitability, and leverage. The results from the PSM-prodecure is also evident when displaying that net-sales trajectories line up much more closely after matching. The aim of this matching process is to improve internal validity by ensuring treated and control firms are comparable on key covariates throughout the observation period.

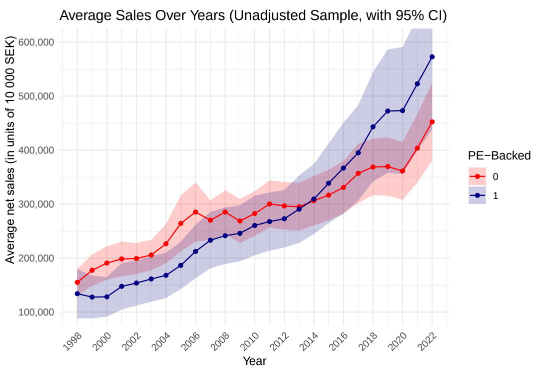

Figure 4.3: Treatment and control firms (unadjusted)

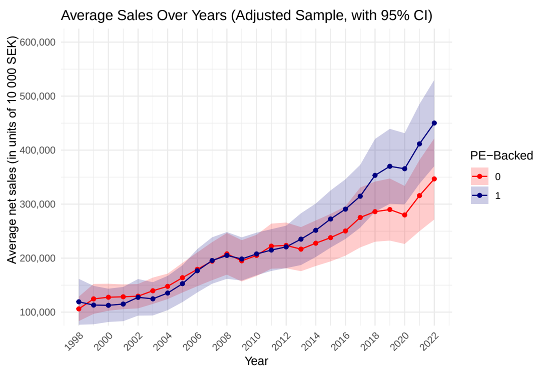

Figure 4.4: Treatment and control firms (adjusted)

4.1.3 Descriptive statistics

Identifying the relevant variables we proceed with descriptive summary statistics over our sample. The tables and figures referenced can be found in the appendix. Table 9.2 reveals that private equity investments during the sample period 1998-2022 in Sweden were primarily concentrated to a few key industries: wholesale and retail trade (25%), professional, scientific and technical activities (17.3%), information and communication (14.6%), and manufacturing (21.3%). This distribution aligns with existing literature showing that PE firms tend to focus on sectors with scalability, recurring revenues, and operational improvement potential. A key reason for this is that PE investors typically target industries with high growth prospects and relatively low business cyclicality, as this increases the likelihood of strong returns at exit regardless of broader economic conditions (Andersson, Kärnä, and Myers, 2025).

Table 9.3 presents summary statistics for the main control variables representing firm size, leverage, and profitability. The three groups appear broadly comparable on these observables. Leverage is fairly consistent across groups, with debt-to-assets ratios ranging from 0.52 to 0.55 on average. However, PE-backed and PE-exited firms tend to be larger, both in terms of number of employees (means of 108 and 124, respectively, compared to 63 for non-PE firms). We also include firm age to capture potential differences in firm maturity. The average age of PE-backed firms in our sample is 25 years. Similar age ranges (mid-20s to early 30s) are also reported in broader European data (Tykvová & Borell, 2012).

Table 9.5 shows the yearly distribution of firms by PE status over the sample period, both in absolute counts and percentages. The share of PE-backed firms increases steadily throughout the 2000s, reaching a peak around 2014–2015 at 21%, before gradually declining to 12% by 2022. Meanwhile, the share of PE-exited firms grows steadily from 2006 onward, when the PE-funds exit their investments. We observe the growing role of PE ownership over time and the natural transition of firms from active PE ownership to post-exit status.

The figure **??** presents the share of firms that default each year by distinguishing between PE-backed and non-PE-backed firms. The plot suggests that between 2007 and 2012, PE-backed firms appear to have a slightly lower default rate compared to non-PE-backed firms. In subsequent years, however, their default rate tends to rise and often exceeds that of the comparison group. Figure **??** presents the median ZM-score measured as a continuous variable, distinguishing between PE-backed firms and their controls over the sample years. Both groups display relatively stable median ZM scores over time, but PE-backed firms generally exhibit higher median (i.e., worse) scores in recent years, suggesting a modestly elevated risk of financial distress.

4.2 Delimitations

The sample period is primarily selected due to key considerations concerning high quality data availability. The Serrano database provides consistent data thought the period 1998-2022 and is the key determinant of our sample period.

Since detailed information on the timing of private equity exits is not systematically available in existing databases unless it involves an IPO, we undertook extensive manual data collection to compile these records at the firm level. This process was both time-consuming and resource-intensive, but critical for distinguishing between actively PE-backed firms and those that had exited PE ownership. Given this, we chose to retain a broad time scope in order to preserve statistical power and ensure a sufficiently large and representative sample. This decision reflects a deliberate trade-off: rather than narrowing our focus to a specific time window with more complete or easily accessible data, we prioritized sample size and variation in PE exposure to enhance the empirical relevance and generalizability of our findings. As we observe, the first exit-year in 2006, seven years into the observation period. Also, by starting in the late 1990's, we incorporate the rise and expansion of the private equity industry in Sweden.

Furthermore, we restrict our sample to Swedish firms due to data availability. The sample includes both listed and unlisted companies where the majority are limited liability companies. In addition, we exclude venture- and growth capital in our sample and focus on LBOs, where the private equity firm plays a pivotal role by obtaining majority control and financing the acquisition through borrowed capital. Regarding the default risk measures, actual bankruptcies, reconstructions, and similar legal outcomes were excluded from the analysis, as the number of observations were too few both in the treatment and control group to make valuable inferences.

5. Methodological framework

In this section, we present the methodological approach and empirical strategy employed in the study. Furthermore, we formulate the research hypothesis and define the key variables of interest.

5.1 Research questions and hypotheses

This study examines how private equity ownership influences firm default risk using both binary and continuous measures. We also assess post-exit effects using PE exit data. To capture both average and dynamic patterns, we apply a staggered difference-in-differences model and a Cox proportional hazards model. The DiD model treats PE exposure as permanent, while the Cox model accounts for changes in ownership over time and includes both ZM-score and interest coverage ratio as default measures. Thus, our methodological framework are based on *and* aims to address the following research questions and compricing hypothesis:

1.How does private equity (PE) ownership affect a firm's risk of default, compared to similar firms not under PE ownership?

H_0 : Private equity ownership does not affect a firm's risk of default relative to non-sponsored firms.

H_1 : Private equity ownership affects a firm's risk of default relative to non-sponsored firms.

2. How does previous private equity (PE) ownership affect a firm's risk of default after exit, compared to similar firms without prior PE ownership?

H_0 : Exiting PE-ownership has no effect on a firm's default risk compared to firms without prior PE-ownership

H_1 : Exiting PE-ownership affects a firm's default risk compared to firms without prior PE-ownership.

5.2 Variable construction and definitions

5.2.1 Independent variables

Having identified the private equity backed companies in our sample, we assign them binary variables indicating the following:

- *PE-backed*: Equals 1 during the years a firm is under private equity ownership following a leveraged buyout, and 0 otherwise. This indicates that a firm is assigned a value of 1 for each year it remains under private equity ownership.

- *PE-exit*: Follows Hotchkiss et al (2021) and equals 1 for five years starting the year after a firm exits PE ownership, , and 0 otherwise. This variable captures potential post-exit effects.

- *PE-ever*: Equals 1 for all years in the sample if a firm was ever PE-backed. Used for robustness checks and to account for selection effects.

5.2.2 Dependent variables

1. Zmijewski Score For our first analysis we rely on the ZM-score, an accounting-based bankruptcy-prediction model introduced by Zmijewski (1984) that uses a set of financial ratios to estimate the probability that a firm will experience financial distress. The ZM-score equals,

$$\mathrm{ZM}_t = -4.336 - 4.513\,\frac{\mathrm{NI}_t}{\mathrm{TA}_t} + 5.679\,\frac{\mathrm{TL}_t}{\mathrm{TA}_t} + 0.004\,\frac{\mathrm{CA}_t}{\mathrm{CL}_t}$$

Net Income / Total Assets (NI/TA): A measure of profitability relative to the firm's asset base. Lower values (including losses) heighten distress risk, as indicated by the coefficient -4.513.

Total Liabilities / Total Assets (TL/TA): A leverage metric reflecting the firm's debt burden. Higher leverage raises the probability of default, captured by the coefficient $+5.679$.

Current Assets / Current Liabilities (CA/CL): A liquidity ratio assessing short-term solvency. Greater liquidity reduces distress risk, although the modest coefficient $+0.004$ indicates a smaller effect once profitability and leverage are accounted for.

This information is integrated into a single, continuous index of financial-distress risk, the ZM-score. The score itself can take on any value but the index is derived from a underlying probit regression,

$$P(\text{Default}) \;=\; \Phi(\text{ZM}) \;\in\; [0,1].$$

However, the Cox-regression survival model framework requires a binary default indicator of whether "default" ever occurs. We follow Zmijewski (1984) in treating scores above zero as indicating financial distress, as this marks a predicted bankruptcy probability greater than 50

$$\text{ZM} > 0 \iff P(\text{Default}) > 0.5.$$

Our default indicator for the Cox-regression framwork thus becomes,

$$\text{Default}_{\text{ZM},t} = \begin{cases} 1, & \text{ZM}_t > 0, \\ 0, & \text{ZM}_t \leq 0. \end{cases}$$

By contrast, in our staggered difference-in-differences analysis we retain the Zmijewski score in its continuous form. Preserving the full range of the score in the Staggered DiD-model thus allows us to capture incremental changes in distress risk over time.

Table 5.1 shows default rates by PE involvement as measured as the binary variable ZM-score>0. PE-backed firms have lower default rates (54.9%) than non–PE-backed firms (74.6%), with rates dropping further to 40.8% after PE exit. These raw figures do not control for firm characteristics or time at risk, which are addressed in later analyses.

Table 5.1: Default incidence by PE-status and by PE-exit status

Panel A: Current PE-backed Status			
PE-backed	**Number of firms**	**Defaults (ZM)**	**% Default**
0	1 356	1 012	74.6%
1	461	253	54.9%
Panel B: PE Exit Status			
Exit status	**Number of firms**	**Defaults (ZM)**	**% Default**
0	1 356	1 050	77.4%
1	306	125	40.8%

Table 5.2 presents summary statistics for the continous Zmijewski score by PE status. Both groups exhibit similar mean scores around –1.1, indicating generally healthy firms, but the non–PE-backed group shows greater dispersion, likely due to a larger sample and more outliers.

