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De-risking Strategies of Defined Benefit Plans: Empirical Evidence from the United States

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De-risking Strategies of Defined Benefit Plans: Empirical Evidence from the United States

Executive Summary

This study[1] investigates defined benefit (DB) retirement plan de-risking activities for United States-based companies. Considering the whole spectrum of DB de-risking strategies including shift (from DB plans to defined contribution (DC) plans), freeze, termination, buyout, buy-in, longevity hedge and liability driven investment (LDI),[2] we present empirical evidence of U.S. pension de-risking activities for the period 1994 to 2014. The study's major target audiences are academics and practitioners in the U.S. It may also provide valuable information to readers in other countries.

Based on de-risking data collected from the SEC's Electronic Data Gathering, Analysis and Retrieval System (EDGAR) and firm-level financial data from Compustat, we explore the determinants of the de-risking decision, evaluate the outcomes of adopting a de-risking strategy and examine the impact of macroeconomic variables on pension de-risking. Our results show that firms with low profitability, poor pension funding status, high pension asset beta, or high earnings/stock volatility are more likely to de-risk DB plans. We find evidence that pension de-risking improves net pension beta. We also find that implementing de-risking strategies helps to create long-term shareholder value. However, our analysis shows that de-risking activities do not directly improve plans' funding status due to the long-term feature of de-risking strategies and short-term costs of de-risking. Furthermore, DB plan sponsors' pension de-risking choices are sensitive to the interest rate level and economy environment. It is more probable that a firm de-risk its DB plan when interest rates are low or during a market downturn.

Our study fills the gap of DB pension de-risking literature by providing empirical evidence from the U.S. market. Through recognizing de-risking determinants and outcomes, we bring value information to firms, plan sponsors and trustees in the U.S. for their de-risking decisions. In addition, innovative techniques such as web crawling, text mining and machine learning employed in this study may be applied in the future to other research projects that need to collect data online.

KEY TAKEAWAYS

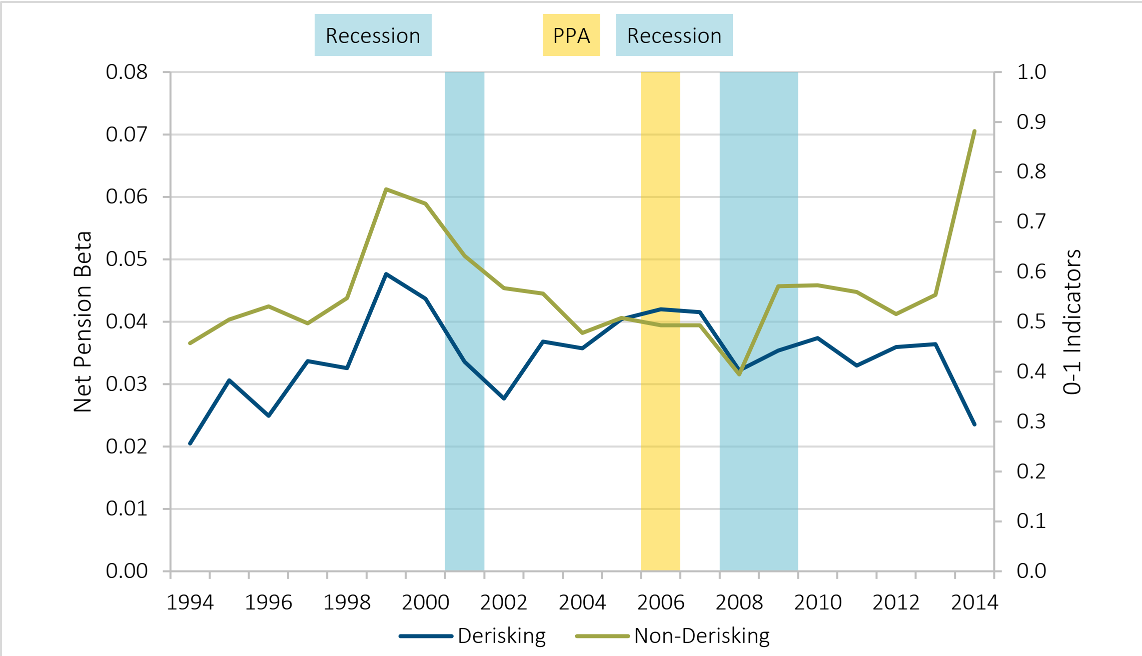
1. Firms with low profitability, poor pension funding status, high pension asset beta, or high earnings/stock volatility are more likely to de-risk DB pension plans.
2. De-risking increases long-term shareholder value and reduces net pension beta (the difference between pension asset beta and pension liability beta). See Figure 1 for the comparison of net pension beta between de-risking firms and those that have not de-risked.

[1] This project was awarded funding by the Society of Actuaries from its Research Expanding Boundaries (REX) pool for the purpose of contributing to actuarial practice expansion.

[2] For the definitions of de-risking terms, please refer to Appendix A: Glossary.

Figure 1

NET PENSION BETA



3. Economic downturns and lower interest rates are driving factors of pension de-risking.
4. Techniques including web crawling, text mining, machine learning and manual judgement were employed to build the de-risking database.
5. Study limitations:
   - Data collection techniques may be better designed to make the process more efficient and reduce errors.
   - The de-risking data collected from SEC EDGAR focus on public companies. It would be of interest to also investigate the de-risking activities of private companies.
   - The univariate and hypothesis tests focus on the period 1994–2014. The analysis results should be revisited with additional data post 2014 in a future study.
   - The firm-level financial data are from the Compustat database. It would be more reliable if instead Form 5500 data are used for regression-based analysis.
   - Different time horizons may be applied to check the robustness of conclusions in the before–after de-risking comparison.
6. Follow-up potential projects include bifurcation strategies based on riskiness of firms, causal relationship between executive compensation and de-risking, studies of individual strategies (i.e. buyout, buy-in, etc.), among others.

1. Background and Existing Studies

1.1 DE-RISKING STRATEGIES

In the recent 30 years, pension plan sponsors have been facing more severe underfunding challenges. Interest rates have been maintained at historically low levels over the past three decades, placing tremendous pressure on retirement plans since lower interest rates lead to higher pension liabilities. The market drops of 2008 worsened the financial environment. In addition, new regulations such as the Pension Protection Act of 2006 (PPA) also impacted the way plan sponsors view and evaluate their pension plans. Plan sponsors that have found the situation unsustainable have been making every effort to control and reduce pension-related risks such as investment risk, interest rate risk, credit risk and longevity risk. The lack of studies in this area motivated our interest in conducting comprehensive empirical analysis of de-risking transactions in the U.S.

De-risking strategies that are commonly used by DB pension sponsors include shift (from DB to DC), freeze, termination, buyout, buy-in, longevity hedge and liability-driven investment (LDI). Some strategies have causal relationships and pose a sequence of de-risking activities in a firm. For example, freezing a DB plan may be the first step or an early step in a de-risking process that ends with the ultimate de-risking: plan termination. And a terminated DB plan is often replaced by a DC retirement plan such as a 401(k). Another example may involve both buy-ins and buyouts, in which buy-ins are the preparation of the pension buyouts.

1.1.1 SHIFT FROM DB TO DC

DB plans were initially instituted to provide retirement benefits to veterans who served in the Revolutionary War (Adkins, 2019). Afterwards, the number of DB plans increased to meet the demands of employers, legislators and participants, especially in the 1940s and 1950s. Employers are the major risk takers of financial market risk and longevity risk in DB plans. Traditional DB pension plans have gradually lost their dominance. Over the last three decades, there has been a significant shift in retirement plan design, from DB to DC plans (Office, 2009). The first Fortune 500 firm, Johnson & Johnson, adopted a 401(k) plan in 1979 (Employee Benefit Research Institute, 2018). In 2009, there were only 29,000 single employer DB plans compared to about 92,000 single employer DB plans in 1990 (Leatherberry, 2013). According to the Willis Towers Watson 2015 FTSE (Financial Times Stock Exchange) Survey and the 2016 Fortune 100 Survey, 71% of the FTSE 100 in 2015 offer only DC plans, leaving 29% of FTSE 100 providing DB plans (traditional or hybrid) to newly hired salaried employees. The Fortune 500 companies reported a similar trend. As of 2017, "only 16% of Fortune 500 companies offered a DB plan (traditional or hybrid) to new hires, down from 59% among the same employers back in 1998 (MaFarland, 2018)."

The shift from DB towards DC pensions is considered less costly for employers since it transfers the primary responsibility of preparing for retirement along with corresponding risks (e.g., investment and longevity risks) to employees. Although the risk transfer from employer to employees can present more risk to employees, the shift can also provide advantages to employees. Specifically, DC plans make employees' benefits portable from one employer to another. Since traditional DB valuation formulas build slowly at first and grow more quickly later as cumulative years worked interact with higher salaries to earn higher retirement benefits, DB plans favor long-tenured employees (Gustman et al., 1994). The shift can increase workforce mobility, which protects mobile workers from losing benefits when changing employers.

Figure 2 is graphed based on statistical data provided by the Investment Company Institute (ICI).[3] It shows the market share of pension assets of the five major types of retirement plans, i.e., IRA, DC plans, private-sector DB plans, government DB plans (including state and local government DB plans and federal DB plans) and annuities, over the period from 1974 to 2019. The assets of DB plans (including "Government DB Plans" and "Private-sector DB Plans") accounted for only 31.9% of the total retirement assets in 2019, while they accounted for 60.5% in 1985. Note that the market share of

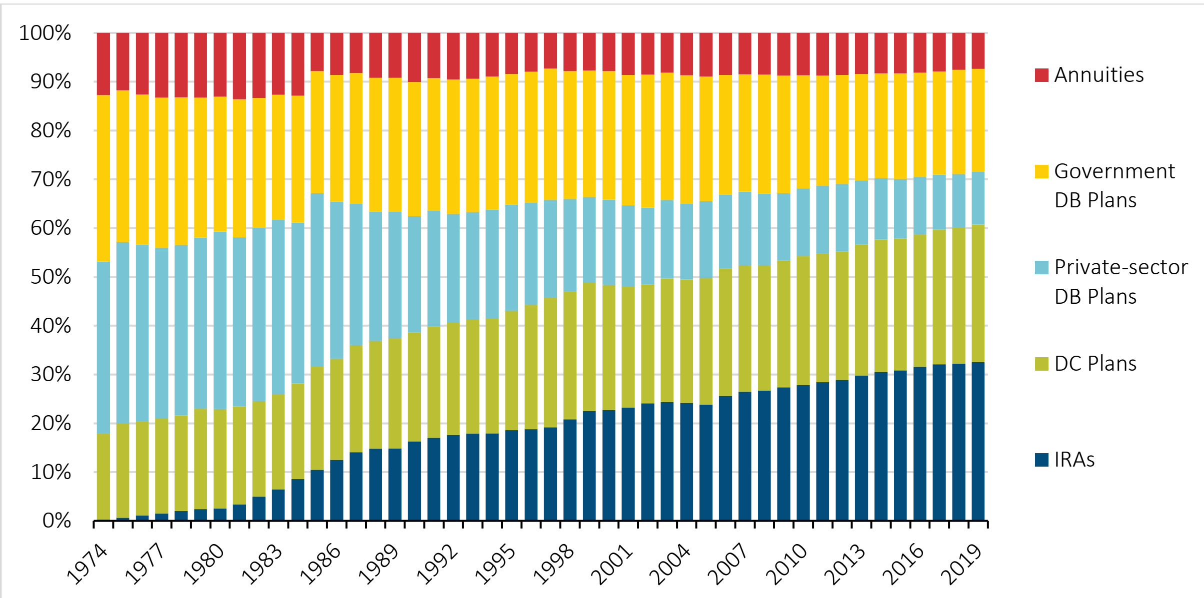
[3] Data are downloaded from https://www.ici.org/research/stats/retirement on November 6, 2019. Data from 2017 to 2019 are estimated.

DC plans[4] in terms of pension assets does not dominate and was only 28.2% in 2019, although the IRA category includes rolled over DC assets from terminated and retired employees.

The DB/DC split across countries can be significantly different. Figure 3 was presented by Willis Towers Watson (Watson, 2019) in its annual pension report. The DC split in Figure 3 counts all types of retirement plans other than traditional DB plans[5] but excludes Social Security. The last ten-year trend shows that even though the market share of DB plans in the U.S. has been declining over time, it still accounted for nearly 40% of total pension assets in 2018. This supports the necessity of analyzing DB pension plans.

Figure 2

CONSTITUTION OF U.S. TOTAL RETIREMENT ASSETS DURING 1974–2019



Source: Investment Company Institute (ICI)—Retirement Market.