Table 5.2: Summary statistics for ZM-score by ownership status

Ownership Status	**Obs.**	**Mean**	**Median**	**SD**	**Min**	**Max**	**Q25**	**Q75**
Non-PE-backed	24,544	-1.11	-1.38	20.80	-38.36	2847.30	-2.70	-0.16
PE-backed	3,667	-1.10	-1.20	3.16	-31.94	75.72	-2.45	-0.03

2. Interest Coverage Ratio Next, we use an alternative default measure: an Interest Coverage Ratio (ICR) below 1 for three consecutive years, indicating EBIT is insufficient to cover interest costs. Since our focus is on financial distress rather than firm maturity, we apply only the ICR criterion and omit the age requirement from the OECD definition. We use the reported figures in our data for EBIT divided by the external interest expenses paid each year by the firm. We then create firm specific lagged ICR's for every third year. If the condition is fulfilled the firm is denoted as defaulted.

$$\mathrm{ICR}_t = \frac{\mathrm{EBIT}_t}{\text{External Interest Expense}_t},$$

$$\mathrm{Default}_{\mathrm{ICR},t} = \begin{cases} 1, & \text{if } \mathrm{ICR}_t < 1,\ \mathrm{ICR}_{t-1} < 1,\ \mathrm{ICR}_{t-2} < 1, \\ 0, & \text{otherwise.} \end{cases}$$

In leveraged buyouts, private equity firms typically finance acquisitions with a substantial debt burden, thereby magnifying potential returns on their equity investment. As studies showed, PE-backed firms exhibit significantly higher leverage than other leveraged-loan borrowers which mechanically raises their annual interest burden and making it more likely their EBIT falls below interest expenses (ICR $<$ 1) in any given year. Recognizing this effect, and while a single year of ICR $<$ 1 may reflect a transient downturn, we believe that three consecutive years of insufficient coverage identifies firms that cannot service debt on an ongoing basis. As shown in Figure **??**, we observe that the average interest coverage ratio falls sharply in the year following PE-backing and then gradually recovers over the subsequent decade. Prior to entry, average ICR consistently exceeds the break-even threshold (horizontal blue line at ICR = 1), indicating healthy interest coverage. However, leading up to the PE-buyout the ICR displays a downfall on average and immediately following the buyout there is a sharp collapse under 1 during the first year, reflecting the new debt burden. Over the subsequent decade, ICR recovers steadily.

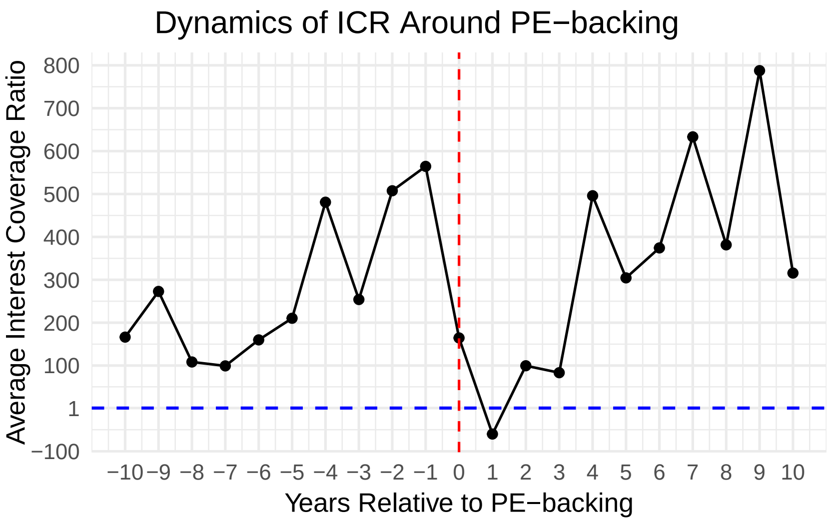

Figure 5.1: Dynamics of Average Interest Coverage Ratio Around PE-Backing

In light of all this, the interest of our study therefore lies in investigating whether PE-backing influences default risk, defined as an inability to cover interest expenses, not only during the holding period but also after the PE sponsor has exited. By including a PE-exit indicator we can test whether the risk-mitigating effects of PE ownership persists, dissipates, or even reverse, providing new insight into the longer-term impacts of private-equity deals. Table 5.3 reports the average ICR for firms by their PE-backing status. Firms in the control group that are not PE-backed cover their interest expenses on average 4.97× (SD = 35.94), whereas PE-backed firms cover interest only 2.98× on average (SD = 31.85). In the years following PE divestiture, average ICR for exited firms rebounds to 4.32× (SD = 45.81), but remains below the 4.70× (SD = 34.90) observed for firms that have not exited PE-ownership or are non PE-backed. These findings confirm both the substantial coverage shortfall imposed by buyout leverage and a partial recovery in interest service capacity following PE exit.

Table 5.3: Average Interest Coverage Ratio by PE-backing and PE-exit Status

	PE-backed			**PE-exit**		
Group	**n_obs**	$\overline{\text{ICR}}$	SD(ICR)	**n_obs**	$\overline{\text{ICR}}$	SD(ICR)
0	24 544	497	3 594	27 125	470	3 490
1	3 667	298	3 185	1 086	432	4 581

5.2.3 Control variables

To estimate the causal effect of PE financing on corporate default risk, we rely on a carefully selected set of control variables in both the staggered adoption model and the Cox proportional hazards model. We account for:

- **Industry and year fixed effects**, to control for macroeconomic trends and sector-specific shocks,
- **Firm age**, to capture lifecycle effects and test for systematic differences between PE-backed and non-backed firms,
- **Firm size**, proxied by the number of employees,
- **Profitability**, measured by return on assets (ROA),
- **Leverage**, captured by the debt-to-asset ratio.

These variables are inspired by the framework in Hotchkiss et al (2021) and help isolate the effect of PE ownership on financial distress.

5.3 Cox Proportional Hazard Model

5.3.1 Model overview

Building on the methodology of Hotchkiss et al (2021) we conduct a survival analysis by estimating a Cox proportional hazard model that describes the conditional likelihood of default as a function of a set of time-varying explanatory covariates. The Cox proportional hazards model (Cox, 1972) is a widely used method for analyzing time-to-event data. It models the hazard rate described as the instantaneous risk of experiencing an event (such as default) as a function of a baseline hazard that can vary over time, together with a set of covariates. Since firm-level covariates change with time in this empirical setting, the Cox model can be extended to handle time-dependent covariates. To implement this, we organize the data in line with a (start, stop] interval framework, described by Therneau et al. (2024). Each row in the panel then corresponds to a period in which the covariates remain constant. For each firm, time is broken into yearly intervals, thus the model accounts for the fact that both the covariates and the risk set change across time. We begin by mapping each firm–year observation onto a one-year risk interval in the $(t_{\text{start}}, t_{\text{stop}}]$ format:

$$t_{\text{start}} = t - \text{year}_0, \quad t_{\text{stop}} = t_{\text{start}} + 1,$$

where year_0 is the firm's entry year into our sample. We then define the event indicator:

$$\text{event} = \begin{cases} 1, & \text{if } t_{\text{start}} < \text{default year} \leq t_{\text{stop}}, \\ 0, & \text{otherwise,} \end{cases}$$

so that firms with no observed default carry event = 0 in all intervals. Structuring the data this way allows us to incorporate time-varying covariates while preserving the exact timing of defaults. In our implementation, after a firm's first default (`event=1`), all subsequent intervals for that firm are omitted, so that each firm contributes observations only up to and including its default event. While covariate values such as private equity ownership or financial ratios are allowed to vary across time, the Cox model still assumes that the effect of each covariate on the hazard is constant over time.

We estimate the following baseline Cox Proportional Hazards model:

$$h_{it}(t) = h_0(t) \exp\left(\beta_1 \cdot \text{PE\_backed}_{it}\right), \tag{5.1}$$

where $h_{it}(t)$ denotes the hazard of default for firm i at time t, and $h_0(t)$ is the baseline hazard function. The indicator variable PE_backed_{it} equals one if the firm is owned by a private equity fund in year t. In our analysis we also estimate the fuction using the binary variable PE_exit_{it} as the independent variable, indicating whether a firm has been PE-backed, measured from the year after the private equity fund has exited and five years ahead. The model includes stratification by industry and calendar year, and standard errors are clustered at the firm level. Stratifying by industry and year allows the baseline hazard $h_0(t)$ to vary flexibly across these dimensions, while clustering standard errors at the firm level accounts for within-firm correlation over time. In the baseline specification, the hazard for firm i at time t is proportional to $\exp(\beta_1)$ if the firm is PE-backed. The exponential form implies that the effect of private equity ownership is multiplicative on the hazard scale and the hazard ratio between PE-backed and non-PE-backed firms is assumed to be constant over time.

This assumption applies even when PE-status changes over time; the effect of being PE-backed is assumed to be time-invariant, conditional on that status. In other words, the model allows PE-status to change over time, but it assumes that the effect of being PE-backed is the same in every year. If the effect changes (e.g., PE-ownership reduces default risk early on, but increases it later), the proportional hazards assumption is violated. This assumption is tested by estimating the Schoenfeld residuals.

5.3.2 Assessment of the Proportional-Hazards assumption

To assess whether the effect of private-equity backing remains constant over time during the observation period, we apply the critical Schoenfeld residual test. The test statistic for `PE_backed` on default, As measured by the Zmijewski score in the adjusted sample, the test yields $\boldsymbol{\chi^2(1) = 0.0129, p = 0.91}$ for both the covariate-specific and global tests. Since $p > 0.05$, we fail to reject the null hypothesis of proportional hazards, meaning that the effect of PE backing on the hazard of default can be assumed constant over time.

Figure 5.3 plots the time-varying coefficient $\beta(t)$ for `PE_backed` against the percentile of follow-up time. The plot displays scaled Schoenfeld residuals for the PE-backed covariate. The solid line remains flat around 0 within the 95% confidence bands, indicating no time-dependent pattern. This supports the proportional-hazards assumption suggesting that the effect of PE-backing on default risk is constant over the observation period.

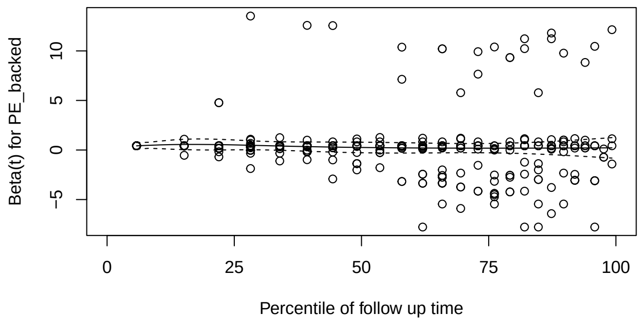

Figure 5.2: Schoenfeld residual test for PE-backed on the adjusted sample using the Zmijewski Score as the default indicator: Plotted against percentile of follow-up time.