1.1.2 FREEZE

When a company freezes its DB pension plan, benefits of some or all the employees stop accruing, but the plan continues to exist, and the assets remain in the plan. The company cannot take away any benefit that its employees have already earned up to the point of the freeze. The benefits will be paid to the employees when they reach retirement age.

In the 1980s and early 1990s, DB-plan freezes (or terminations) were limited mostly to financially strapped companies facing bankruptcy or engaged in mergers or acquisitions (Blitzstein et al., 2006). However, in the last 20 years, even profitable companies have joined the chorus of freezing their DB plans. Sometimes the freeze and termination happen simultaneously and sometimes the freeze is a first step toward termination to happen at some later point when the company can afford to terminate. But not all terminations go through the "intermediate" freeze step, and not all freezes end up with terminations either.

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[4] This category includes private employer-sponsored DC plans (including 401(k) plans), 403(b) plans, 457 plans, and the Federal Employees Retirement System (FERS) Thrift Savings Plan (TSP).

[5] The 2019 Willis Towers Watson report mentioned that "in January 2017, the UK's Office for National Statistics stated that the figures previously disclosed for DC entitlements were significantly overestimated."

Due to the complication and flexibility of pension freezes, different databases may categorize freezes into different sub-groups. Choy et al. (2014) consider the following three types of freezes that a firm can impose on its DB pension plan, i.e., the hard/total, soft and partial freezes.

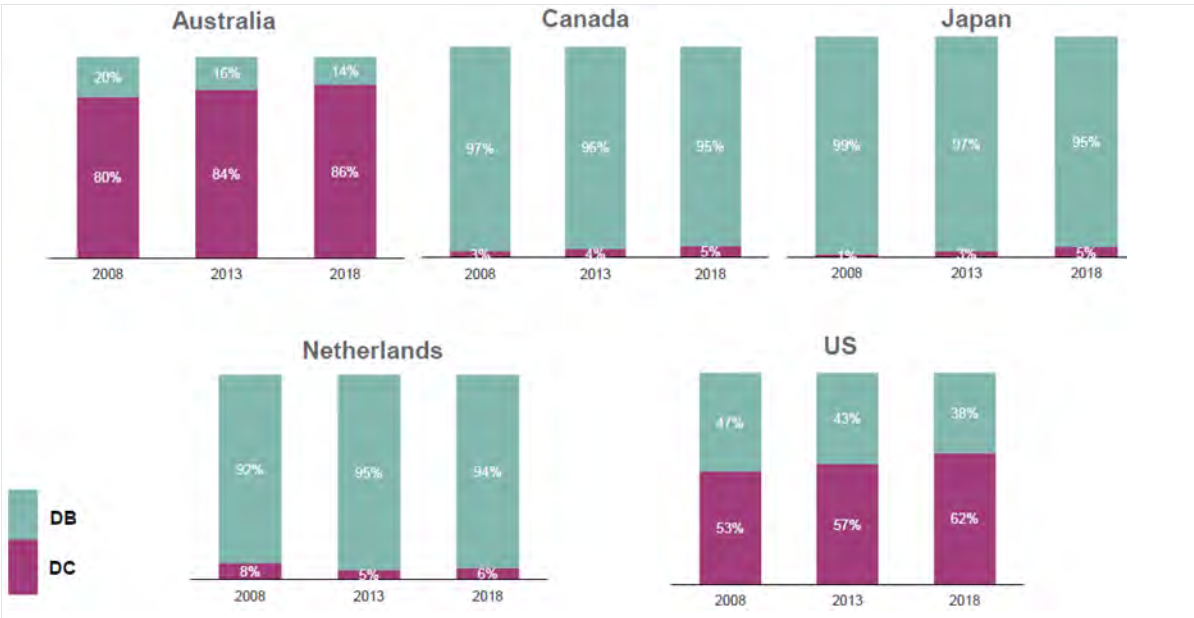
A1. **Hard/total freeze**: The firm completely stops the accrual of future benefits to all participants. That is, there is no further accrual of benefits even to existing plan participants.

A2. **Soft freeze**: The plan is closed to new entrants but the accrual of benefits of current participants continues (potentially with a change in the formula used to compute the future benefits).

A3. **Partial freeze**: The firm ceases or limits the accrual of further benefits for some but not all participants.

Figure 3

DB/DC SPLIT OVER THE LAST TEN YEARS IN AUSTRALIA, CANADA, JAPAN, THE NETHERLANDS AND THE U.S.



Source: Willis Towers Watson and secondary sources.

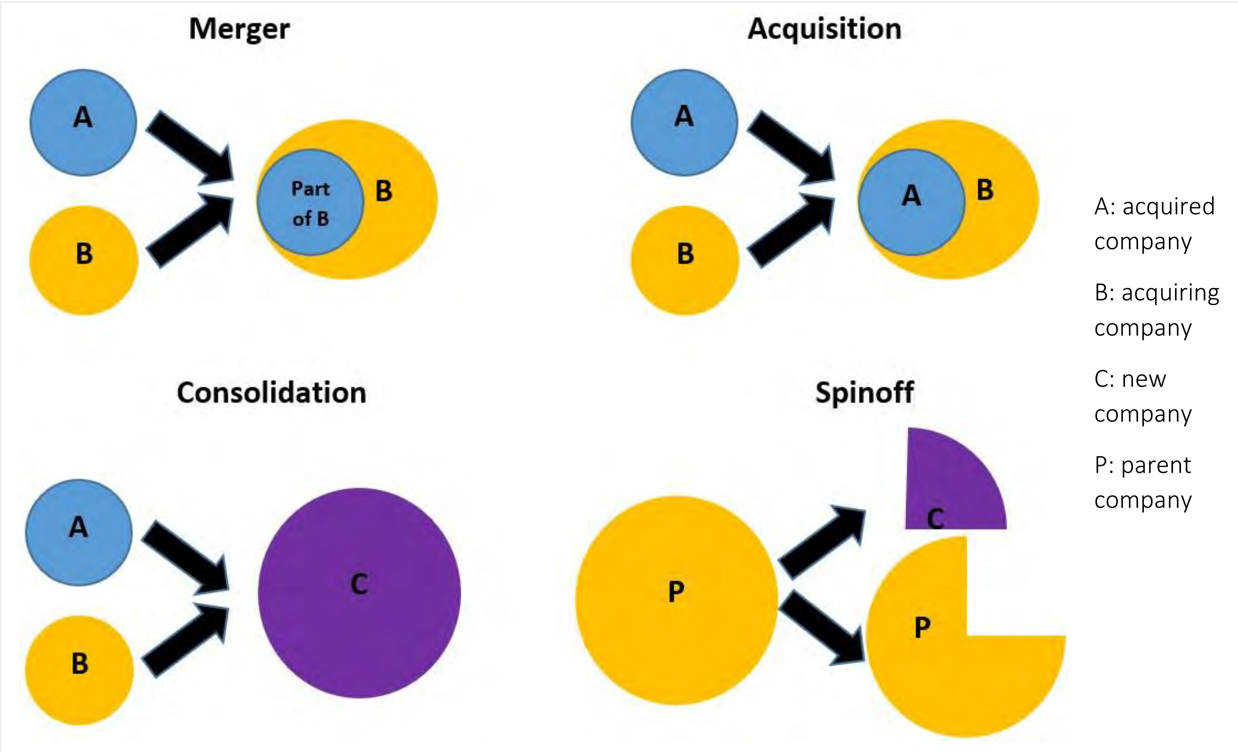
Most academic studies focus only on hard freezes (e.g., Comprix and Muller (2011), Choy et al. (2014), and Vafeas and Vlittis (2018)) since cases of "soft freeze" and "partial freeze" are hard to judge. The Pension Benefit Guaranty Corporation (PBGC) defines the following two types of "freeze":

B1. **Participation freeze**: In a plan, participation is limited to participants who are covered by the plan as of a specified date, i.e., the plan is closed to new entrants.

B2. **Benefit accrual freeze**: the plan is partially or totally frozen for benefit accrual purposes. There are five possible cases: (1) both pay and service are frozen for all participants, (2) both pay and service are frozen for some participants, (3) for all participants, service is frozen, but pay is not, (4) for some participants, service is frozen, but pay is not, or (5) some other type of accrual freeze is in effect (in which case you must provide a description of the freeze).

B2. **Benefit accrual freeze**: the plan is partially or totally frozen for benefit accrual purposes. There are five possible cases: (1) both pay and service are frozen for all participants, (2) both pay and service are frozen for some participants, (3) for all participants, service is frozen, but pay is not, (4) for some participants, service is frozen, but pay is not, or (5) some other type of accrual freeze is in effect (in which case you must provide a description of the freeze).

Figure 4
ILLUSTRATION OF MERGE, ACQUISITION, CONSOLIDATION AND SPINOFF



The PBGC's "participation freeze" (B1) is comparable to Choy et al. (2014)'s "soft freeze" (A2). While the PBGC's five cases of "benefit accrual freeze" (B2) could be any of the Choy et al. (2014)'s cases (A1, A2, or A3). The SEC filings contain more detailed information of firms' retirement plans, covering plans' features, eligibility and amendments. In this study, we use the SEC EDGAR database as the major source to identify pension de-risking activities. Specifically, we consider the following cases from SEC filings as "partial freeze" (A3) cases:

C1. **Single plan freeze**: One out of multiple DB plans of a firm is frozen.

C2. **Overseas plan freeze**: One or more of a firm's overseas plans are frozen.

C3. **Freeze due to merger/acquisition/consolidation/spinoff**: DB pension freezes caused by companies' organizational adjustments such as merger, acquisition, consolidation, or spinoff.

C4. **Sequential freezes**: A firm's DB pension freeze is accomplished through a sequence of partial freezes that apply to different divisions (e.g., factories in different states) or different employee groups (e.g., union employees vs. non-union employees).

C5. **Temporary freeze**: A frozen DB plan is reinstated a few years/months later.

Different from Choy et al. (2014), our study counts the "partial freeze" in the first four cases (C1–C4). In a time-series database, the last case (C5) is considered as "freeze" in the year when the plan was frozen and considered as "non-freeze" after the plan was reinstated.

Figure 4 demonstrates the four transactions that may affect DB plan sponsors' structure of pension plans. In a merger, the acquired company's plan transfers all of its assets and liabilities to the acquiring company's plan and, as a result, ceases to exist. While a consolidation transfers the assets and liabilities of both the acquired and acquiring companies to a new plan, both transferor plans cease to exist. In an acquisition, the acquiring company obtains the majority stake in the acquired firm, which does not change its name or alter its legal structure. Different from the first three transactions, spinoff does not fall under the Mergers & Acquisitions (M&A) umbrella. A spinoff takes an existing DB plan and creates a new plan, sometimes with a new/independent company sponsor (e.g., if there was a merger). In a spinoff, "a plan (the transferor plan) transfers a portion of its assets and/or liabilities to another plan (the transferee plan). The transferee plan may be a new plan or a preexisting plan that simply receives part of the assets and/or liabilities of the transferor plan" (Pension Benefit Guaranty Corporation, 2018).

These four transactions may accompany pension plan amendments, which may cause pension shifts, terminations, or freezes. Strictly speaking, pension shifts/terminations/freezes due to these transactions are not typical de-risking activities since pension plans do not actively seek risk transfer. But we still recognize them when building our database as those "passive" de-risking cases could be partially driven by risk-shifting purpose and their aftermath resemble the aftermath of "active" de-risking activities.

1.1.3 TERMINATION

A pension termination is different from a pension freeze. In a termination, a company must pay out all benefits no longer than one year after the termination date. The benefits can be distributed as a lump sum or an annuity that pays benefits to employees over time. The PBGC allows two types of pension terminations, i.e., the standard and distress terminations. In a standard termination, a plan will meet all benefit obligations accrued to the termination date. In this case, the DB firm permanently removes its pension obligations and the corresponding risks. A distress termination happens when a company goes bankrupt. The company in bankruptcy will transfer its pension liabilities to the PBGC. After distribution, the plan ceases.

A DB freeze is often the first step toward termination. In a survey of 174 senior finance executives conducted by CFO Research in collaboration with Mercer, Cretex CFO Steven Ragaller said that "even a frozen pension still runs up expenses, requiring maintenance in the form of administrators, investment managers and advisors, among others (Mercer, 2017)." Therefore, companies may choose to terminate the plan to avoid additional maintenance and administrative costs. "Plan terminations are the ultimate form of de-risking. Purchasing annuities or paying lump sums to all participants and getting rid of the plan eliminates the pension-related risk for the sponsor—but usually at a cost of 110% or more of the pre-termination liability (Tepfer, 2012)."