Next, we estimate the effect of the independent variable `PE_backed` on our alternative default measure, the Interest Coverage Ratio (ICR). The test statistic shows $\boldsymbol{\chi^2(1) = 0.0562, p = 0.81}$ Again, since since $p > 0.05$ we fail to reject the proportional-hazards assumption at the 5 percent level. Concluding that effect of private equity backing on default risk, measured by three consecutive years of ICR < 1, appears constant over the observation period.

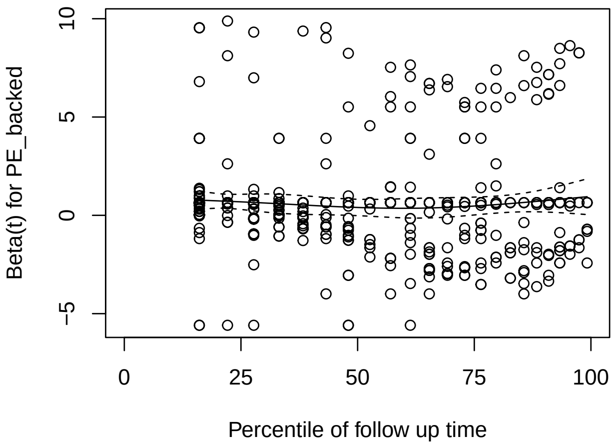

Figure 5.3: Schoenfeld residual test for PE-backed on the adjusted sample using the Interest Coverage Ratio as the default indicator: Plotted against percentile of follow-up time.

We note in the plot that in the earliest percentiles of follow-up there are no failures. This is natural and a by-product of our design, since it requires a firm to go at least three consecutive years without covering its interest expenses before being classified as defaulted. Having confirmed that the proportional-hazards assumption holds for our baseline specification with the two different default proxies, we expand the model by adding a set of time-varying firm controls. We estimate the following extended version of the model:

$$h_{it}(t) = h_0(t) \exp\left(\beta_1 \cdot \text{PE\_backed}_{it} + \boldsymbol{X}'_{it}\boldsymbol{\gamma}\right), \tag{5.2}$$

where $\boldsymbol{X}_{it}$ is a vector of time-varying control variables. Following Hotchkiss et al (2021) we control for return on assets (ROA), debt-to-assets ratio, total assets and EBITDA/Sales. We also add additional variables such as number of employees and firm age. Dummy variables for PE-exit for additional analysis and PE-ever are later added for for robustness checks. The model is stratified by industry and year, robust standard errors are clustered at the firm level.

In a Cox proportional-hazards regression, each estimated coefficient $\hat{\beta}_j$ corresponds to the logarithmic effect of a one-unit increase in covariate X_j on the instantaneous hazard of default. In our regression analysis, we report the *hazard ratio* (HR), defined for covariate X_j as $\text{HR}_j = \exp(\beta_j)$. A hazard ratio greater than one ($\text{HR}_j > 1$) indicates a positive association with the hazard; for example, if $\exp(\beta_{\text{PE\_backed}}) = 1.20$, then PE-backed firms face a 20% higher instantaneous risk of default compared to otherwise identical non-PE-backed firms.

5.4 Staggered difference-in-difference model

5.4.1 Model overview

To identify and estimate the causal effect of private equity ownership on corporate default risk, we implement a staggered difference-in-differences approach, following the methodology proposed by Callaway and Sant'Anna (2021). This approach allows treatment at different points in time, making it suitable for our purpose. Further, it addresses key limitations with standard two-way fixed effect (TWFE) estimators, such as heterogeneity across treatment groups and the use of non-transparent or negative weights.

5.4.2 Identification strategy and model assumptions

Embedded in the staggered DiD setup suggested by Callaway and Sant'Anna (2021) is a set of key identification assumptions that is crucial for the model's validity and for ensuring consistency in the estimated treatment parameters.

The staggered DiD model allows for multiple time periods $t = 1, \ldots, T$, where T denotes the final period in the sample. The first assumption, *(1) Irreversibility of treatment*, states that no unit is treated in period $t = 1$, and once a unit is assigned to treatment, it remains treated in the subsequent period and throughout the sample period. If we let D_{it} be a binary variable indicating whether firm i receives PE funding in period t, then for $t = 2, \ldots, T$, the following condition holds:

$$D_{i,t-1} = 1 \Rightarrow D_{it} = 1.$$

In line with Callaway and Sant'Anna (2021), we define treatment groups G based on the period in which the firm first received treatment (PE_backed = 1). The control group consists of firms that never receive treatment ($G = \infty$). For each firm in this setup, several potential outcomes are defined, but only one is realized depending on the timing of PE funding. The DiD methodology is then able to estimate the causal effect of PE funding on default risk by comparing treated firms to similar firms conditional on pre-treatment covariates in the same period t.

The second assumption, *(2) Random sampling,* states that the sample should be I.I.D (independent and identically distributed). As discussed by Baker et al. (2025), random sampling in DiD settings requires that each unit is independently drawn from the population, prior to treatment status assignment. Further, the remaining assumptions (3-6) must be satisfied to identify the average treatment effect on the treated **ATT (g,t)**. Unlike traditional DiD models, this parameter represents a family of causal effects that captures the average treatment effect for units first treated in period g observed in period t, and is defined as:

$$\text{ATT}(g,t) = \mathbb{E}[Y_t(g) - Y_t(0) \mid G_g = 1]$$

where Y_t denotes the outcome variable at time t, in our case, corporate default risk. Assumption (3) requires that there are no systematic differences in potential outcomes between treated and untreated units before treatment. In the formulation of Callaway and Sant'Anna (2021), assumption (3) is satisfied if potential outcomes are similar for all pre-treatment periods where $t < g - \delta$, with $\delta \geq 0$ representing the anticipation horizon.

Assumption (4) and (5) is based on conditional parallel trends. This assumption allows for heterogeneous trends across groups, conditional on covariates. This is necessary to ensure valid comparisons between treated and untreated firms in the absence of treatment. Assuming limited treatment anticipation, the following condition must hold for each unit treated in period g and for all $t = 2, \ldots, T$ such that $t \geq g - \delta$:

$$\mathbb{E}[Y_t(0) - Y_{t-1}(0) \mid X, G_g = 1] = \mathbb{E}[Y_t(0) - Y_{t-1}(0) \mid X, C = 1]$$

where $C = 1$ denotes firms that are never treated, and $G_g = 1$ denotes firms first treated in period g.

The last assumption *(6) Overlap assumption* both requires enough variation in treatment timing across groups *and* sufficient similarity in pre-treatment characteristics between treatment and control units. In Callaway and Sant'Anna (2021), the overlap assumption is formulated as follows: for each unit treated in period g and for each $t = 2, \ldots, T$, there exists some $\varepsilon > 0$ such that $\mathbb{P}(G_g = 1) > \varepsilon$ and $p_{g,t}(X) < 1 - \varepsilon$.

Assessment of assumptions

By identifying the year in which a firm is acquired by a private equity company and treating it as continuously PE-backed throughout the entire sample period, Assumption 1 (Irreversibility of treatment) is naturally fulfilled. Further, given our panel data structure, comprising firm-level data of Swedish companies with broad coverage during the period 1998–2022, it is reasonable to assume that Assumption 2 (Random Sampling) is satisfied. As for the first assumption, the same applies to Assumption 3 (Limited Treatment Anticipation) since the `did` package in R assumes zero anticipation by default, following Callaway and Sant'Anna (2021).

Following Callaway and Sant'Anna (2021), we impose conditional parallel trends based on a "nevertreated" group, which is preferred when the sample includes a sizable number of never-treated units. In our sample, 66% never receives treatment. To assess this, we investigate and rule out potential pre-trends in our sample. Figure 5.4 displays the dynamic treatment effects relative to the treatment timing. We observe only minimal trends in outcomes prior to treatment, particularly at event times -4 and -5. However, since the corresponding confidence intervals covers zero, we find no statistical evidence that the conditional (or unconditional) parallel trends assumption is violated.

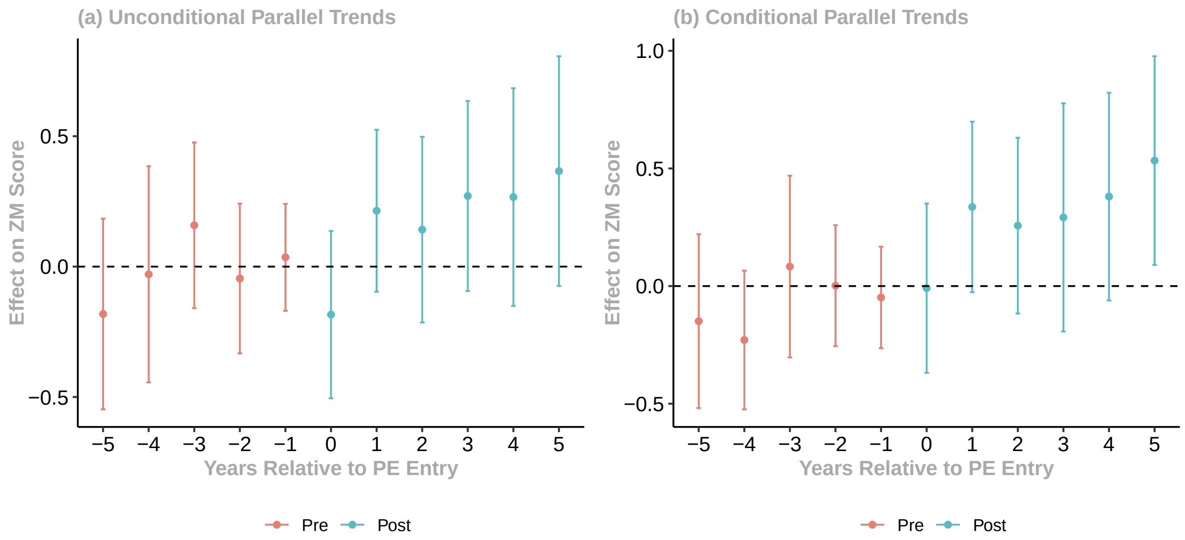

Figure 5.4: Dynamic treatment effect estimates relative to treatment timing. Panel (a) shows unconditional estimates. Panel (b) shows conditional estimates (on industry and firm age).