1.1.4 BUYOUT

In the early 2010s, pension buyout started to be the utilized de-risking option for DB pension sponsors. A buyout transfers all or part of the pension obligations and assets to an insurer using a bulk annuity contract, hence it transfers a whole spectrum of pension-related risks including interest rate risk, inflation risk, asset risk and longevity risk. Under a buyout contract, the transferred liabilities are completely removed from the pension plan and are no longer the company's responsibility. A full buyout of a plan's pension liabilities to retirees and non-retirees winds up the plan. Manganaro (2017) claims that "single premium pension buyout sales totaled $1.4 billion in the first quarter of 2017, marking the highest first-quarter results in at least 15 years." Mercer maintains an index called US Pension Buyout Index that tracks the relationship between the accounting liability for retirees and the estimated cost of transferring the pension liabilities to an insurance company (i.e., a buyout). The 2016–2019 average cost of purchasing annuities from an insurer was 104.3% of the accounting liability (Mercer, 2019).

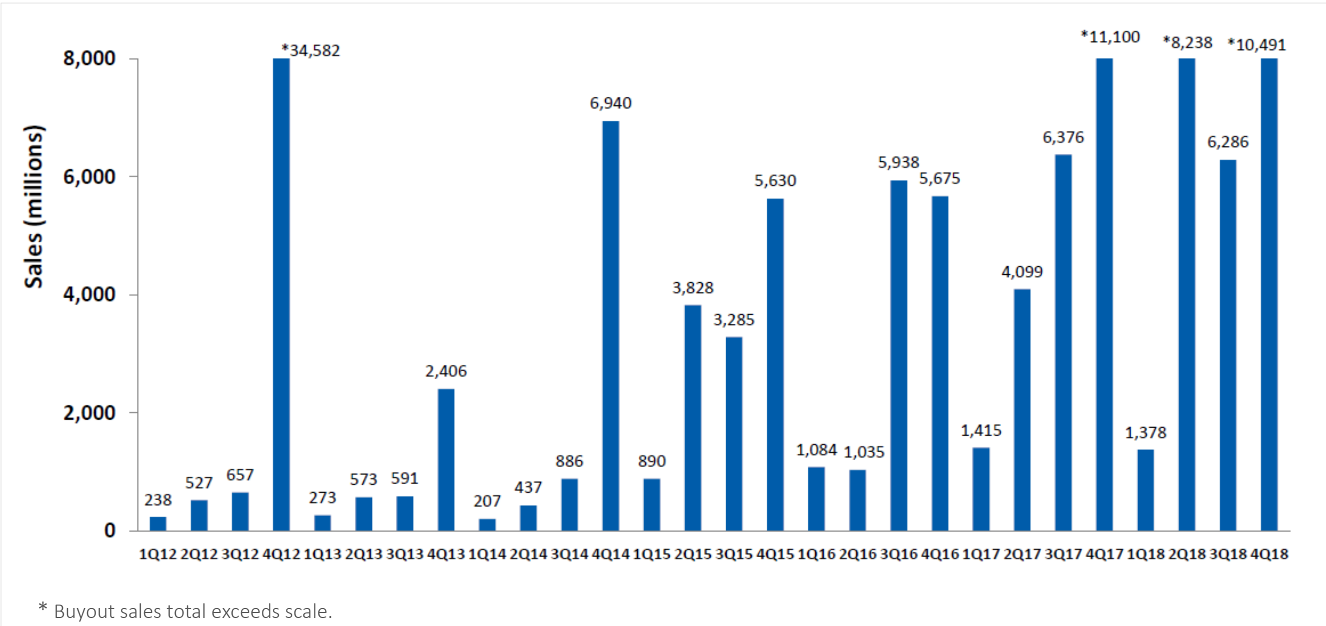
Figure 5 summarizes the buyout sales in billion dollars from 2012 to 2018 by quarter. Although with fluctuations, the buyout sales were increasing over time, with sales in 2017 and 2018 the highest. The first, second and third peaks occurred respectively in 2012Q4, 2017Q4 and 2018Q4. Notice that the later quarters of a year typically have more sales than the earlier quarters. For example, in 2015, 2017 and 2018, sales in Q2–Q4 are significantly higher than those in Q1 of the same year.

1.1.5 BUY-IN

A buy-in is the process by which a pension plan purchases an annuity contract as an investment to match some or all of its future obligations to retirees. A buy-in provides a partial hedge for several types of pension related risks. Different from a buyout in which both the assets and liabilities of a pension plan are transferred to an insurer, the assets and liabilities in a buy-in remain on the sponsor's balance sheet. The trustee maintains the plan and is subject to counter-party risk. This means that the plan sponsor has the responsibility to pay benefits to retirees if a chosen insurer (who offers the bulk annuity) becomes insolvent or defaults on its obligations at some point in the future. Buy-ins are subject to counter-party risk while buyouts are not, but a buy-in may provide additional flexibility of the unwind provision which can add a premium over a buyout. Therefore, "pricing for a buy-in is generally expected to be similar to that of a buyout (Mercer, 2014)."

Figure 5

BUYOUT SALES (PREMIUMS COLLECTED BY INSURERS) FROM 2012 TO 2018



Source: LIMRA Secure Retirement Institute. Based on 17 companies that provided single-premium buyout sales.

Buy-ins may be the first stage in a full buyout process, or a buyout may be anticipated at some stage in the future. "Buy-ins are more common in the United Kingdom than in the United States, but interest in these contracts seems to be increasing" (Mercer, 2017).

1.1.6 LONGEVITY HEDGE

Longevity hedges allow a pension plan to transfer the risk of retirees living longer than expected to a third party. Different from buyouts and buy-ins, longevity hedges, through longevity-linked securities, "de-risk" only the longevity risk but not the investment risk, interest rate or inflation risks. Few pension plans have directly tackled the longevity risk. However, if a plan has effectively improved its funding position and reduced investment risk, the longevity risk becomes a larger proportion of its total risk. For such a DB plan, a longevity hedge may serve as an inexpensive but effective de-risking strategy. Longevity hedges are also subject to counter-party risk—if the insurer (who offers the longevity swaps or longevity insurance) defaults, the DB pension sponsor is still responsible for paying the pension benefits (Lin et al., 2015).

Longevity-hedge solutions include longevity derivatives (e.g., longevity bonds, forwards, options and swaps), longevity insurance, longevity annuities (also called deferred income annuities, or DIAs), etc. The SEC EDGAR reports firms' longevity management strategies, but barely provides details about hedging products. As long as a pension provider seeks financial solutions to hedge its longevity risk, we consider such cases as longevity hedge in our database.

1.1.7 LIABILITY-DRIVEN INVESTMENT (LDI)

DB pension plans are responsible to provide retirement payments for their members. Therefore, a plan aims to have sufficient assets to cover its liabilities. This has led many DB plans to adopt liability-driven investment (LDI) strategies to better match pension liabilities with pension assets. There are three liability-related risks: interest rate risk, inflation risk and longevity risk. So LDI providers (investment banks or reinsurers) may also provide a longevity-hedge platform.

Different from the traditional "asset-only" pension investment that focuses on maximizing the asset return for a given level of investment risk, LDI additionally considers the correlation between the asset classes and the pension plan's liabilities. LDI focuses less on making gains and more on protecting against downside risk as the plan's funded status improves. The general rationale of LDI is: If the goal of a pension plan is to meet liabilities, then the investing goal should be focused on that larger plan goal.

An LDI strategy aligns a plan's assets with its liabilities by immunizing part of the portfolio with fixed-income securities, pooled funds and derivatives. For example, a corporate vice president and principal accounting officer at the Memphis-based delivery service of FedEx, discloses that "six years ago, about one-quarter of the pension fund's investments were in fixed-income investments; now about half of these assets are invested in fixed-income securities, including corporate bonds and international investments (29%) and government fixed-income securities (22%)." As the duration of the company's liabilities has changed, "we have revised our investments to match the liability." (Mercer, 2017).

Table 1

COMPARISON OF DE-RISKING STRATEGIES

	Shift	Freeze	Termination	Buyout	Buy-in	Longevity Hedge	LDI
Transaction costs	Medium	Medium	High	High	High	Low	Low
Managed risks	All risks	–	–	All risks	All risks	Longevity risk	Liability risks
Counter-party risk	–	–	–	No	Yes	Yes	Yes
Sequential transactions	No	Possible	No	Possible	Possible	Possible	Possible
Reinstate	No	Possible	No	No	–	–	–

LDI targets more stability in funded status, required contributions and balance sheet impact. However, LDI can be problematic for underfunded plans. In such cases, a dynamic LDI strategy might be structured to adjust the investment according to the plan's funded status and the interest rate environment. LDI solutions are complex and the details typically are not released in publicly available databases. Therefore, although the LDI strategy is discussed, we did not collect LDI data for this study.

1.1.8 THEORETICAL COMPARISON OF DE-RISKING STRATEGIES

Table 1 compares the key features of the seven de-risking strategies discussed in this study. In terms of transaction costs, buyouts (especially full buyouts) are the most expensive, followed by buy-ins. A longevity hedge is one of the most inexpensive options as it transfers only longevity risk, while the cost of LDI is also low but may vary depending on the complexity of the LDI solution. We expect terminations are costlier than freezes as terminations require plans to pay out benefits in one year. As a shift/freeze/termination does not physically transfer the pension-related risks to a third-party insurer, it's not proper to discuss their counter-party risk. Sequential transactions are commonly used in freezes and buyouts. Furthermore, a freeze can be potentially reinstated, although such cases are very rare. Conducted through transaction-related products, a plan's buy-in, longevity hedge, or LDI can be sequentially achieved. Due to the same reason, it's not meaningful to discuss the reversibility of these three transactions as the plan can adjust its investment in transaction-related products if needed.

1.2 LITERATURE REVIEW

The majority of existing literature that analyzes pension de-risking strategies is theoretical research that either examines hypothetical hedging products or models de-risking strategies mathematically with arbitrary market assumptions. Recent theoretical works include Blake (2000), Lin et al. (2015), D'Amato et al. (2018), among others. Blake (2000) discusses the choice between DB and DC pension plans from a pensioner's point of view, focusing on the UK markets. Lin et al. (2015) develop theoretical models to investigate the impact of transaction cost, counter-party default probability and under-funding ratio on the total pension cost (TPC) of a DB pension plan if a de-risking strategy of a buyout, a buy-in, or a longevity hedge is adopted. D'Amato et al. (2018) analyzes longevity spread buy-ins based on a similar framework to Lin et al. (2015).

There have been relatively few studies on empirical de-risking analyses. Most of the empirical studies that have DB pension analysis do not tackle de-risking strategies. Some investigate pension freezes, but there has been almost no work that empirically analyzes DB pension plans' buyouts and buy-ins, mainly due to data availability, or the difficulty of pension data collection. Below we list most of the relevant empirical papers that examine DB plans' de-risking strategies. We intentionally highlight the data range of the studies. Stone (1991) is one of the earliest papers that discusses the switch from DB plans to DC plans. Analyzing a sample of 40 firms switching to DC plans and 16 firms continuing DB plans during the period from 1981 to 1985, Stone (1991) finds that the switching firms were less able to pay dividends and were more financially stressed. His results are somewhat counter-intuitive, which may be due to the small data sample investigated. Atanasova and Hrazdil (2010) examine firm decisions in freezing their DB pension plans and its effect on shareholders' wealth with data from 2002-2006. They find evidence that a pension plan freeze has a positive impact on sponsors' equity returns and credit ratings. Considering a data sample ranging from 1991 to 2008, Comprix and Muller (2011) provide evidence that, when hard freezing their DB pension plans, employers select downward biased accounting assumptions to exaggerate the economic burden of their benefit plans. An et al. (2013) point out that for financially distressed DB sponsors and sponsors that freeze, terminate, or convert DB to DC plans, the risk-shifting incentive (moral hazard) dominates their pension fund investment given data from Compustat and Form 5500 from 1990 to 2007. Choy et al. (2014) examine the impact of a DB pension plan freeze on the sponsoring firm's risk and risk-taking activities using a sample of firms declaring a hard freeze on their plans between 2002 and 2007. They find an increase in risk-taking following DB plan freezes, consistent with theories that DB plans act as "inside debt" that aligns managers' interests with bondholders' interests. Vafeas and Vlittis (2018) study the role of outside directors in DB pension plan freezes by using firm-level data between 2000 and 2015.

There are few empirical studies on buyouts and buy-ins. As the UK pension de-risking market has a longer history and is more mature than the U.S. de-risking market, more robust UK data are available for researchers and practitioners (e.g., Li, 2017). Although the U.S. is the largest global retirement market in terms of total pension assets, as far as we know, Cantor et al. (2017) is the only empirical study that targets U.S. buyouts and buy-ins. The paper employs an event study approach for a small window of time (2012–2016) that consists of only 22 buyout cases. It examines the stock market reaction to the adoption of buyout strategy. The lack of studies in this area motivates our interest in collecting data and conducting more comprehensive empirical analysis of buyout and buy-in transactions in the U.S.