To assess Assumption 6 (Overlap assumption), we follow the recommended approach in Baker et al (2025) by estimating propensity scores based on pre-treatment covariates. Firm age and industry classification, are selected as model covariates in accordance with Callaway and San't Anna (2020), which highlights that these covariates should be observed pre-treatment and closely related to the evolution of the outcome variable, but can not be affected by the treatment, i.e. PE-ownership. The overlap assumption requires that these propensity scores are bounded away from 0 and 1. Figure 9.4 (appendix) shows that, conditional on the pre-treatment variables firm age and primary industry, the probability of receiving PE funding is not substantially different between treated and untreated firms.

5.4.3 Estimation and aggregation of ATT

There are three different estimation approaches, all of which identify the same causal parameters. Hence, the ATT(g,t) can be recovered using either the outcome regression (OR), the inverse probability weighting (IPW) or the combined doubly robust (DR) approach. However, there are differences in the parameter estimation strategies.To avoid model misspecifications, we adopt the DR estimator which generates consistent estimators if either model is correctly specified. As a robustness check, we include results with all three estimators in the appendix. In a setting with multiple time periods and variation in the timing of treatment, generating and interpreting an individual ATT for each cohort g and period t becomes impractical. Therefore, aggregation is necessary for interpretation. The formal expression for this aggregated treatment effect parameter, θ, is:

$$\theta = \sum_{g \in \mathcal{G}} \sum_{t=2}^{T} w(g,t) \cdot ATT(g,t),$$

where $w(g,t)$ defines weighting functions, which can vary depending on the specific research question. In this study, we primarily focus on event-time aggregation to capture the dynamics of treatment effects relative to treatment adoption, following a structure similar to that of an event-study specification in a TWFE model. As discussed in the model overview, these sometimes generate misleading average treatment effect estimates due to problems with negative weighting (e.g., Borusyak and Jaravel, 2017; Goodman-Bacon, 2019). Based on this reasoning, Callaway och Sant'Anna (2021) suggest a similar approach that directly aggregates group-time average treatment effects, thereby avoiding the potential biases associated with traditional TWFE estimators.

In the case of event-time aggregation, with *e* and *e'* representing the time to treatment respectively length of exposure post treatment, the aggregated effect can be formulated as follows:

$$\theta_{es}^{bal}(e; e') = \sum_{g \in \mathcal{G}} \mathbf{1}\{g + e' \leq T\} \, ATT(g, g+e) \, P(G = g \mid G + e' \leq T),$$

where the first term is the indicator function which takes the value 1 if cohort g is observed e' years post treatment. The second term calculates the group-specific weighted average of ATT(g,t)'s included in the aggregation, conditional on being observed until the event time e'. Event time is denoted as $e = t - g$, where t denotes the calendar time and g the first period of treatment.

5.4.4 Empirical strategy: Staggered DiD analysis

Estimation is conducted using the `did` package in R, with default settings: Doubly Robust (DR) estimation and no anticipation ($\delta = 0$). We identify the year each firm is first acquired by a PE firm and, following assumption 1, consider them treated throughout the sample period. The same applies to the analysis including PE exit. Next, identification of ATT(g,t) is conducted, along with a review of relevant assumptions (3, 4, and 6). With the continuous default risk indicator Zmijewski-score (ZM), we obtain the following expression:

$$\text{ATT}(g,t) = \mathbb{E}[\text{ZM-score}_t(g) - \text{ZM-score}_t(0) \mid G_g = 1],$$

which captures the average effect of becoming PE-backed in period g on a firm's ZM-score in period t.

The estimation process proceed as follows:

1. We use the `att_gt` function in the `did` package to estimate the group-time average treatment effects, with industry and firm age as pre-treatment covariates, ZM-score as an outcome variable and "nevertreated" as control group

2. We use the `aggte` function in the `did` package to aggregate the group-time avarage treatment effect over event time, by setting type "Dynamic".

To estimate causal treatment effects in a staggered DiD setting without encountering problems arising from changes in group composition across different lengths of exposure, we incorporate the balanced event-time aggregation estimator (Callaway and San't Anna, 2021). In line with Baker et al. (2025, section 5), we choose an event window of ± 5 years relative to treatment adoption and restrict our analysis to firms with complete data for all years within this window, ensuring consistency in our model estimates.

5.4.5 Robustness checks and limitations

A key methodological challenge in assessing the effect of private equity (PE) ownership on firm-level default risk is the risk of selection bias due to unobserved heterogeneity. Specifically, selection into treatment. PE firms do not acquire portfolio companies randomly; rather, selection is guided by both observable factors (e.g., firm size, leverage, profitability) but more importantly, also by unobservable characteristics such as management quality, strategic growth potential and plans, or latent operational risks.

These unobservables are problematic because they may simultaneously influence both the likelihood of receiving PE investment and the probability of financial distress, thereby confounding the relationship of interest. For instance, firms with hidden operational inefficiencies may be more attractive to PE sponsors seeking turnaround opportunities, but such inefficiencies could also elevate default risk, regardless of PE involvement. Similarly, high-quality firms with unobservable growth opportunities may be selectively targeted by PE, biasing post-investment outcomes in a favorable direction. This issue is closely related to the concept of ex ante selection, as discussed in empirical finance literature (e.g., Kaplan & Strömberg, 2009; Bernstein et al., 2019), where PE investors are shown to engage in extensive due diligence and target firms with specific turnaround potential. The result is that any post-buyout performance or distress outcome may reflect initial screening rather than a causal effect of PE involvement.

In our analysis, we address this concern in two ways. First, we include a rich set of firm-level controls—such as leverage, profitability, firm age, and size, to account for observable differences at baseline. Second, we distinguish between firms that are currently PE-backed and those who are ever PE-backed, to test whether effects persist beyond the holding period. A significant effect only for currently PE-backed firms would be more indicative of a causal impact of PE ownership. In contrast, if the effect is driven by ever PE-backed status, this could suggest selection bias, where the observed outcome is rooted in pre-existing differences rather than the treatment itself.

Given limitations in observing all relevant firm characteristics, caution is warranted when interpreting the results as causal and the estimates should be viewed as conditional associations.

6. Results

6.1 Results from Cox proportinal Hazard model

6.1.1 Default risk measured with ZM-score

The Cox Proportional Hazards model yields the results presented below. Panel A in Table 6.1 reports regressions on the adjusted sample consisting of 461 treatment firms and 1,356 control firms during the sample period 1998-2022. Panel B (in appendix) displays the results on the unadjusted sample.

Table 6.1 presents sequence models estimating the instantaneous default risk of PE-backed firms. The variable PE-backed here is measured as being currently PE-backed. In the bivariate specification (column 1), PE-backed status increases the hazard by **53%**. Adding firm size (proxied by number of employees) leaves the PE effect essentially unchanged. When we introduce firm age, each additional year reduces the hazard by about 0.4% while the PE hazard remains elevated. Needed to be mentioned here is the fairly low Concordance index. The C-index, reported at the bottom of each column, reflects the model's ability to accurately rank firms by their risk of default: a value of 0.5 indicates no better than random prediction, while 1.0 indicates perfect discrimination. In our models, the C-indexes range from about 0.51 to 0.96 suggesting an increase from modest to meaningful predictive power.

We observe that once **leverage** is included as a control, the PE hazard ratio falls to 1.291 and loses conventional significance, as a one-percentage-point increase in debt/asset ratio raises default risk by nearly 5.9%. Introducing profitability (ROA), further attenuates the PE-coefficient to 1.224 and shows that higher ROA modestly lowers hazard.In the fully specified model (which adds previously omitted controls for PE-exit and EBITDA/Sales) the hazard ratio for PE-backed firms declines to 1.224 and loses statistical significance. Overall, these results imply that the elevated default risk of PE-backed firms is largely mediated by the additional leverage and profitability compression characteristic of leveraged buyouts, rather than PE sponsorship per se.

Table 6.1: Panel A: Adjusted sample (default ZM score)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PE-backed	1.531**	1.529**	1.526*	1.291	1.224	1.350	1.224
	(0.164)	(0.164)	(0.165)	(0.162)	(0.158)	(0.196)	(0.161)
PE-exited							0.985
							(0.275)
Number of employees		1.000					1.000
		(0.000)					(0.000)
Total assets (% change)					1.000	1.000	1.000
					(0.000)	(0.000)	(0.000)
Debt/Asset (% change)				1.059***	1.060***	1.109***	1.060***
				(0.004)	(0.004)	(0.005)	(0.004)
ROA (% change)					0.990*	0.987**	0.990*
					(0.004)	(0.004)	(0.004)
EBITDA/Sales (% change)						0.9998	
						(0.000)	
Firm age			0.996*				1.001
			(0.002)				(0.002)
Year & industry FE	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes
Concordance (C-index)	0.507	0.465	0.545	0.895	0.912	0.962	0.912
	(0.006)	(0.020)	(0.020)	(0.016)	(0.015)	(0.007)	(0.015)
n	11 715	11 715	11 715	11 715	11 715	10 748	11 715
events	1 058	1 058	1 058	1 058	1 058	890	1 058

Note: Hazard ratios (exp(coef)), with the robust SE of the log-hazard in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

To address potential selection bias, we re-estimate the analyses based on two dummy-variables: PE-backed and PE-ever. According to Hotchkiss et al. (2021), if only the currently PE-backed variable is significant while PE-ever is not, this pattern supports a causal interpretation of PE ownership's effect on default risk. Conversely, a significant coefficient on PE-ever but not on currently PE-backed would imply ex ante selection, i.e., that private-equity sponsors systematically choose firms already predisposed to the distress risk. The estimation results indicate, that the results are not driven by ex-ante selection. While our results in Table 9.7 (appendix) show that the PE-backed status initially remains a significant predictor of default when both indicators are included, we know from earlier estimations that this effect disappears once leverage is accounted for. As mentioned, this suggests that the elevated default risk is primarily driven by higher leverage levels, rather than PE ownership itself.

6.1.2 Default risk measured with ICR

The table below (Panel A) presents the Cox proportional hazards estimates for default as defined as three consecutive years of ICR below 1. In the baseline specification (column 1), PE-backed firms face a **91%** higher instantaneous risk of entering prolonged coverage distress compared to their non-PE peers. This implies that, at any given point in time, conditional on survival up to that time, PE-backed firms are nearly **twice as likely** to default. The relatively small standard error around the hazard ratio indicates high precision in the estimate, which enhances the credibility of this strong effect. As we progressively control for firm-level covariates such as firm size, age, leverage, and profitability (columns

2–7), the hazard ratio for PE-backed firms decreases modestly but remains statistically significant throughout. Even in the most exhaustive model (column 7), the estimated hazard premium remains at **88%**. This consistency across specifications suggests that the elevated default risk associated with PE ownership is not fully explained by other observable firm characteristics, reinforcing the robustness of the main result. PE ownership itself still seems to be linked to higher default risk. The C-index reports valules from 0.53-0.68 suggesting modest to better predictive power.