2. Data Description

2.1 DATA SOURCES

In this section, we explain the major data sources from which one can obtain pension de-risking data. As discussed in Section1.1 De-risking Strategies, the understanding of de-risking strategies may not be consistent across various data sources.

2.1.1 FORM 5500

The Internal Revenue Service (IRS), Department of Labor (DoL) and Pension Benefit Guaranty Corporation (PBGC) jointly developed the Form 5500-series returns for employee benefit plans to satisfy annual reporting requirements under the Employee Retirement Income Security Act (ERISA) and the Internal Revenue Code.

Form 5500 provides an annual report of the employee benefit plan. Any employer maintaining a plan or any plan administrator of a pension or welfare benefit plan covered by ERISA must generally file the Form 5500 to report information concerning the qualification of the plan, its financial condition, investments and the operations of the plan. In this study, we do not directly use the data from Form 5500. The Form 5500 data are used only for reference purposes.

2.1.2 SEC EDGAR

The Electronic Data Gathering, Analysis and Retrieval (EDGAR) system "performs automated collection, validation, indexing, acceptance and forwarding of submissions" of filed forms with the U.S. Securities and Exchange Commission (SEC).[6]

The SEC requires companies in the filings to provide information about their retirement plans, eligibility, benefit payment details, related plan amendments and possible terminations. Therefore, the EDGAR database is a good resource to acquire public companies' pension related information and adjustment activities. The SEC EDGAR database is the major source of our de-risking data. In this study, we conducted web crawling, text mining and machine learning to identify firm-level de-risking cases. More details are provided in Section 2.2 Data Collection.

2.1.3 LIFE INSURANCE AND MARKET RESEARCH ASSOCIATION (LIMRA)

Life Insurance and Market Research Association (LIMRA),[7] is a worldwide research, consulting and professional development not-for-profit trade association, serving the industry since 1916. LIMRA provides research and educational solutions (related to customers, markets, distribution channels, competitors, etc.) to about 600 insurance and financial services companies in 64 countries. LIMRA data are privately owned by entrepreneurs and top managers of the member firms of the association. We do not have access to the firm-level de-risking data from LIMRA, but we can refer to some aggregated data for reference purposes.

2.1.4 PENSION BENEFIT GUARANTY CORPORATION (PBGC)

The Pension Benefit Guaranty Corporation (PBGC) is a federal government agency that insures pension plans. Established by the Employee Retirement Income Security Act of 1974 (ERISA), PBGC pays monthly retirement benefits, up to a guaranteed maximum, to retirees in failed plans. If a pension sponsor goes bankrupt, its pension liabilities will be transferred to the PBGC. The PBGC provides some aggregated data, but no firm-level details. In this study, data from the PBGC serve only as reference.

2.2 DATA COLLECTION

We built a database of U.S. de-risking transactions based on the Compustat database, Form 5500 database, data from the Department of Labor, and the 5500-CRR database compiled by the Center for Retirement Research at Boston College (CRR). Before our study, the most complete publicly available U.S. pension database was the 5500-CRR database from the CRR for the period 1990 to 2007. After 2007, firm-level data with detailed pension information are not directly available from any public databases. Our goal was to fill that vacuum with compiled data after 2007 and bring the most up-to-date analysis concerning the newly available de-risking strategies such as buyouts, buy-ins and longevity hedges. To the best of our knowledge, this is the first study that investigates U.S. DB pension de-risking activities with a relatively complete range of empirical data.

We follow the literature in accounting research to examine 10-K filings on the SEC EDGAR database. To identify de-risking activities in the U.S. market, we conducted extensive web crawling and text mining in 10-K reports through keyword searches for the period 1993 to 2018.[8] For the detailed steps of web crawling and text mining and the complete list of

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[6] https://www.sec.gov/edgar/aboutedgar.htm.
[7] https://www.limra.com.
[8] 1993 is the first year for the SEC to initiate EDGAR.

keywords for each individual de-risking strategy, please refer to Appendix B: Web Crawling and Text Mining. For example, to identify a buyout, we used the following set of keywords: "pension buyout," "plan buyout," "benefit buyout" and "retirement buyout."

We then manually judge the information containing keywords based on retrieved texts from text mining. That means, when a key term is found, we review the context in which the key term appears in the report to confirm/disconfirm the adoption of a pension de-risking strategy. For termination, as there are many retrieved false cases (most false cases contain keywords "terminations" + "retirement/pension plan"), we apply Level 3 filter, along with machine learning and manual judgment to identify the true pension termination cases. Then the terminations are cross verified with termination data from Form 5500. The empirical analysis also requires firms' financial information and stock price information, so, as mentioned above, we also compile our de-risking database with data from Compustat, CRSP, the 5500-CRR database and Form 5500.

2.3 DATA STATISTICS

2.3.1 DE-RISKING DATASET

Table 2 reports the total number of de-risking cases identified from the SEC EDGAR database for the period 1994–2018, categorized into the six de-risking strategies discussed in Section 1.1 De-risking Strategies. The column "SEC filing" provides the total number of filings retrieved from the SEC EDGAR's website based on the Level 1 and Level 2 filtering described in Appendix B: Web Crawling and Text Mining. The column "Firm" counts the number of de-risking firms with unique CIK (Central Index Key) number.[9] The column "Firm & GVKEY" shows the number of de-risking firms with GVKEY. The Global Company Key, or GVKEY, is a unique six-digit number key assigned to each company (issue, currency, index) in the Capital IQ Compustat database.

As the number of filings from the Level 1 and Level 2 filtering for the de-risking strategies "shift," "freeze," "buyout," "buy-in" and "longevity hedge" ("LH") are manageable through manual judgment, they are all judged manually. However, the matched SEC filings for "termination" are 15 times those for the second largest category "freeze." This is because the web crawling and text mining keywords for termination (e.g., "terminate" + "pension") include a large volume of false cases that describe benefits of employment termination due to retirement. Since the number of SEC filings is too big for direct manual judgment, we used the three methods described below to identify the termination cases.

First, we tried text detection and recognition through machine learning methods. Refer to Appendix C: Description of The Machine Learning Process for more details. But the accuracy of machine learning was not satisfactory. For most of the years, there are still 20% false negative and 15% false positive errors. Therefore, the machine learning results can only serve as a reference, not the final outcome. Second, to narrow down the termination filing pool for manual judgment, we further conduct a Level 3 process on the basis of the results from the Level 1 and Level 2 search. We constructed a list of true/false phrase combinations to select/exclude cases. A true phrase combination contains one or more phrases that commonly appear in sentences that indicate true cases, while a false phrase combination is a typical expression observed in false cases. A list of more than 170 true phrase combinations and more than 120 false phrase combinations enabled us to reduce the candidate termination filings to 10% of the searching results from the Level 1 and Level 2 filtering. We then manually judge the cases after Level 3 filtering. Third, we cross confirm the termination data obtained from SEC EDGAR with those from Form 5500. Based on the pension asset information from Form 5500, we screen out the pension plans that are presumably terminated by the sponsors. Particularly, the screening criteria requires a pension plan to have a positive ending-balance of assets in year t and a zero ending-balance of assets in year $t+1$ (or not reported in year $t+1$). This identification approach has an advantage in quantitatively measuring the plan assets, but it introduces the bias that liquidating plan assets may be triggered by business failure, takeovers, or simply, missed submission of Form 5500

[9] A CIK number is a number given to an individual, company, or foreign government by the United States Securities and Exchange Commission to identify its filings in several online databases, including EDGAR.

documents. In addition, this method cannot recognize partial terminations because the cutoff threshold is 0. But we can use the termination data from Form 5500 to double check the data from SEC EDGAR by matching the overlapped firms. For this study, termination data collected from SEC EDGAR are preferred because they give us a better understanding of the firms' motivation in terminating a pension plan through their statements. And SEC termination cases are more comparable to the cases of other de-risking strategies, obtained also from SEC EDGAR.

At the general firm level (the second column "Firm" for each de-risking strategy), the total number of freezes are greater than that of terminations, which are much more than the remaining de-risking strategies. But the number of firms reduces significantly when considering only Compustat firms with GVKEY (the third column "Firm & GVKEY"). Notice that we did not find any longevity hedge cases before 2014 although "longevity" is mentioned in SEC filings. This is consistent with other studies which claim that markets for longevity hedge have not taken off in the U.S. In those SEC filings that contain the keyword "longevity," either longevity products are discussed in financial/insurance companies' reports as their financial products or services, or longevity management is conducted through updated reference mortality tables or adjusted longevity expectation. None of them are pension de-risking cases. We did recognize 3 true longevity cases after 2014, but the number of longevity cases is negligible compared to those from the other de-risking strategies.

Table 2

THE NUMBER OF DE-RISKING CASES DURING 1994–2018

	Shift			Freeze			Termination		
Year	SEC Filing	Firm	Firm & GVKEY	SEC Filing	Firm	Firm & GVKEY	SEC Filing	Firm	Firm & GVKEY
1994	150	3	3	469	25	18	6,348	70	59
1995	248	28	14	476	104	78	9,541	104	85
1996	307	15	1	586	233	139	19,243	77	55
1997	466	14	14	846	313	151	26,078	163	105
1998	442	9	2	901	327	175	29,777	291	98
1999	374	5	3	1,200	405	162	29,677	184	93
2000	407	0	0	640	329	159	24,699	130	75
2001	384	6	4	650	330	144	27,113	120	66
2002	359	14	10	723	332	201	28,962	130	68
2003	513	18	14	1,421	354	179	39,632	91	59
2004	775	31	24	3,166	760	280	48,243	113	63
2005	1,301	27	16	2,218	460	280	47,638	261	100
2006	938	15	12	2,828	896	473	45,198	162	94
2007	656	36	31	3,311	686	389	46,337	273	101
2008	553	25	22	3,569	1,249	571	35,254	177	103
2009	682	23	19	2,912	669	388	33,897	169	89
2010	1,080	12	10	3,181	1,006	522	42,814	139	76
2011	1,990	31	20	5,233	1,130	421	40,342	165	77
2012	1,617	63	17	4,195	1,221	596	50,157	156	88
2013	2,245	69	23	3,669	836	477	41,693	133	57
2014	1,302	14	11	3,633	917	621	38,766	109	49
2015	1,261	13	12	2,566	520	475	32,750	76	39
2016	1,230	36	33	2,860	299	260	31,571	22	20
2017	884	56	55	2,939	204	175	31,188	18	17
2018	816	7	7	2,110	115	99	25,437	6	6
Total	20,980	570	377	56,302	13,720	7433	832,355	3,339	1742

Table 2 Continued

THE NUMBER OF DE-RISKING CASES DURING 1994–2018 (CONTINUED)

Year	Buyout			Buy-in			Longevity Hedge		
	SEC Filing	Firm	Firm & GVKEY	SEC Filing	Firm	Firm & GVKEY	SEC Filing	Firm	Firm & GVKEY
1994	2,164	1	1	1	0	0	2	0	0
1995	598	0	0	1	0	0	36	0	0
1996	325	0	0	2	0	0	46	0	0
1997	387	0	0	3	0	0	58	0	0
1998	245	0	0	11	0	0	51	0	0
1999	334	0	0	11	0	0	21	0	0
2000	206	3	0	2	0	0	23	0	0
2001	210	0	0	3	0	0	27	0	0
2002	183	0	0	6	0	0	22	0	0
2003	259	1	1	3	0	0	35	0	0
2004	212	3	2	2	0	0	58	0	0
2005	370	0	0	5	0	0	64	0	0
2006	533	8	6	8	0	0	81	0	0
2007	723	3	1	13	0	0	164	0	0
2008	2,078	5	3	8	1	1	107	0	0
2009	1,089	4	3	9	0	0	117	0	0
2010	1,026	1	1	6	0	0	300	0	0
2011	2,008	143	0	27	0	0	328	0	0
2012	2,681	9	8	11	1	1	288	0	0
2013	351	12	10	5	4	4	1,114	0	0
2014	410	12	12	12	0	0	501	0	0
2015	611	23	23	21	6	6	1,034	1	1
2016	775	21	20	74	3	3	596	0	0
2017	1,226	23	18	22	8	8	632	0	0
2018	535	9	8	25	2	2	606	2	2
Total	**19,539**	**281**	**117**	**291**	**25**	**25**	**6,311**	**3**	**3**

Buyout became more popular since the late 2000s, while buy-in was not used until the early 2010s. Table 3 reports the LIMRA data of the total dollar premiums for buyout and buy-in during the period 2012–2018. Notice that the "buyout" column in Table 3 is actually the summary of the buyout transactions in Figure 5 sold by 17 insurance companies. The total dollar premium of buyout are hundreds of times larger than that of buy-in, while the difference is decreasing over time. The trend of number of buyouts and buy-ins in Table 2 does not perfectly match the trend of dollar premiums from the LIMRA data, because the dollar amount of transaction per de-risking event varies. In addition, Table 3 focuses only on the 17 companies that provided single-premium buyout/buy-in sales, while our database considers a larger set of buyout and buy-in providers.