Leverage does, however, emerge here as a particularly important driver: a one-percentage-point increase in the debt-to-asset ratio raises the hazard of default by approximately **1.3%** (HR = 1.013, SE = 0.002), and remains highly significant in every model where it is included. The precision of this estimate (with a very small standard error) underscores its central role in the risk transmission mechanism. Leverage is the only covariate that consistently shows statistical significance across all relevant model specifications, but notably it does not take away variation from the PE-backed variable.

The **concordance index (C-index)** rises from **0.531** in the **baseline** to approximately **0.649** in the **full model**. This improvement reflects increased discriminative power as more covariates are added, moving the model from near-random prediction to a level of moderate predictive accuracy. While not exceptionally high, a C-index close to 0.65 is common in corporate default studies and indicates that the Cox model offers meaningful improvements in risk stratification over random guessing. Lastly, we note that ROA was excluded from the fully adjusted model due to perfect separation, which led to infinite variances and a failed Wald test. This suggests that profitability, while potentially informative, may exhibit non-random patterns across risk strata that violate Cox model assumptions when stratified by year and industry.

Table 6.2: Panel A: Adjusted sample (default ICR)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PE-backed	1.906***	1.887***	1.892***	1.831***	2.071***		1.882***
	(0.126)	(0.126)	(0.126)	(0.125)	(0.127)		(0.125)
PE-exited						1.657*	1.862*
						(0.246)	(0.254)
Number of employees		1.0004·	1.0004·				
		(0.001)	(0.000)				
Total assets (% change)							1.000***
							(0.001)
Debt/Asset (% change)				1.013***	1.015**	1.013***	1.013***
				(0.002)	(0.002)	(0.002)	(0.002)
ROA (% change)							
EBITDA/Sales (% change)					0.9999***		
					(0.000)		
Firm age			1.001				1.003·
			(0.002)				(0.002)
Year & industry FE	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes
Concordance (C-index)	0.531	0.535	0.543	0.643	0.658	0.644	0.649
	(0.013)	(0.023)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
n	20 808	20 808	20 808	20 808	19 081	20 808	20 808
events	632	632	632	632	561	632	632

Note: Hazard ratios (exp(coef)), with robust SE in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, . $p < 0.10$.

While these hazard ratios highlight a strong link between PE ownership and liquidity-driven distress, the results should be interpreted with care. Importantly, although PE-backed firms exhibit a heightened risk of failing to cover interest expenses with EBITA, this may not immediately signal distress. Private equity owners often have access to alternative financing tools, such as intercompany loans, equity injections, or refinancing, which can temporarily mask underlying risk and delay formal default.

Another important consideration is the potential for ex-ante selection bias. As illustrated previously in Figure 5.1, firms that eventually become PE-backed already exhibit a marked decline in their ICR in the years leading up to the buyout. This pattern suggests that private equity sponsors may intentionally target firms already under liquidity pressure or carrying a heavy leverage burden, perhaps viewing them as turnaround opportunities or as suitable candidates for value creation, where financial engineering can amplify returns through leverage. If left unaccounted for, this pre-treatment deterioration could overstate the estimated hazard of default during the PE ownership period. To address this concern, we re-estimate the Cox model using both a time-varying indicator for current PE ownership and a static indicator for whether a firm was ever PE-backed, allowing us to separate treatment effects from selection effects (Table 6.3).

The results show that the ever PE-backed indicator remains strongly significant, while the effect of current PE-backing weakens and is only marginally significant.

Table 6.3: Cox Model of ICR-based Default: Current and Ever PE-Backing

	Hazard Ratio	Robust SE
PE-backed	$1.293^{\cdot}$	(0.147)
PE-ever	1.642^{***}	(0.108)
Concordance (C-index)	0.560 (0.019)	
n	20 808	
Events	632	

This pattern provides evidence consistent with a selection mechanism: firms acquired by PE are already on a trajectory toward distress before the buyout, and once this elevated baseline risk is captured through the ever-backed variable, the incremental risk of being PE-owned at any given moment appears limited. In other words, the higher hazard observed in prior models may partly reflect the types of firms that PE investors choose to acquire, rather than purely the consequences of PE ownership itself.

6.2 Results from the staggered DiD analysis

In the following section, we present the results from our Staggared Difference-in-difference analysis, following the framework proposed by Callaway and San't Anna (2020).
First, we report the estimates of the overall average treatment effect analysis (overall ATT). Second, we present the results from the dynamic average treatment effect analysis, where all group-time ATT (g,t) estimates are aggregated by event time (e) to examine how the average treatment effect evolves relative to treatment timing. The control group consists of never-treated units, and no anticipation is assumed. An effect is considered statistical significant on the 5% level, if the simultaneous 95% confidence interval does not include zero. As discussed in section 4.1.2, a higher ZM score is associated with increased likelihood of default.

6.2.1 Overall ATT analysis

The table below reports the overall ATT estimates by estimation method. This parameter represents the causal average effect of being PE-backed on corporate default risk, averaged across all treated units and time periods. The results show positive and statistically significant (at the 5% level) estimates across all methods: outcome regression (OR), inverse probability weighting (IPW), and doubly robust (DR). These findings support our first hypothesis: PE-backed firms, on average, experience an increased likelihood of default throughout the entire post-treatment period, compared to firms that never receive PE funding. The DR estimate indicates an average increase of 0.2984 units in the ZM-score, reflecting a modest but statistically meaningful increase in financial distress. Regarding the OR and IPW estimators, we observe a similar relationship, although the OR estimate of 0.2669 implies a slightly weaker positive average effect of PE funding on ZM-score.

In addition, the fact that all estimates are positive and closely aligned supports the robustness of our findings. As shown in Table 5.6, reported standard errors range from approximately 0.12 to 0.13. Considering their size compared to the point estimates, it is reasonable to assume that the effect is not driven by random variation.

Table 6.4: Overall ATT by Estimation Method
Independent variable: PE-Backed

Method	**Estimate**	**SE**	**Lower CI**	**Upper CI**
Outcome Regression (OR)	0.2669*	0.1179	0.0358	0.4980
Inverse Probability Weighting (IPW)	0.2927*	0.1161	0.0651	0.5202
Doubly Robust (DR)	0.2984*	0.1313	0.0411	0.5556

Simultaneous 95% confidence band does not cover zero.
Control group: never-treated; $\delta = 0$ (zero anticipation).

While the above table incorporates *PE-backed* as the treatment indicator, Table 5.7 instead focuses on the overall ATT estimates for the *PE-exit* variable. The analysis is conducted using the same methodology but provides a different interpretation by focusing on the second hypothesis of this study. In contrast to our above results, we find no support (no statistical significance) for a positive overall average treatment effect of exiting PE ownership on corporate default risk. These findings suggest that we cannot draw any conclusions indicating that private equity firms leave their portfolio companies in poor financial condition after exit. Consistently across all estimation methods, we observe slightly low values of the point estimates, ranging from 0.09 to 0.1, and comparatively large standard errors, ranging from 0.14 to 0.15. Hence, signaling a weak or negligible average treatment effect and potential imprecision in the results.

Table 6.5: Overall ATT by Estimation Method
Independent variable: PE-Exit

Method	**Estimate**	**SE**	**Lower CI**	**Upper CI**
Outcome Regression (OR)	0.0994	0.1467	-0.1881	0.3869
Inverse Probability Weighting (IPW)	0.0899	0.1419	-0.1881	0.3680
Doubly Robust (DR)	0.0859	0.1390	-0.1865	0.3584

Simultaneous 95% confidence bands include zero for all methods.
Control group: never-treated; $\delta = 0$ (no anticipation).

6.2.2 Dynamic ATT analysis

The dynamic ATT analysis offers insights into the temporal dynamics of PE ownership status by aggregating each ATT(g, t) estimate by event time e, where $e = t - g$. In contrast to the Cox Proportional Hazard model, this allows us to capture the average effect of PE funding on default risk prior to, at the time of, and following treatment.

According to the point estimates presented in Table 5.8, we first observe no statistically significant pre-trends, as all estimates lie within the 95% confidence intervals that include zero. This supports several key model assumptions, ensuring consistency and credibility of the estimated average treatment effects. Considering assumption (3), limited treatment anticipation, and assumption (4), conditional parallel trends, we find no evidence of violation, as there is no indication that PE-owned firms differ systematically from non-PE-owned firms in terms of their ZM-score prior to treatment.

Regarding the post-treatment effects, we observe a positive and gradually increasing average effect starting one year after firms receives pe funding, although these estimates are not statistically significant. However, in event time +5, i.e., five years after a firm has been acquired by a PE company, the effect becomes statistically significant, suggesting a delayed yet positive impact of PE ownership on financial default risk. The results indicate that firms receiving PE funding in period g have, on average, a 0.5334-unit higher ZM-score five years after treatment. This is relative to the firm's untreated potential outcome.

Table 6.6: Overall and Dynamic ATT: PE-BACKED (Doubly Robust)

	DR			
Event time e	**Estimate**	**SE**	**Lower CI**	**Upper CI**
Dynamic effects				
-5	-0.1490	0.1397	-0.5185	0.2205
-4	-0.2291	0.1113	-0.5237	0.0654
-3	0.0829	0.1459	-0.3030	0.4689
-2	0.0019	0.0971	-0.2551	0.2589
-1	-0.0483	0.0815	-0.2638	0.1673
0	**-0.0088**	**0.1359**	**-0.3684**	**0.3509**
1	0.3365	0.1370	-0.0259	0.6990
2	0.2570	0.1412	-0.1167	0.6306
3	0.2918	0.1833	-0.1932	0.7767
4	0.3803	0.1668	-0.0611	0.8217
5	0.5334*	0.1677	0.0898	0.9771
Overall ATT	0.2984*	0.1204	0.0624	0.5343

* Estimate significant at 5% (simultaneous 95% band excludes 0).
Control group: never-treated; no anticipation ($\delta = 0$); balanced support ± 5.

Lastly, Table 5.9 reports the results from the event-time aggregated ATT(g, t) estimates. In line with the previous table, we find no evidence of a violation of key model assumptions, as the pre-treatment estimates all include zero and are therefore not statistically significant. Nevertheless, the post-treatment effects are not statistically significant. Therefore, no definite conclusions can be drawn about the long-term effect of PE-ownership and whether PE-exited firms experience an increased likelihood of default after leaving PE-ownership.