Table 3

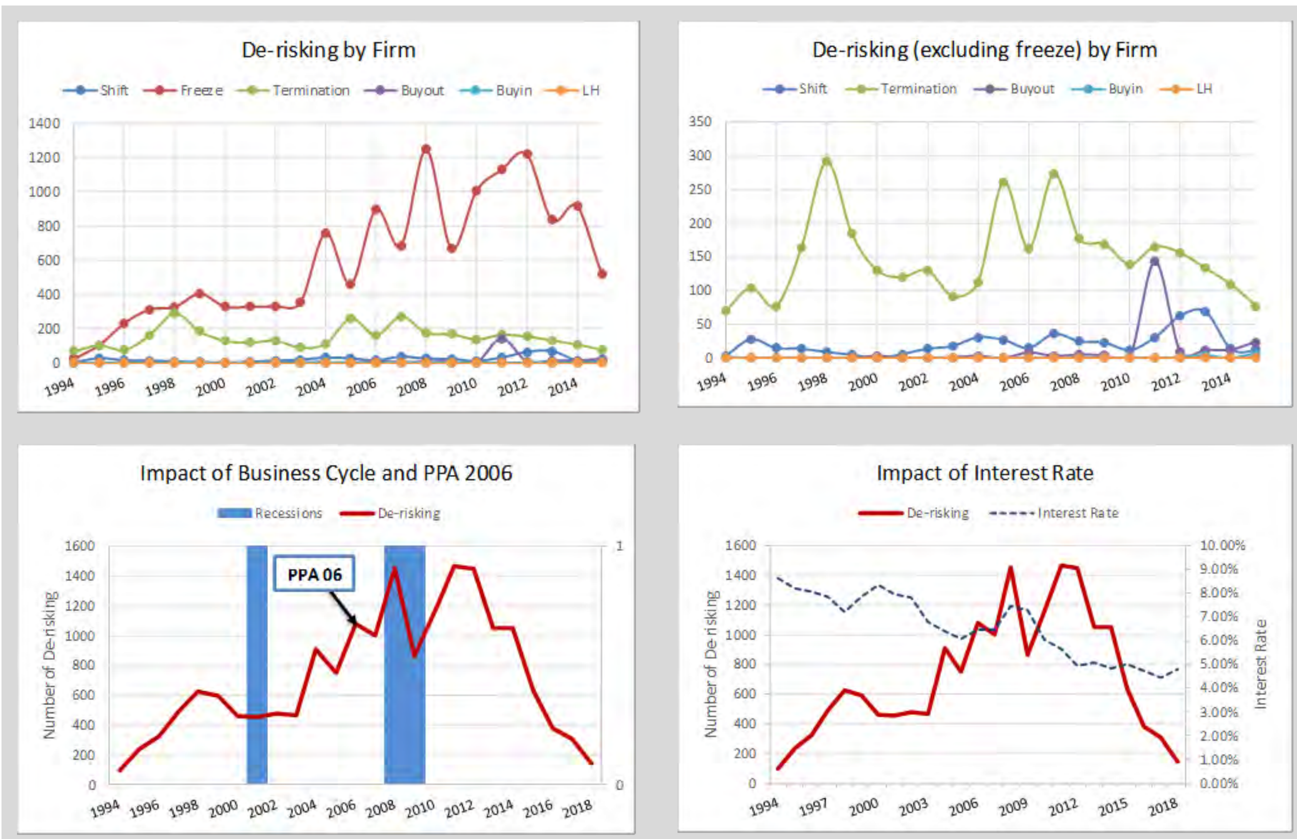
DOLLAR PREMIUMS IN MILLIONS FOR BUYOUT AND BUY-IN BY LIMRA

Year	Buyout	Buy-in
2012	36,004	–
2013	3,843	–
2014	8,470	143
2015	13,633	7
2016	13,732	16
2017	22,990	103
2018	26,393	867

In Figure 6, we show the trend of de-risking firms in the SEC EDGAR database (the column "Firm" for each de-risking strategy in Table 2) for the period 1994–2018. We compare the six de-risking strategies in the top left chart. We recognize more freeze cases than the other strategies. As the number of freezes dominate the trend, we redraw the chart in the top right chart of Figure 5 to show the comparison of the five de-risking activities other than freeze. We investigate the impact of the business cycle and interest rates on the overall de-risking activities (aggregated data), respectively, in the bottom left and right charts of Figure 6. When pooling all six types of de-risking activities together, interestingly, the total de-risking over the last 25 years did not follow a monotonic rising trend. The aggregated de-risking events increased till 2012 and then declined in the recent few years. This might be because we report the total number of de-risking events, which does not directly reflect the total dollar amount of transactions. In addition, as the total number of DB plans in the U.S. decreases, it's reasonable to expect the number of DB de-risking events drops accordingly.

Figure 6

TREND ANALYSIS FOR DE-RISKING FIRMS IN THE SEC EDGAR DATABASE



In the lower left chart of Figure 6, the solid bars represent the early 2000s dotcom bubble burst and Great Recession (2007–2009), respectively.[10] It shows that the breakout of the 2007–2009 Great Recession did trigger a peak of de-risking activities in 2008. But the firms' de-risking descended in 2009. In addition, the recession in the early 2000s did not drive a period of fast growth of firms' pension de-risking in 2001. We also investigated the impact of pension-related regulation on de-risking activities. During the time period of our study, the most impactful regulation was the Pension Protection Act (PPA) of 2006.[11] The PPA of 2006 modified funding requirements significantly for single employer DB plans. After the PPA

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[10] The data of recession indicators are downloaded from https://fred.stlouisfed.org/series/USREC. This time series is an interpretation of US Business Cycle Expansions and Contractions data provided by The National Bureau of Economic Research (NBER).

[11] Besides the PPA 2006, three laws enacted in the 1980s also significantly affected private sector pensions. They are the Tax Equity and Fiscal Responsibility Act (1982), the Retirement Equity Act (1984), and the Tax Reform Act and Single Employer Pension Plan (1986).

2006 went into effect, maintaining funded status required higher levels for private sector pension plans. Therefore, we expect the PPA 2006 is a driving factor of pension de-risking activities. In the bottom left chart of Figure 6, the PPA 2006 caused a 44.52% increase of de-risking events in 2006. This regulatory-driven peak was comparable to the one triggered by the Great Recession, which led to a 45.99% rise in de-risking in 2008.

Typically, the DB pension funding status is sensitive to interest rates. A small adjustment of the pension discount rate can lead to a great amount of modification of pension obligations. A high pension discount rate can effectively reduce pension liabilities and improve pension funding status. In both 2017 and 2018 PBGC reports (Pension Benefit Guaranty Corporation, 2017; Pension Benefit Guaranty Corporation, 2018), it is mentioned that "under Section 402 of PPA 2006, certain plans may elect to use an 8.25% discount rate for funding purposes and other plans may elect to use an 8.85% discount rate." But firms have autonomy to determine their own pension obligation discount rates, which usually follows the general interest environment of the market.

Since the pension discount rates are different across individual firms, it makes sense to consider the impact of the general interest environment on pension de-risking activities. In the lower right chart of Figure 6, we choose Moody's Seasoned Baa Corporate Bond Yield to proxy the market interest rate level. The chart demonstrates the inverse relationship between interest rates and pension de-risking. Before 2012, as the interest rate level decreased over time, pension de-risking activities kept an overall increasing trend. After 2012, the interest rate kept at a relatively stable level—around 5%. This "flat" trend of interest rate was accompanied with a decline of total de-risking activities. However, the investigated period (1994–2018) is still too short to determine the causal relationship between interest rates and de-risking. We need more interest rate cycles to test the causality between them more rigorously.

2.3.2 UNIVARIATE TESTS

After matching the de-risking events with the financial information of firms compiled in the Compustat database, we arrive at a smaller sample for univariate and multivariate analyses.[12] Since we do not have Compustat data post 2014, our univariate analysis in this section and hypothesis tests in Section 3. Hypotheses and Empirical Results focus only on the period 1994–2014. Specifically, the analyses in the following sections are based on the dataset presented in Table 4. In future work, we will revisit the analysis results in this study after the post 2014 data become available.

Since a univariate test involves only one dependent variable, its sample size does not have to be balanced. This means we can use as many available observations as possible. It makes it possible to compare the change or difference of a given measure across sub-samples. In addition, a univariate test can include multiple measures of the same variable because multicollinearity is not an issue. Compared with univariate tests, regression analysis can reveal the marginal impact of each factor. However, there is a multicollinearity issue if we add all measures in regressions at the same time for hypothesis tests since the correlation between these measures may introduce biases to the estimated coefficients. Therefore, in Section 3. Hypotheses and Empirical Results, variables considered in regressions need to be carefully selected. These selected variables should represent the firms' characteristics from different profiles and have the lowest multicollinearity among each other.

[12] First, since not all firms in the SEC EDGAR database are included in Compustat, the column "Firm" has more cases than the column "Firm & GVKEY" in Table 2. Second, some firms have records in Compustat, but their data do not cover the whole considered period 1994-2014. Only those firms in Compustat with complete data records for the period 1994-2014 are considered in the univariate tests and regressions. In other words, firms in Table 4 are a subset of the firms in column "Firm & GVKEY" of Table 2.

Table 4

NUMBER OF DE-RISKING CASES CONSIDERED IN THE EMPIRICAL ANALYSIS

Year	Shift	Freeze	Termination	Buyout	Buy-in	LH
1994	1	11	31	1	0	0
1995	3	31	28	0	0	0
1996	0	34	6	0	0	0
1997	4	26	11	0	0	0
1998	0	28	11	0	0	0
1999	0	14	7	0	0	0
2000	0	13	4	0	0	0
2001	1	18	5	0	0	0
2002	1	21	4	0	0	0
2003	2	24	3	0	0	0
2004	6	43	4	1	0	0
2005	7	43	10	0	0	0
2006	6	75	8	1	0	0
2007	9	37	20	0	0	0
2008	4	57	11	0	0	0
2009	3	21	11	0	0	0
2010	0	39	6	0	0	0
2011	3	25	6	0	0	0
2012	2	30	6	3	0	0
2013	6	24	4	4	1	0
2014	0	2	1	0	0	0
Total	**58**	**616**	**197**	**10**	**1**	**0**

We first check the de-risking activities across different industries. In Table 5, we summarize the de-risking cases for the firms with complete matching data from Compustat, based on the North American Industry Classification System (NAICS) for the United States[13]. Table 5 shows that around 50% of the de-risking activities were conducted by firms from the "Manufacturing" industry, in which the automobile industry is included. The second largest industry involved in pension de-risking is "Finance, Insurance and Real Estate." In addition, private sectors in the "Transportation, Communications, Electric, Gas, & Sanitary Services" also actively de-risked their pension plans during the period of 1994–2014. Alternatively, we can partition the de-risking activities based on the 12-industry classification by Fama and French[14], which is reported in Table 6. Under the Fama French 12-industry classification, "Manufacturing" is still the most active industry for pension de-risking, followed by "Money" that includes financial and insurance companies.

[13] In 1997, the Office of Management and Budget (OMB) elected to adopt the North American Industry Classification System (NAICS) for the United States to replace the 1987 Standard Industrial Classification (SIC) for statistical purposes. The NAICS codes cover all the companies currently in the Compustat database.

[14] The Fama French 12-industry categories in the first column of Table 6 are (1) "Consumer NonDurables" includes Food, Tobacco, Textiles, Apparel, Leather, Toys; (2) "Consumer Durables" includes Cars, TV's, Furniture, Household Appliances; (3) "Manufacturing" includes Machinery, Trucks, Planes, Off Furn, Paper, Com Printing; (4)"Energy" includes Oil, Gas, and Coal Extraction and Products; (5) "Chem.& Allied Prod." stands for Chemicals and Allied Products; (6) "Business Equipment" includes Computers, Software, and Electronic Equipment; (7) "Telecom." includes Telephone and Television Transmission; (8) "Utilities" stands for Utilities; (9) "Shops" includes Wholesale, Retail, and Some Services (Laundries, Repair Shops); (10) "Healthcare" includes Healthcare, Medical Equipment, and Drugs; (11) "Money" stands for Finance; and (12) "Other" includes Mines, Construction, Building Management, Transportation, Hotels, Business Service, and Entertainment.