Table 6.7: Overall and Dynamic ATT: PE-EXIT (Doubly Robust)

	DR			
Event time e	**Estimate**	**SE**	**Lower CI**	**Upper CI**
Dynamic effects				
-5	-0.0089	0.1998	-0.5490	0.5312
-4	0.3146	0.1528	-0.0987	0.7278
-3	-0.2417	0.1862	-0.7451	0.2618
-2	0.0053	0.1533	-0.4091	0.4198
-1	0.2158	0.1911	-0.3007	0.7324
0	**0.0237**	**0.1699**	**-0.4355**	**0.4830**
1	0.1804	0.1923	-0.3396	0.7005
2	0.4197	0.1942	-0.1052	0.9446
3	0.0270	0.3122	-0.8171	0.8712
4	-0.1041	0.2882	-0.8832	0.6750
5	-0.0312	0.2495	-0.7058	0.6434
Overall ATT	0.0859	0.1473	-0.2028	0.3747

* Estimate significant at 5% (simultaneous 95% band excludes 0). Control group: never-treated; no anticipation ($\delta = 0$); balanced support ± 5.

7. Discussion

7.1 Review of results

A PE firm, acting as an acquiring entity, can generate substantial returns and earn significant profits through the use of high leverage, placing considerable debt on the balance sheet of the acquired company. As long as the cost of debt remains low relative to the expected risk-adjusted return, this form of financial engineering can be highly profitable. However, it raises an important question: at what cost? Leveraging a unique dataset and having outlined two methodological strategies, our findings reveal complementary and overlapping patterns across both strategies, answering the above question.

Beginning our analysis by estimating default risk using the ZM-score within the **survival analysis** framework, we observe that PE-backed firms face a higher risk of default, measured as the instantaneous hazard at each point in time, conditional on the firm having survived up to that point. The hazard rate is elevated by about 53 % and is statistically significant. However, we also find that although the risk remains higher compared to the control group, it decreases sharply and loses significance once we control for leverage, which is in line with the findings of Hotchkiss et al. (2021). Notably, leverage is the only covariate that remains significant across all model specifications in the CPH model. This finding reinforces the interpretation that the default risk associated with PE ownership is largely driven by the capital structure transformation imposed through the buyout process, which leverages the target firm's balance sheet, rather than by unobservable firm-level weaknesses. Andrade and Kaplan (1998) and Bergström et al. (2007) emphasizes this relationship and report a similar interpretation. Since our matching procedure balances firms on pre-treatment characteristics, the remaining effect can be interpreted as stemming from within-firm changes in financial structure following PE entry. Hence, leverage is not merely a control variable but a core transmission channel of the observed risk.

Based on the above discussion, it is relevant to examine the post-exit period to assess whether default risk persists. We find no evidence of an increased default risk during the post-exit period, suggesting that the elevated default risk associated with PE ownership is concentrated around the active ownership period, likely driven by the leveraged capital structure introduced at entry. When assessing this second research question, previous research is limited and shows mixed results. In contrast to Ayash and Rastad (2020), our findings are more in line with the results reported in Hotchkiss et al. (2021), as we do not find any support suggesting that PE-firms leave their portfolio companies in poor financial conditions.

One key limitation of our study is that we do not extend the analysis to examine portfolio companies' ability to manage financial distress, through more efficient restructuring or capital injections. The majority of previous research studying this relationship finds that PE firms better manage financial risk and that, although default risk is elevated during PE ownership, actual bankruptcy rates tend to be systematically lower for PE-backed firms. While we cannot draw any conclusions on this specific question, it would be valuable to do so in a Swedish context.

To assess the robustness of our findings and to offer an alternative perspective, we perform a **staggered difference-in-differences analysis.** We believe our study is one of the first to employ a staggered DiD analysis to examine the relationship between private equity ownership and financial distress. In contrast to the survival analysis (where the control group is: never PE-backed, not yet PE-backed, or already exited PE ownership), here we use a control group consisting of those never treated. This approach enables a clearer counterfactual comparison. Another advantage of the event study approach is that it enables analysis of *dynamic* treatment effects by event time, showing how default risk changes in the years after PE entry.

The results align with our previous findings and confirm that PE-backed firms, on average, experience an increased likelihood of default throughout the post-treatment period, compared to their never-treated counterparts. Since the default measure is continuous, the findings show that PE-backing is associated with an increase of approximately 0.3 units in the ZM-score. In our Data section, we showed that the median ZM-score fluctuated between –1.75 and –0.15 during the main observation period (2001–2022), indicating that a 0.3 increase is non-negligible. In this context, it represents a meaningful movement within the observed distribution of the ZM-score, particularly given that values above zero indicate financial distress. Importantly, the dynamic treatment effects reveal a more nuanced temporal pattern. Although the year-by-year estimates post-treatment are not statistically significant in the early periods, we observe a gradual upward trend. By event time +5 (five years after the PE acquisition), the estimated effect becomes statistically significant, indicating that PE-backed firms, on average, exhibit a 0.53-unit increase in their ZM-score. This delayed effect underscores that the financial consequences of PE ownership may take several years to fully materialize.

Taken together, this suggest that the impact of PE ownership on financial health is both persistent and time-dependent, with risk accumulating gradually, rather than immediately according to our results. This emphasizes the importance of studying post-treatment dynamics, as the static estimates could understate the full extent of the financial strain associated with leveraged buyouts. Consistent with the Cox model, no effect on default in the post-treatment years upon exit was discovered.

Finally, we turn to an alternative default measure: the ICR. Unlike the ZM-score, where most variation in predicted default was ascribed to leverage, the ICR results tell a slightly different story. The PE-backed variable remains significant at the one percent level across all specifications, suggesting that the increased default risk associated with PE ownership is not solely attributable to leverage, but likely reflects broader operational and financial dynamics unique to PE-backed firms.

In contrast to the previous results, the PE-exit variable here also indicates an elevated risk of default, with only a modest decrease in the hazard of default after PE firms exit their investments. Even after the PE sponsor has exited, these firms continue to experience higher interest expenses relative to EBITDA, suggesting that the increased debt burden and financial structure introduced during the buyout may not be easily unwound. These findings align with the contrasting evidence in Ayash and Rastad (2021), who showed that the 10-year default risk were significantly higher for previously PE-owned firms. Their results confirmed Merton's (1974) theoretical prediction that aggressive leverage strategies increase the risk of bankruptcy and the cost of financial distress, providing a rare but important counterpoint to the more optimistic narrative in earlier studies.

However, as observed in our results, there is an important caveat to consider: the issue of selection bias. Private equity firms tend to systematically target firms that that possess a high initial debt burden. This selection effect needs to be accounted for to ensure that the observed effects are not simply due to pre-existing vulnerabilities in the firms being acquired, although that would raise the interest in examining if PE amplifies or reduces the risk, compared to the counterfactual. While our analysis attempts to control for this bias, the self-selection of distressed firms by PE sponsors remains a crucial consideration. This leads us to reflect on the work of Hotchkiss et al (2021), who identify two opposing mechanisms by which private equity can influence default outcomes. On one hand, PE firms may exacerbate financial fragility by engaging in short-term value extraction strategies, such as dividend recapitalizations, which can deplete liquidity and heighten the likelihood of distress. On the other hand, PE sponsors may actively mitigate distress by injecting capital and facilitating restructuring processes, which could potentially prevent bankruptcy and stabilize operations. Our results from the ICR analysis seem to support the view that, at least in the short to medium term, the negative effects of private equity ownership tend to predominate.

The tension between these two mechanisms underscores the complex nature of PE ownership. While PE involvement can sometimes lead to financial engineering that amplifies risk through excessive leverage, it can also lead to positive restructuring outcomes. Our findings suggest that, at least in the context of interest coverage and default risk, the negative aspects of high leverage may outweigh the potential benefits that PE sponsors bring through their intervention, even post-exit.

7.2 Policy implications

Our findings suggest that private equity ownership can increase a firm's financial risk, primarily due to the high leverage introduced during buyouts. While this risk appears mostly concentrated during the period of PE ownership, we also find signs that financial strain, particularly in the form of high interest costs, can persist even after the PE firm has exited. This delayed effect raises important questions about how long the financial footprint of PE involvement remains and how well it is understood by regulators and creditors.

As outlined in the introduction, Andersson et al. (2025) raises concerns about private equity and its implications for the financial stability. Particularly since the private credit market has grown significantly in recent years. While our results are mixed and potentially affected by selection bias in the ICR-analysis, we do find evidence of both short- and long-term effects of private equity ownership on firm-level financial distress. This implies that policymakers may need to consider whether increased regulation and oversight of the private credit market is needed, to prevent firms from taking on excessive loan amounts that could potentially lead to financial distress on firm-level. If private credit suddenly restrict lending and offer less flexible loan conditions, *and* portfolio companies cannot manage rising interest rates, it could have consequences for financial stability in Sweden.

Second, there is a case for improving data availability on PE ownership and exit timing. Given this, policymakers should consider steps to improve visibility around PE-owned firms, both during and post ownership. As PE firms operate in this quiet space, it becomes more difficult for outside stakeholders to assess the true financial condition of firms. This can reduce transparency and make it harder to spot broader financial vulnerabilities across the economy.

To conclude, while PE can facilitate efficient restructuring and capital access, our findings suggest that these benefits may come at the cost of elevated financial fragility. A nuanced policy response is therefore suggested, one that balances the productive role of private capital with safeguards to ensure that financial engineering does not result in hidden systemic vulnerabilities.

7.3 Limitations and suggestion of future research

While our study introduces a novel dataset not previously explored in the Swedish context and offers new insights into how private equity ownership influences default risk, several limitations should be acknowledged. First, despite careful matching and covariate control, the risk of residual selection bias remains and is a concern for all studies examining this area of research. This limits the internal validity of our causal claims regarding the direct effect of PE ownership versus the effect of acquiring financially vulnerable firms.

Second, the external validity of our findings is shaped by the Swedish institutional context. Sweden has strong creditor rights and a well-developed system for managing financial distress through informal negotiations rather than formal legal processes (Andersson et al., 2025). This institutional environment may influence how financial risk manifests and is managed in PE-owned firms. As such, the generalizability of our results to other economies, particularly those with less flexible financial systems or different restructuring norms, should be interpreted with caution.

Third, while we observe statistically significant effects, our default measures are based on accounting proxies such as the ZM-score and interest coverage ratio, rather than actual bankruptcy filings. These indicators are widely used and provide valuable insights, but remain imperfect proxies for long-term firm survival. Consequently, generalizing our findings to other countries should be done with caution. At the same time, this limitation may also be a strength, since accounting-based measures like the ZM-score and ICR are simple ratios less influenced by country-specific legal frameworks compared to formal bankruptcy filings, possibly allowing for broader cross-country comparisons.

Despite these limitations, our study opens suggestions for future research. Most importantly, using a similar approach and methodology, it would be highly relevant to extend the analysis beyond 2022, covering recent years identified by rising interest rates following the pandemic. Additionally, one suggestion is to investigate heterogeneity in PE behavior, comparing more aggressive financial engineering strategies with more operationally focused approaches, testing how each affects distress risk. Given the importance of debt in our findings, future work could also explore the role of lender relationships, debt covenants, and refinancing dynamics in amplifying or mitigating distress.

Finally, future research would benefit from cross-country comparisons that explicitly incorporate variation in bankruptcy regimes, financial regulation, and corporate governance structures. Such analyses could illuminate how institutional contexts mediate the impact of PE ownership and help distinguish conditions under which PE involvement contributes to firm stability rather than fragility.

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9. Appendix

9.1 A1. Sample characteristics

Table 9.1: Balance Measures

Measure	**Type**	**Diff. Un.Adj.**	**Diff. Adj.**
Distance	Distance	0.0507	−0.0003
ROA (lag 1)	Continuous	0.0145	−0.0476
Debt to assets (lag 1)	Continuous	0.0006	0.0354
Number of employees (lag 1)	Continuous	−0.0583	0.0045

Table 9.2: Distribution of industrial sectors in the full sample and PE-backed observations.

Industry Label	**Full Sample**	**PE-backed**
Manufacturing activities	9233 (25.3%)	802 (21.3%)
Wholesale and retail trade; repair of motor vehicles	7085 (19.4%)	943 (25%)
Professional, scientific and technical activities	5328 (14.6%)	654 (17.3%)
Information and communication	5126 (14.1%)	552 (14.6%)
Financial and insurance activities	2051 (5.6%)	219 (5.8%)
Rental and leasing activities	1507 (4.1%)	149 (4%)
Construction	1368 (3.8%)	99 (2.6%)
Human health and social work activities	932 (2.6%)	84 (2.2%)
Real estate activities	863 (2.4%)	50 (1.3%)
Transportation and storage	862 (2.4%)	79 (2.1%)
Education	762 (2.1%)	52 (1.4%)
Accommodation and food service activities	457 (1.3%)	33 (0.9%)
Other service activities	284 (0.8%)	14 (0.4%)
Arts, entertainment and recreation	277 (0.8%)	21 (0.6%)
Supply of electricity, gas, steam and air conditioning	166 (0.5%)	6 (0.2%)
Water supply; sewerage, waste management and remediation	150 (0.4%)	15 (0.4%)
Other	14 (0%)	0 (0%)
Public administration and defence; compulsory social security	5 (0%)	0 (0%)

Table 9.3: Firm characteristics by PE-status

	PE-backed			Non PE-backed			PE-exited			Total		
Characteristic	N	Mean	Median	N	Mean	Median	N	Mean	Median	N	Mean	Median
Return on Assets	3667	0.07	0.06	23458	0.07	0.08	1086	0.02	0.05	28211	0.07	0.08
Debt-to-Assets Ratio	3667	0.55	0.57	23458	0.52	0.55	1086	0.54	0.58	28211	0.53	0.55
Number of Employees	3667	107.65	42.00	23458	63.40	21.00	1086	123.83	39.00	28211	71.48	23.00
Firm Age	3667	25.20	19.00	23458	24.90	19.00	1086	29.10	24.00	28211	25.1	19

Table 9.4: Number of units treated in the full sample

Category	**Number of firms**	**% of full sample**
Total number of firms	1,356	100.0
Firms ever PE-backed	461	34.0
Firms never PE-backed	895	66.0

Table 9.5: Yearly counts and shares by PE-status

	Counts				Shares		
Year	Total	PE-backed	PE-exit	Non PE-backed	PE-backed (%)	PE-exit (%)	Non PE-backed (%)
1998	831	0	0	831	0	0	100
1999	873	3	0	870	0	0	100
2000	934	11	0	923	1	0	99
2001	996	20	0	976	2	0	98
2002	1035	24	0	1011	2	0	98
2003	1068	35	0	1033	3	0	97
2004	1105	54	0	1051	5	0	95
2005	1137	85	0	1052	8	0	92
2006	1162	112	1	1049	10	0	90
2007	1188	139	2	1047	12	0	88
2008	1203	162	17	1024	14	1	85
2009	1216	168	21	1027	14	2	84
2010	1243	197	26	1020	16	2	82
2011	1245	225	32	988	18	3	79
2012	1257	241	36	980	19	3	78
2013	1252	250	31	971	20	2	78
2014	1241	265	40	936	21	3	75
2015	1237	256	58	923	21	5	75
2016	1212	255	81	876	21	7	72
2017	1195	242	96	857	20	8	72
2018	1169	239	109	821	20	9	70
2019	1148	212	124	812	18	11	71
2020	1124	185	135	804	16	12	72
2021	1084	165	125	794	15	12	73
2022	1056	122	152	782	12	14	74

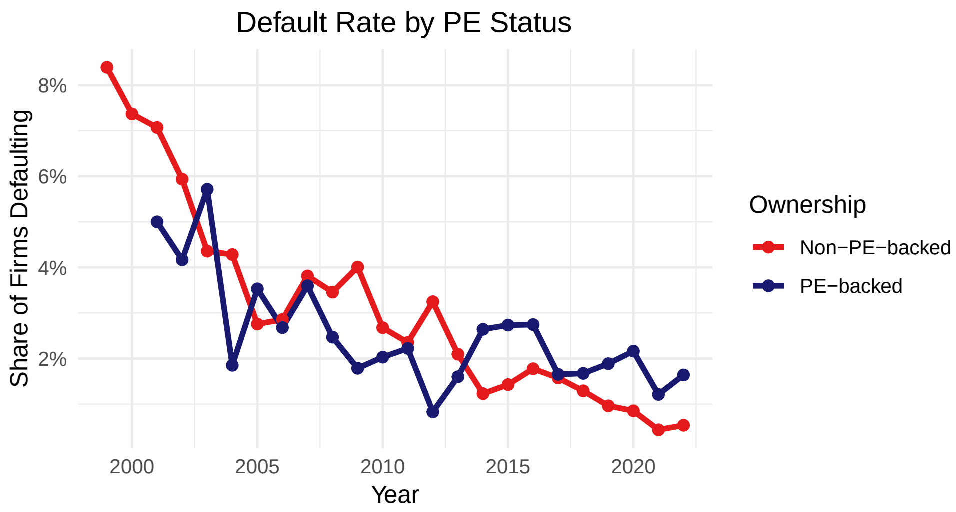

Figure 9.1: Deafalt rates yearly shares with binary default indicator ZM score >1

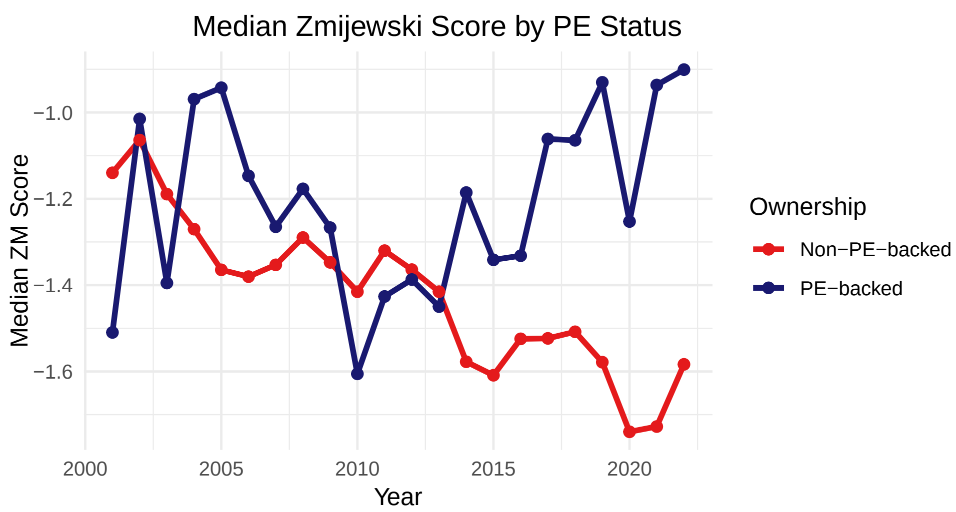

Figure 9.2: Plot of the median ZM-score over years (starting from year 2001 due to concentration in number of observations)

9.2 A2. Results from CPHM: Unadjusted sample

Table 9.6: Panel B: Unadjusted sample (default ZM score)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PE-backed	1.509**	1.511**	1.501**	1.245	1.183	1.225	1.185
	(0.152)	(0.152)	(0.153)	(0.154)	(0.150)	(0.187)	(0.151)
PE-exited							1.010
							(0.256)
Number of employees		1.000					0.9997*
		(0.000)					(0.000)
Total assets (% change)					1.000	1.000	1.000
					(0.000)	(0.000)	(0.000)
Debt/Asset (% change)				1.059***	1.060***	1.109***	1.060***
				(0.003)	(0.004)	(0.004)	(0.004)
ROA (% change)					0.989*	0.984***	0.989**
					(0.004)	(0.004)	(0.004)
EBITDA/Sales (% change)						1.000**	
						(0.000)	
Firm age			0.996**				1.002
			(0.001)				(0.001)
Year & industry FE	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes
Concordance (C-index)	0.504	0.545	0.550	0.893	0.909	0.963	0.909
	(0.005)	(0.017)	(0.017)	(0.014)	(0.013)	(0.006)	(0.013)
n	15 423	15 423	15 423	15 423	15 423	14 167	15 423
events	1 383	1 383	1 383	1 383	1 383	1 160	1 383

Note: Hazard ratios (exp(coef)), with robust SE in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 9.7: Robustness check: Cox Model with Ever and Current PE-Backing

	Hazard Ratio	Robust SE
PE-backed	1.617**	(0.178)
PE-ever	0.934	(0.081)
Concordance (C-index)	0.519 (0.016)	
n	11 715	
Events	1 058	

Table 9.8: Panel A: Unadjusted sample (default ICR)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PE-backed	1.762***	1.760***	1.759***	1.708***	1.892***	1.528·	1.753***
	(0.125)	(0.125)	(0.125)	(0.123)	(0.124)	(0.242)	(0.123)
PE-exited						1.528·	1.668*
						(0.242)	(0.247)
Number of employees		1.0000	1.0001				
		(0.000)	(0.000)				
Total assets (% change)							1.000***
							(0.000)
Debt/Asset (% change)				1.014***	1.016***	1.014***	1.015***
				(0.0017)	(0.0020)	(0.0017)	(0.002)
ROA (% change)							
EBITDA/Sales (% change)					0.989***		
					(0.0023)		
Firm age			0.9998				1.002
			(0.0017)				(0.0017)
Year & industry FE	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes
Concordance (C-index)	0.522	0.529	0.519	0.633	0.640	0.634	0.636
	(0.010)	(0.019)	(0.019)	(0.019)	(0.020)	(0.019)	(0.019)
n	27 130	27 130	27 130	27 130	24 948	27 130	27 130
events	799	799	799	799	715	799	799

Note: Hazard ratios (exp(coef)), with robust SE in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, . $p < 0.10$.