Table 5

PENSION DE-RISKING FOR COMPUSTAT FIRMS ACROSS NAICS INDUSTRIES (1994–2014)

Industry Name	Shift	Freeze	Termination	Buyout	Buy-in	LH
Agriculture, Forestry, & Fishing	0	3	0	0	0	0
Mining and Construction	2	21	9	0	0	0
Manufacturing	31	314	99	9	0	0
Trans., Comm., Elect., Gas, & Sani Ser.	6	69	15	0	0	0
Wholesale Trade & Retail Trade	1	55	20	0	0	0
Finance, Insurance, & Real Estate	13	111	36	1	1	0
Services	5	42	18	0	0	0
Public Administration	0	1	0	0	0	0
Total	**58**	**616**	**197**	**10**	**1**	**0**

Table 6

PENSION DE-RISKING FOR COMPUSTAT FIRMS ACROSS FAMA FRENCH 12 INDUSTRIES

Industry Name	Shift	Freeze	Terminatio	Buyout	Buy-in	LH
Consumer NonDurables	4	50	13	2	0	0
Consumer Durables	1	24	11	1	0	0
Manufacturing	17	133	37	2	0	0
Energy	2	21	10	1	0	0
Chem.& Allied Prod.	5	34	12	0	0	0
Business Equipment	2	50	17	3	0	0
Telecom.	1	25	8	0	0	0
Utilities	5	33	9	0	0	0
Shops	1	59	18	0	0	0
Healthcare	0	27	10	0	0	0
Money	13	111	36	1	1	0
Other	7	49	16	0	0	0
Total	**58**	**616**	**197**	**10**	**1**	**0**

We then conduct univariate tests. Denote D_{it} the de-risking dummy indicator of firm i at time t, which takes the value of 1 if firm i implements a de-risking strategy in year t and 0 otherwise. Then we define the following post-de-risking dummy indicator as:

$$\mathbb{I}_{it}^{D} = max\{D_{it}, \mathbb{I}_{i,t-1}^{D}\} \quad t = 1,2, \dots, \tag{1}$$

where $\mathbb{I}_{i0}^{D} = 0$. With this setup, if firm i takes the first time de-risking activity at time τ , we have $\mathbb{I}_{it}^{D} = 0$ for $t = 0,1, \dots, \tau - 1$ and $\mathbb{I}_{it}^{D} = 1$ for $t = \tau, \tau + 1, \dots$We first compare the DB plan sponsors that conducted and didn't conduct pension de-risking during the period 1994–2014. The data statistics is presented in Table 7, where N is number of companies. Please refer to Appendix D1 and Appendix D2 for the variable description. The statistics "Mean" and "Median" help to "remove" the incomparability of a variable across different samples. In this "with–without" comparison, the "Without De-risking" sector includes the records of the non-de-risking firms that never de-risk their DB plans and the records of the de-risking firms in the periods before taking the first de-risking activity (i.e., the periods with post-de-risking dummy indicator $\mathbb{I}^{D}$equals 0). And the "With De-risking" sector considers all the records of the de-risking firms in the periods after taking the first de-risking activity (i.e., the periods with post-de-risking dummy indicator $\mathbb{I}^{D}$ equals 1).

The total assets for firms that conducted de-risking strategies are higher than those that did not de-risk their DB plans—both the mean and median of the difference of total assets are statistically significant at the 5% level. The median of market-to-book value ratio for the de-risking firms is 1.60% higher than that for the non-de-risking firms, although the difference of the mean is statistically insignificant. Although the difference in the leverage ratio is insignificant, the comparisons of the stock return volatility and earnings volatility indicate that de-risking firms on average are riskier than non-de-risking firms, significant at 1% level. The difference of the distance-to-default probability between de-risking and non-de-risking firms is statistically insignificant. But the S&P credit rating for de-risking firms on average is significantly lower. This might suggest that firms with lower credit rating are more likely to de-risk their DB plans to reduce their pension-related liabilities. On the other hand, since the causality is unclear in the univariate test, we could also conclude that on average de-risking did not reduce firms' default risk. In other words, the market did not perceive de-risking activities as a positive signal for the improvement of firms' credit rating.

Table 7

UNIVARIATE TESTS WITH/WITHOUT DE-RISKING AT FIRM LEVEL

	Without De-risking			With De-risking			With-Without	
	N	Mean	Median	N	Mean	Median	$Mean_{Diff}$	$Median_{Diff}$
Total Assets	15,643	9211	1410	710	11255	1938	2,044**	528**
Market-to-book	15,643	1.435	1.192	710	1.435	1.208	0.000	0.016*
Leverage	15,643	0.220	0.181	710	0.212	0.168	-0.008	-0.013
Cash Holding/TA	15,643	0.068	0.036	710	0.076	0.046	0.008	0.010
Altman's Z-score	15,643	2.139	2.035	710	2.078	2.050	-0.061	0.015
Stock Return Volatility	13,565	0.095	0.082	649	0.104	0.091	0.009***	0.009***
Earnings Volatility	15,354	0.031	0.020	705	0.035	0.023	0.004***	0.003***
Distance-to-default Prob.	11,930	0.057	0.000	566	0.069	0.000	0.013	0.000
S&P Credit Rating	14,317	9.235	12.000	668	9.016	11.000	-0.219**	-1.000
Pension Deficit Ratio	13,075	0.005	0.003	644	0.018	0.007	0.013***	0.003***
Underfunding Ratio	14,438	0.152	0.098	674	0.234	0.180	0.082**	0.082***
Pension Funding Ratio	14,454	0.944	0.909	675	0.877	0.847	-0.067**	-0.062***
Pension Assets Beta	10,403	0.648	0.720	463	0.650	0.738	0.002**	0.018***
Net Pension Beta	**15,643**	**0.043**	**0.004**	**710**	**0.039**	**0.003**	**-0.004*****	**-0.001*****

Notes: *, ** and *** denote significance at the 10, 5 and 1 percent level, respectively. The values of "Total Assets" are in million dollars. The "Market-to-book," "Leverage," "Cash Holding/TA," "Altman's Z-score," "Stock Return Volatility," "Earning Volatility," "Distance-to-default Prob," "Pension Deficit Ratio," "Underfunding Ratio" and "Pension Funding Ratio" are ratios. The "S&P Credit Rating," "Pension Assets Beta" and "Net Pension Beta" are simply numbers.

Now we define three pension funding measures. The pension deficit ratio (equation (2)) is the difference between pension liabilities and pension assets, adjusted by the market value of the firm. In our study, it is calculated as the difference between Pension Project Benefit Obligation (Compustat Mnemonic: PBPRO) and the Pension Plan Assets (Compustat Mnemonic: PPLAO) divided by the firm's market value.[15] The pension underfunding ratio (equation (3)) equals the same pension deficit (difference between pension liabilities and assets) divided by the amount of pension assets. A positive pension deficit ratio or pension underfunding ratio means the plan is underfunded. The pension ratio (equation (4)) is simply the ratio of pension assets to pension liabilities.[16] If the pension funding ratio is greater than 100%, the plan is overfunded, otherwise the plan is underfunded.

$$\text{Pension Deficit Ratio} = \frac{PL - PA}{\text{MV of the Firm}}, \tag{2}$$

where *PA* and *PL* stand for pension assets and liabilities, respectively.

$$\text{Pension Underfunding Ratio} = \frac{PL - PA}{\text{PA}} \tag{3}$$

[15] Please refer to the Compustat data guide for the detailed data description: https://www.etsu.edu/cbat/acct/documents/printed_data_guide.pdf

[16] It's easy to derive the pension underfunding ratio from the pension funding ratio, or vice versa. Setting the pension underfunding ratio as x, then pension funding ratio $= \frac{PA}{PL} = \frac{1}{1+x}$.

$$\text{Pension Funding Ratio} = \frac{PA}{PL} \tag{4}$$

The pension deficit ratio (i.e., the pension deficit scaled by a firm's market value) is typically small because the market value "dilutes" the pension deficit as the pension assets generally count only a small portion of the firm's total assets. In Table 7, both the mean and median of pension deficit ratio difference are statistically significant from zero at the 1% level, indicating that pension deficit for de-risking firms is statistically higher than that for non-de-risking firms. The comparison of pension underfunding ratio and pension funding ratio further confirms the relationship between pension assets and pension liabilities between de-risking and non-de-risking firms. The mean pension underfunding ratio of de-risking firms is 8.20% higher than that for non-de-risking firms, and the mean pension funding ratio for de-risking firms is 6.7% lower than that for non-risking firms, both significant at the 5% level. Since de-risking strategies are long-term strategies, we do not expect the funding status will be improved immediately after de-risking. The balance sheet does not measure the reduction of future risk as insolvency risk currently is not a big concern of most DB plans. In addition, the short-term de-risking costs could deteriorate plans' funding status in the short run. Our second set of univariate tests that investigate de-risking firms before and after de-risking also indicates that the pension status did not significantly improve after de-risking.

Table 8
HOLISTIC BALANCE SHEET

Balance Sheet	
Operation Assets	Debt
Pension Assets	Equity
	Pension Liabilities
Total Assets	**Total Liabilities & Equity**

Table 8 defined a simplified holistic balance sheet that considers pension assets and liabilities. The empirical study of Jin et al. (2006) proves that the market takes into account the holistic balance sheet. The estimation of weighted average cost of capital (WACC) will be significantly biased if one considers only the accounting balance sheet. Following Jin et al. (2006)'s idea, the following equation holds:

$$OA + PA = D + E + PL, \tag{5}$$

where *OA*, *D*, *E* stand for operating assets, debt and equity, respectively. Then we have:

$$\beta_{OA} \times OA + \beta_{PA} \times PA = \beta_{D+E} \times (D + E) + \beta_{PL} \times PL$$

Following Jin et al. (2006), we define the weighted average beta for debt and equity, β_{D+E}, as the measure of firm's risk, which is the systematic risk borne by the equity and debt holders of the firm.

$$\beta_{D+E} = \frac{\beta_{OA} \times OA + \beta_{PA} \times PA - \beta_{PL} \times PL}{D+E}. \tag{6}$$

We further define net pension beta as pension asset beta minus pension liabilities beta, adjusted by value of pension assets and pension liabilities as a percentage of the firm's total market value (the sum of equity market value (E) and debt book value (D)). That is,

$$\beta_{\text{Net Pension}} = \beta_{PA} \frac{PA}{D+E} - \beta_{PL} \frac{PL}{D+E} \tag{7}$$

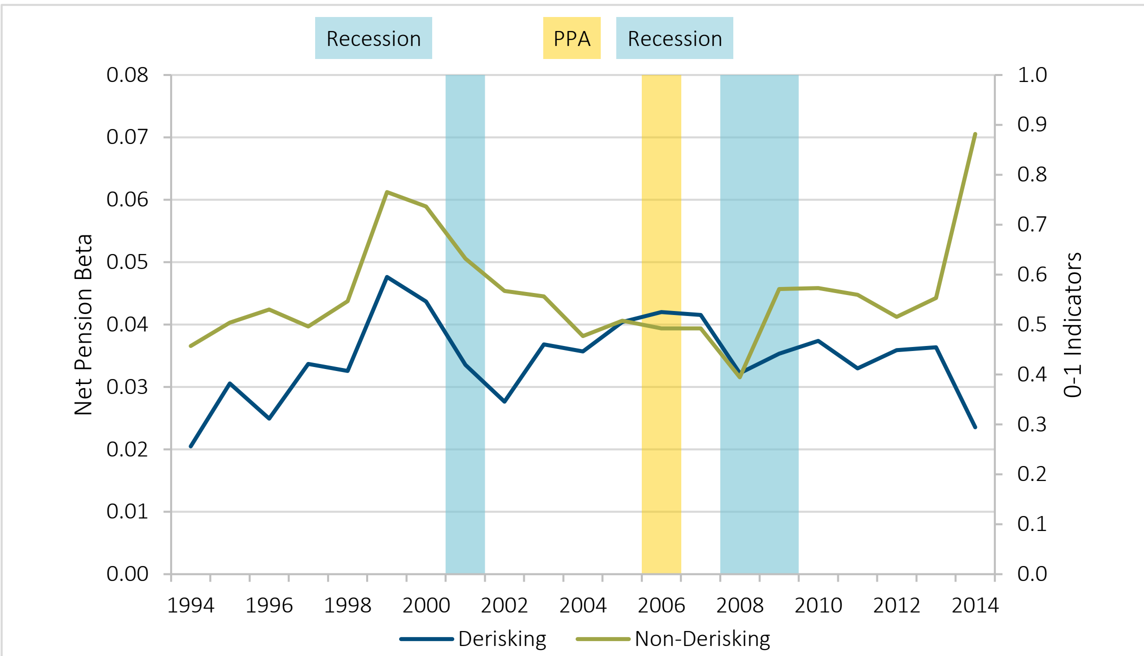
Then equation (6) can be simplified as:

$$\beta_{D+E} = \beta_{OA} \frac{OA}{D+E} + \beta_{\text{Net Pension}} \tag{8}$$

Equation (8) implies that a higher net pension beta will increase a firm's risk. In Table 7, the pension asset beta for de-risking firms is higher than that for non-de-risking firms, significant at 5% level. But in terms of the net contributor to the firm's risk, the lower net pension beta of de-risking firms will reduce a firm's risk. Since the de-risking activities effectively reduce the pension liability beta (β_{PL}), de-risking firms have more flexibility to invest in more aggressive pension assets, taking higher pension asset risk while earning higher return to improve pension funding status. We further check the comparison of net pension beta year by year. Specifically, in Figure 7we compare the net pension betas for de-risking and non-de-risking firms for the years 1994–2014. The light blue solid bars in 2001 and 2008-2009 represent the early 2000s recession and Great Recession, respectively. The yellow solid bar in 2006 stands for the Pension Protection Act of 2006.