9.3 A3. Results from Staggered DiD: Unconditional and conditional parallel trends for PE-exit

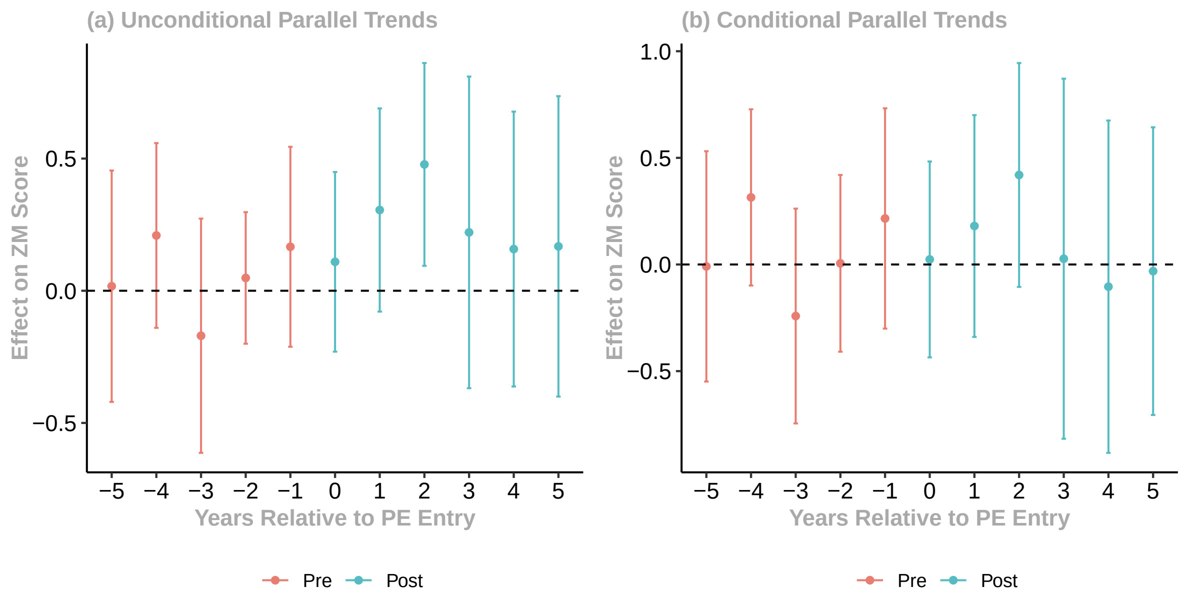

Figure 9.3: Dynamic treatment effect estimates relative to treatment timing. Panel (a) shows unconditional estimates, and panel (b) shows estimates conditional on industry and firm age.

9.4 A4. Overall and dynamic ATT by Estimation Method for PE-backed and PE-exited Firms

Table 9.9: Overall and Dynamic ATT by Estimation Method (PE-backed)

	OR				IPW				DR			
Event time e	**Estimate**	**SE**	**Lower CI**	**Upper CI**	**Estimate**	**SE**	**Lower CI**	**Upper CI**	**Estimate**	**SE**	**Lower CI**	**Upper CI**
Dynamic effects												
-5	-0.1318	0.1413	-0.5208	0.2572	-0.1580	0.1438	-0.5376	0.2215	-0.1490	0.1389	-0.5204	0.2224
-4	-0.1869	0.1401	-0.5727	0.1989	-0.2182	0.1116	-0.5128	0.0764	-0.2291	0.1146	-0.5357	0.0774
-3	0.0563	0.1462	-0.3461	0.4588	0.0774	0.1503	-0.3196	0.4743	0.0829	0.1434	-0.3005	0.4664
-2	0.0154	0.1003	-0.2607	0.2916	-0.0029	0.1066	-0.2845	0.2786	0.0019	0.0999	-0.2653	0.2691
-1	0.0042	0.0927	-0.2509	0.2593	-0.0398	0.0811	-0.2539	0.1742	-0.0483	0.0800	-0.2623	0.1658
0	**-0.0192**	**0.1365**	**-0.3949**	**0.3565**	**-0.0275**	**0.1248**	**-0.3569**	**0.3020**	**-0.0088**	**0.1311**	**-0.3594**	**0.3419**
1	0.3029*	0.1344	-0.0671	0.6729	0.3332*	0.1387	-0.0332	0.6995	0.3365*	0.1278	-0.0052	0.6783
2	0.2369	0.1474	-0.1687	0.6426	0.2525	0.1350	-0.1040	0.6090	0.2570	0.1368	-0.1088	0.6227
3	0.2675	0.1901	-0.2557	0.7908	0.2894	0.1838	-0.1958	0.7746	0.2918	0.1783	-0.1850	0.7686
4	0.3383	0.1695	-0.1283	0.8049	0.3760	0.1637	-0.0563	0.8083	0.3803	0.1634	-0.0566	0.8173
5	0.4748	0.1906	-0.0500	0.9996	0.5324*	0.1656	0.0952	0.9696	0.5334*	0.1667	0.0876	0.9793
Overall ATT	0.2669*	0.1179	0.0358	0.4980	0.2927*	0.1161	0.0651	0.5202	0.2984*	0.1313	0.0411	0.5556

* Estimate significant at 5% (simultaneous 95% band excludes 0).
Control group: never-treated; no anticipation ($\delta = 0$); balanced support ± 5.

Table 9.10: Overall and Dynamic ATT by Estimation Method (PE Exit)

	OR				IPW				DR			
Event time e	**Estimate**	**SE**	**Lower CI**	**Upper CI**	**Estimate**	**SE**	**Lower CI**	**Upper CI**	**Estimate**	**SE**	**Lower CI**	**Upper CI**
Dynamic effects												
-5	-0.0073	0.1880	-0.4943	0.4797	-0.0082	0.2005	-0.5363	0.5199	-0.0089	0.1876	-0.4942	0.4764
-4	0.3186	0.1546	-0.0818	0.7190	0.3144	0.1661	-0.1232	0.7520	0.3146	0.1633	-0.1079	0.7370
-3	-0.2250	0.2039	-0.7531	0.3031	-0.2439	0.1856	-0.7328	0.2449	-0.2417	0.1975	-0.7526	0.2693
-2	-0.0039	0.1470	-0.3847	0.3768	0.0026	0.1610	-0.4215	0.4267	0.0053	0.1507	-0.3846	0.3953
-1	0.2203	0.1779	-0.2405	0.6812	0.2155	0.1924	-0.2915	0.7224	0.2158	0.1796	-0.2487	0.6803
0	0.0219	0.1560	-0.3821	0.4259	0.0257	0.1685	-0.4181	0.4696	0.0237	0.1606	-0.3916	0.4391
1	0.1935	0.1810	-0.2752	0.6623	0.1812	0.1951	-0.3328	0.6952	0.1804	0.1896	-0.3100	0.6709
2	0.4511	0.1892	-0.0388	0.9409	0.4220	0.1934	-0.0876	0.9316	0.4197	0.2077	-0.1176	0.9570
3	0.0518	0.2914	-0.7030	0.8066	0.0296	0.3071	-0.7792	0.8385	0.0270	0.2893	-0.7213	0.7753
4	-0.0950	0.2882	-0.8832	0.6750	-0.0941	0.2781	-0.8265	0.6384	-0.1041	0.3053	-0.8938	0.6856
5	-0.0272	0.2546	-0.6867	0.6322	-0.0249	0.2595	-0.7085	0.6587	-0.0312	0.2503	-0.6788	0.6163
Overall ATT	0.0994	0.1467	-0.1881	0.3869	0.0899	0.1419	-0.1881	0.3680	0.0859	0.1390	-0.1865	0.3584

* Estimate significant at 5% (simultaneous 95% band excludes 0).
Control group: never-treated; no anticipation ($\delta = 0$); balanced support ± 5.

9.5 A5. Assessment of overlap assumption

Figure 9.4 shows the distribution of propensity scores between treated and untreated firms.

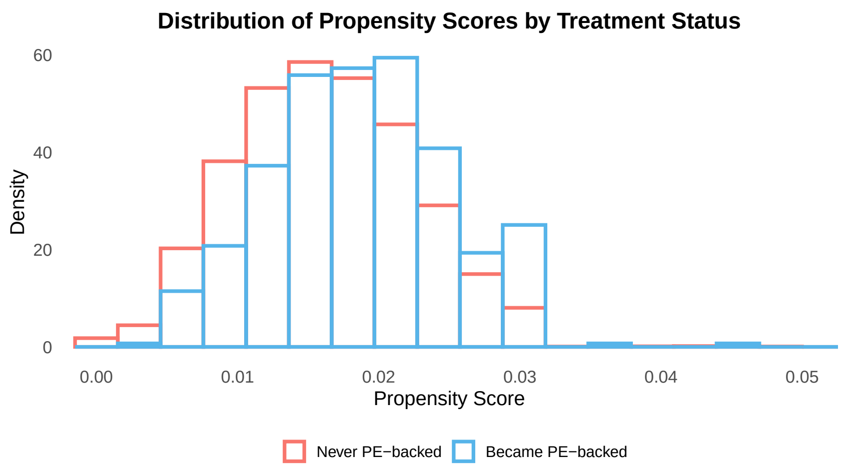

Figure 9.4: Assessing Overlap: Propensity Score Distributions by Treatment Status

10. Declaration of AI technologies in the research process

During the preparation of this study, we used ChatGPT (OpenAI) to enhance the language and readability of this work, as well as a helping tool for coding. After using this tool, we reviewed and edited the content as needed and take full responsibility for the content of the study.