Figure 7

NET PENSION BETA FOR DE-RISKING AND NON-DE-RISKING FIRMS DURING 1994–2014



During the 20 years of study, except a short period between 2006–2008, the net pension beta for de-risking firms was always lower than that for non-de-risking firms. But the difference was changing over time. The difference of net pension beta between de-risking and non-de-risking firms was smaller during recessions. The difference is even positive in 2008–the beginning year of the Great Recession. This might be because economic downturns increase pension asset beta and make pension de-risking less effective, so the net pension beta for de-risking firms are closer to that for non-de-risking firms. The Pension Protection Act of 2006 is another factor that drove up the net pension beta of de-risking firms. The reason might be that the more stringent pension funding requirements of PPA 2006 pushed more financially distressed DB plan sponsors to join the de-risking firm group.

We then investigate the key features of de-risking firms before, during and after their de-risking activities. In Table 9, we report the univariate test comparison for de-risking firms one-year before and one-year after de-risking. Different from the "with-without" univariate test, the "before-during-after" test considers only de-risking firms—those firms that had taken one or more de-risking activities during the investigated period 1994–2014. Mathematically, if firm $\boldsymbol{i}$ takes a de-risking activity at time $\boldsymbol{\tau}$, the "One-year Before," "Year of De-risking" and "One-year After" sectors consider the records of de-risking firms at time $\boldsymbol{\tau - 1}$, $\boldsymbol{\tau}$, and $\boldsymbol{\tau + 1}$, respectively. Consistent with the comparison between with and without de-risking firms, the average pension asset beta increased after de-risking. Interestingly, the differences in mean or median between "One-year Before" and "One-year After" are significant only for distance-to-default probability and pension betas. This might be because one year is too short to observe significant changes between one-year before and one-year after a de-risking event.

Table 9

UNIVARIATE TESTS BEFORE/AFTER DE-RISKING AT FIRM LEVEL

	One-year Before			Year of De-risking			One-year After			After-Before	
	N	Mean	Media	N	Mean	Media	N	Mean	Media	$Mean_{Diff}$	$Median_{Diff}$
Total Assets	6	102	171	7	112	193	5	127	212	2506	414
Market-to-book	6	1.4	1.20	7	1.4	1.20	5	1.4	1.22	0.026	0.020
Leverage	6	0.2	0.16	7	0.2	0.16	5	0.2	0.17	0.006	0.008
Cash Holding/Total	6	0.0	0.04	7	0.0	0.04	5	0.0	0.04	0.002	0.003
Altman's Z-score	6	2.1	2.04	7	2.0	2.05	5	2.0	2.04	-0.019	0.000
Stock Return Volatility	5	0.1	0.08	6	0.1	0.09	5	0.1	0.09	0.003	0.004
Earnings Volatility	6	0.0	0.02	7	0.0	0.02	5	0.0	0.02	0.001	0.001
Distance-to-default	5	0.0	0.00	5	0.0	0.00	4	0.0	0.00	-	0.000
S&P Credit Rating	5	9.1	11.00	6	9.0	11.00	5	9.3	11.00	0.221	0.000
Pension Deficit Ratio	5	0.0	0.00	6	0.0	0.00	5	0.0	0.00	0.000	0.000
Underfunding Ratio	6	0.2	0.18	6	0.2	0.18	5	0.2	0.18	-0.017	-0.001
Pension Funding Ratio	6	0.8	0.84	6	0.8	0.84	5	0.8	0.84	0.009	0.000
Pension Assets Beta	4	0.6	0.71	4	0.6	0.73	3	0.6	0.75	0.036	0.037**
Net pension beta	**6**	**0.0**	**0.00**	**7**	**0.0**	**0.00**	**5**	**0.0**	**0.00**	**0.003**	**-0.000***

Notes: *, ** and *** denote significance at the 10, 5 and 1 percent level, respectively. The values of "Total Assets" are in million dollars. The "Market-to-book," "Leverage," "Cash Holding/TA," "Altman's Z-score," "Stock Return Volatility," "Earning Volatility," "Distance-to-default Prob," "Pension Deficit Ratio," "Underfunding Ratio" and "Pension Funding Ratio" are ratios. The "S&P Credit Rating," "Pension Assets Beta" and "Net Pension Beta" are simply numbers.

3. Hypotheses and Empirical Results

In this section, we test three hypotheses through regressions. First, it's beneficial for both plan sponsors and pensioners to understand the determinants of choosing an appropriate de-risking strategy based on the market conditions as well as the firm-specific and industry-specific features of a pension plan. Our first hypothesis test is to recognize the determinants of making a de-risking decision. Second, we would like to evaluate the economic outcomes of adopting a de-risking strategy based on firm-level empirical data. We are interested in investigating the impact of a de-risking strategy on the firm's stock price, leverage and the magnitude of pension risk and cost. Our second hypothesis test is to identify the major outcomes of adopting a de-risking strategy. Third, macroeconomic factors such as interest rates, market risk premium, yield spread, and credit risk spread may directly affect pension de-risking, or indirectly affect de-risking through their relationship with economy activities. In the third hypothesis test, we explore the impact of macroeconomic variables on firms' pension de-risking decision.

We first conduct the baseline experiments through a probit regression. In our context, we examine the dichotomous adoption of a de-risking strategy and thus a dummy variable of pension de-risking is the dependent variable. Assume there are T periods and N firms considered, the probit model expressed as a function of the latent variable D_{it}^* is as follows:

$$D_{it}^* = \beta X_{it}' + \gamma I_i + \sigma T_i + \epsilon_{it}, \quad i = 1, \dots, N; t = 1, \dots, T \tag{9}$$

$$D_{it}^* = \beta_0 + \beta_1 X_{1,it} + \beta_2 X_{2,it} + \cdots + \beta_K X_{K,it} + \gamma I_i + \sigma T_i + \epsilon_{it}, \quad i = 1, \dots, N; t = 1, \dots, T$$

where $X_{it} = \left[1, X_{1,it}, X_{2,it}, \dots, X_{K,it}\right]^T$ is the vector of predictor variables, K is the number of the predictor variables, $\beta = [\beta_0, \beta_1, \dots, \beta_K]$ is the coefficient vector, and the error term $\varepsilon_{it} \sim N(0,1)$. Here, I_i and T_i are the industry and time dummies of firm i respectively. Then the de-risking dummy indicator, D_{it}, can be viewed as an indicator for whether the latent variable D_{it}^* is positive:

$$D_{it} = \begin{cases} 1, & \text{if } D_{it}^* > 0 \\ 0, & \text{otherwise.} \end{cases} \tag{10}$$

Table 10

REGRESSIONS OF BASELINE PROBIT MODEL ON DB PLANS

	[1]	[2]	[3]	[4]	[5]	[6]
log(Total Assets)	0.022**	0.027***	0.010	0.007	0.009	0.010
	(2.254)	(2.595)	(0.936)	(0.667)	(0.831)	(0.916)
Leverage	-0.072	0.014	0.140	0.111	0.139	0.163
	(-0.700)	(0.131)	(1.271)	(1.005)	(1.262)	(1.125)
Profitability	-0.632***	-0.821***	-0.738***	-0.828***	-0.791***	-0.740***
	(-2.872)	(-3.520)	(-3.132)	(-3.470)	(-3.352)	(-3.138)
Earnings Volatility	1.024***	0.946**	1.110***	1.156***	1.061***	1.114***
	(2.896)	(2.508)	(2.986)	(3.115)	(2.835)	(2.995)
Cash Holding	0.380**	0.225	0.068	0.208	0.078	0.065
	(2.139)	(1.186)	(0.339)	(1.019)	(0.389)	(0.325)
Non-cash Working	0.288**	0.223	0.175	0.257	0.168	0.173
	(2.336)	(1.475)	(1.110)	(1.588)	(1.066)	(1.101)
Capital Expenditure	-0.666	-0.376	-0.116	0.297	-0.104	-0.117
	(-1.512)	(-0.755)	(-0.243)	(0.606)	(-0.219)	(-0.244)
Tangible Assets				-0.368***		
				(-2.819)		
Sales Growth					0.114**	
					(2.118)	
Private Debt						-0.048
						(-0.245)
Constant	-1.842***	-2.370***	-2.074***	-1.741***	-2.053***	-2.074***
	(-19.219)	(-5.914)	(-4.105)	(-3.336)	(-4.059)	(-4.104)
Industry-fixed Effect	No	Yes	Yes	Yes	Yes	Yes
Time-fixed Effect	No	No	Yes	Yes	Yes	Yes
Number of Observations	18,293	18,293	18,293	18,293	18,293	18,293
Pseudo R^2	0.005	0.016	0.044	0.045	0.045	0.044

Note: *, ** and *** denote significance at the 10, 5 and 1 percent level, respectively.

For robustness (Noreen, 1988), we also conduct the OLS (Ordinary Least Squares) regression[17]. The equation for the OLS regression is:

$$D_{it} = \beta X'_{it} + \gamma I_i + \sigma T_i + \epsilon_{it}, \quad i = 1, \dots, N; t = 1, \dots, T, \tag{11}$$

where all the variables are defined the same as in the probit model. The results of probit and OLS regression are reported in Table 10 and Table 11, respectively. The robust standard errors are used to calculate the Z-statistics. We follow the literature to control for industry effects and time effects by using industry dummies and year dummies. For both the probit and OLS models, the pseudo/adjusted R^2s of specifications [3]–[6] that include both industry and time dummies are close to each other. Since the dependent variable is binary, the OLS regression does not fit the data very well as the adjusted R^2s for all the specifications are lower than the pseudo R^2s of their probit counterparts.

[17] Given the nature of our dependent variable, the OLS regression performs as a linear probability model in our study. Comparing to the OLS model, the probit model recognizes that the decision of de-risking is a probability and estimates through an iterative process of maximum likelihood. In contrast, the linear probability model also has its advantage, especially in terms of effectiveness of estimation when the binary outcome is rare. But when the predicted probabilities fall into a moderate range, both probit and OLS models can reasonably fit the real probabilities.

Table 11

REGRESSIONS OF BASELINE OLS MODEL ON DB PLANS

	[1]	[2]	[3]	[4]	[5]	[6]
log(Total Assets)	0.002**	0.002**	0.001	0.000	0.001	0.001
	(2.188)	(2.432)	(0.732)	(0.482)	(0.633)	(0.712)
Leverage	-0.007	0.001	0.013	0.011	0.013	0.016
	(-0.708)	(0.112)	(1.209)	(1.024)	(1.201)	(1.094)
Profitability	-0.062***	-0.080***	-0.068***	-0.076***	-0.074***	-0.069***
	(-2.911)	(-3.424)	(-2.894)	(-3.191)	(-3.121)	(-2.902)
Earnings Volatility	0.110**	0.101**	0.114**	0.118***	0.110**	0.114**
	(2.518)	(2.241)	(2.500)	(2.593)	(2.414)	(2.510)
Cash Holding	0.036*	0.021	0.007	0.019	0.008	0.006
	(1.960)	(1.096)	(0.348)	(0.954)	(0.388)	(0.335)
Non-cash Working	0.025**	0.020	0.016	0.024	0.016	0.016
	(2.204)	(1.368)	(1.137)	(1.617)	(1.105)	(1.131)
Capital Expenditure	-0.054	-0.031	-0.011	0.025	-0.009	-0.011
	(-1.524)	(-0.754)	(-0.264)	(0.581)	(-0.227)	(-0.269)
Tangible Assets				-0.036***		
				(-2.639)		
Sales Growth					0.012*	
					(1.852)	
Private Debt						-0.006
						(-0.330)
Constant	0.032***	0.022	0.060	0.090*	0.061	0.059
	(3.639)	(0.573)	(1.133)	(1.674)	(1.162)	(1.129)
Industry-fixed Effect	No	Yes	Yes	Yes	Yes	Yes
Time-fixed Effect	No	No	Yes	Yes	Yes	Yes
Number of Observations	18,293	18,293	18,293	18,293	18,293	18,293
Adjusted R^2	0.002	0.003	0.013	0.013	0.013	0.013

Note: *, ** and *** denote significance at the 10, 5 and 1 percent level, respectively.

The results from these two types of regressions are somewhat consistent with each other. For example, in both Table 10 and Table 11, the variable of "log(Total Assets)" is statistically positively significant in the first two model specifications (i.e., [1] and [2]) without any fixed effect. It indicates that a large firm with more total assets is more likely to de-risk its DB pension plan. The "Profitability" is statistically negative, and the "Earnings Volatility" is statistically positive in all the six specifications for both probit and OLS models. The coefficients of "Tangible Assets" in both models are statistically negative, indicating firms with less tangible assets are more likely to de-risk their pension plans.

The baseline experiments recognize a set of fundamental independent variables, which include "log(Total Assets)," "Leverage," "Profitability," "Earnings Volatility," "Cash Holding," "Non-cash Working Capital" and "Capital Expenditure." These variables will be used as fundamental explanatory variables in the hypothesis tests. In Table 10 and Table 11, models considering both industry effect and time effect have better performance, so we will include both types of controlling variables in the following experiments. Since the results from probit models are typically better than the results from the corresponding OLS models (with higher pseudo/adjusted R2), in the following tests, we only report the results from probit models.

Table 12

IMPACT OF FUNDING STATUS AND PENSION BETA ON DE-RISKING

	[1]	[2]	[3]	[4]
Underfunding Ratio	1.381***			
	(2.907)			
Pension Deficit Ratio		0.016		
		(0.314)		
Pension Assets Beta			-0.167***	
			(-2.612)	
Net Pension Beta				-0.096
				(-0.448)
log(Total Assets)	0.012	0.010	0.011	0.012
	(1.070)	(0.857)	(0.778)	(0.857)
Leverage	0.273**	0.174	0.230*	0.225
	(2.039)	(1.511)	(1.658)	(1.620)
Profitability	-0.628**	-0.674***	-0.617**	-0.630**
	(-2.357)	(-2.652)	(-2.080)	(-2.121)
Earnings Volatility	1.123***	1.262***	1.224***	1.253***
	(2.693)	(3.188)	(2.847)	(2.915)
Cash Holding	0.147	0.038	0.134	0.143
	(0.698)	(0.181)	(0.556)	(0.592)
Non-cash Working	0.168	0.105	0.233	0.217
	(1.024)	(0.650)	(1.186)	(1.101)
Capital Expenditure	-0.226	-0.265	0.195	0.147
	(-0.440)	(-0.531)	(0.329)	(0.249)
Constant	-2.162***	-2.097***	-5.521***	-5.668***
	(-4.251)	(-4.126)	(-14.688)	(-15.022)
Industry-fixed Effect	Yes	Yes	Yes	Yes
Time-fixed Effect	Yes	Yes	Yes	Yes
Number of Observations	15,892	17,114	12,073	12,073
Pseudo R^2	0.044	0.045	0.053	0.052

Note: *, ** and *** denote significance at the 10, 5 and 1 percent level, respectively.

3.1 HYPOTHESIS 1

The determinants of a DB pension plan's de-risking strategy include the firm's funding status (**H1a**), pension asset risk (**H1b**), default probability of the DB firm (**H1c**), profitability (**H1d**), return volatility (**H1e**) and industry features (**H1f**).

H1a. *DB plan sponsors with higher pension underfunding ratio are more likely to de-risk pension plans.*

H1b. *DB plan sponsors with lower pension asset beta are more likely to de-risk pension plans.*

Table 12 presents the results of regressions considering underfunding ratio or pension betas. The dependent variable is still the de-risking dummy.[18] Specification [1] shows that the pension underfunding ratio is statistically positively significant at the 1% level, supporting H1a. The coefficient of pension asset beta is statistically negatively significant, indicating DB plan sponsors with lower pension asset beta are more likely to de-risk their pension plans. Therefore, the data supports H1b. This result is consistent with those obtained in the univariate tests. In the "with–without" comparison in Table 7, the mean/median of pension asset beta with de-risking is statistically higher than that without de-risking. Furthermore, Table 9 shows that pension asset beta significantly increased after de-risking. Notice that the coefficient of net pension beta is statistically insignificant. Therefore, both pension funding status and pension asset beta are driving factors of pension de-risking activities.

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[18] The regression equation still follows equations (9) and (10).

H1c. *DB plan sponsors with higher default probability are more likely to de-risk pension plans.*

H1d. *DB plan sponsors with lower profitability are more likely to de-risk pension plans.*

H1e. *DB plan sponsors with higher return volatility are more likely to de-risk pension plans.*

In Table 13 we investigate the impact of default probability on pension de-risking. Again, the regression equation follows equations (9) and **(10)**. We examine a set of relevant variables that can measure either the firm's default probability as a whole or the firm's liquidity. Specifically, "S&P Credit Rating," "Altman's Z-score" and "Distance-to-Default Probability" measure a firm's default probability, and "Interest Coverage" gauges a firm's long-term liquidity. However, except for the "Distance-to-Default Probability" which is significant at 10% level, the coefficients of the other three variables are statistically insignificant. Therefore, we reject H1c and conclude DB plan sponsors' default probability does not directly relate to the firms' de-risking decision. The "Profitability" is statistically negatively significant at the 5% or 1% levels in all the specifications in Table 13, indicating that firms with lower profitability are more likely to de-risk their pension plans. Therefore, we support H1d. Notice that the two return volatility variables are statistically significant. Both "Stock Return Volatility" and "Firm Return Volatility" positively contribute to DB plan sponsors' pension de-risking choices, supporting H1e.

Table 13

IMPACT OF DEFAULT PROBABILITY ON DE-RISKING

	[1]	[2]	[3]	[4]	[5]	[6]
Stock Return Volatility	0.703**					
	(2.102)					
Firm Return Volatility		0.905***				
		(2.678)				
S&P Credit Rating			0.003			
			(0.838)			
Altman's Z-score				-0.009		
				(-0.391)		
Distance-to-default Probability					0.192*	
					(1.944)	
Interest Coverage						-0.000
						(-0.204)
log(Total Assets)	0.014	0.014	0.001	0.010	0.014	0.011
	(1.155)	(1.147)	(0.049)	(0.913)	(1.122)	(0.937)
Leverage	0.137	0.234*	0.171	0.123	0.020	0.089
	(0.982)	(1.722)	(1.526)	(1.048)	(0.130)	(0.763)
Profitability	-0.595**	-0.594**	-0.694***	-0.654**	-0.776**	-0.808***
	(-2.281)	(-2.282)	(-2.833)	(-2.118)	(-2.567)	(-3.182)
Earnings Volatility	1.089**	1.051**	1.116***	1.100***	1.256***	1.148***
	(2.495)	(2.374)	(2.891)	(2.966)	(2.698)	(2.886)
Cash Holding	0.047	0.073	0.110	0.087	0.128	0.105
	(0.225)	(0.351)	(0.534)	(0.425)	(0.502)	(0.454)
Non-cash Working Capital	0.161	0.171	0.185	0.192	0.191	0.214
	(0.998)	(1.057)	(1.139)	(1.183)	(1.078)	(1.310)
Capital Expenditure	-0.023	-0.041	-0.343	-0.120	-0.043	-0.185
	(-0.046)	(-0.082)	(-0.684)	(-0.252)	(-0.079)	(-0.376)
Constant	-6.044	-6.073	-2.022***	-2.060***	-2.076***	-2.030***
	(-0.642)	(-0.469)	(-3.982)	(-4.075)	(-3.765)	(-3.991)
Industry-fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	16,311	16,270	17,068	18,293	14,611	16,415
Pseudo R^2	0.042	0.042	0.045	0.044	0.041	0.045

Note: *, ** and *** denote significance at the 10, 5 and 1 percent level, respectively.

H1f. *Industry features affect firms' decision on pension de-risking.*

In Section 2.3.2 Univariate Tests, the industry analysis for de-risking activities shows that DB plan sponsors in the manufacturing industry were more often involved in pension de-risking. To further check if firms' key determinants across industries affect firms' de-risking decision, we reran the specification [3] of the baseline probit regression (de-risking dummy as the dependent variable; control for industry and time effects) on the subsamples categorized by the 12 industries classified by Fama and French. The results in Table 14 demonstrate the heterogeneity across industries in affecting firms' de-risking decisions. For these investigated key features, fewer than four industries show significant influence on de-risking. For example, the coefficient of log(Total Assets) is statistically significant only for Telecommunication (Telcm) and Healthcare (Hlth). Large firms from Telecommunication are more likely to adopt de-risking, while the small firms in Healthcare are more likely to adopt de-risking. The impact of financial leverage on de-risking is 10% significant in four out of twelve industries. Among them, firms with low leverage in Energy (Enrgy) and Business Equipment and firms with high leverage in Shops and Healthcare are more likely to de-risk. Profitability is the most influential feature that triggers de-risking activities across different sectors. Low profitability in Manufacturing (Mfg) and Energy may push the firms to de-risk their DB plans, significant at the 1% level. While firms in the Telecommunication industry with high profitability are more willing to de-risk. Overall, the same key feature may lead to different de-risking choices to those firms in different industries, although we did not find a universal firm-related characteristic that has a significant connection with the adoption of a de-risking strategy. Therefore, we support H1f. In other words, firms' industry features do play a critical role in firms' de-risking decision.

3.2 HYPOTHESIS 2

Pension de-risking improves firms' funding status (**H2a**), reduces pension beta (**H2b**), increases firms' stock price (**H2c**) and affects firms' financial leverage and operating performance (**H2d**).

H2a. Pension de-risking improves firms' funding status.

H2b. Pension de-risking reduces firms' pension beta.

The regressions in Table 15 set the dependent variable as pension underfunding ratio, pension deficit ratio, pension asset beta and net pension beta in columns 2–5, respectively. The regression equation takes the form

$$Y_{it} = \beta X_{it}' + \gamma I_i + \sigma T_i + \epsilon_{it}, \quad i = 1, \dots, N; t = 1, \dots, T, \tag{12}$$

where Y_{it} is the independent variable which stands for either funding status or pension beta. As defined in equation (1), the "Post-De-risking Dummy" is an indicator variable that takes the value of one for the event year and all the years thereafter and zero otherwise. The de-risking decision significantly increased a firm's pension underfunding ratio and pension deficit ratio. Therefore, pension de-risking did not improve, but rather deteriorated firms' funding status. The results are consistent to the with-without comparison in the univariate test in Section 2.3.2 Univariate Tests. We reject H2a. As all the six studied pension de-risking strategies are liability-side strategies that target reducing pension liabilities, the impact of pension de-risking on pension asset beta is not statistically significant. But consistent to the trend demonstrated in Figure 6, the influence on net pension beta is statistically negative, significant at the 1% level. As de-risking activities significantly reduce net pension beta, H2b is supported. This finding is also consistent to the result obtained in the univariate test.

H2c. *Pension de-risking increases stock price and value.*

In Table 16, we investigate the influence of pension de-risking on firms' stock price and value. The regression equation follows equation (12) with Y standing for either the market-to-book value ratio (column 2) or the excess equity return (column 3), respectively. The excess equity return is calculated as a firm's estimated stock return following Faulkender and Wang (2006) minus the benchmark returns of Fama and French (Fama and French, 1993) size and book-to-market matched portfolios during the same time period. The pension de-risking activities significantly increased a firm's excess equity return (at 1% significance level), although its impact on the market-to-book value ratio is not statistically significant. So overall, H2c is supported. Given the fact that market-to-book ratio is static while excess equity return is calibrated on the benchmark of size-and-industry categorized portfolios, the distinct difference between the result of market-to-book ratio and that of excess equity return may indicate that the value generation process of de-risking varies across the firms with different sizes and in different sectors.

Table 14

KEY FEATURES OF DE-RISKING FIRMS ACROSS 12 FAMA-FRENCH INDUSTRIES

	Consumer NonDurab	Consumer Durables	Mfg	Energy	Chems	Business Equipment	Telcm	Utilities	Shops	Health	Money	Other
log(Total Assets)	-0.024	0.009	0.006	-0.046	-0.028	0.011	0.141**	0.046	0.008	-0.102*	0.028	-0.018
	(-0.627)	(0.147)	(0.226)	(-0.740)	(-0.546)	(0.316)	(2.390)	(0.965)	(0.191)	(-1.713)	(1.296)	(-0.570)
Leverage	0.376	-0.480	0.377	-1.278*	0.207	-1.051*	-0.168	-0.405	0.638*	1.235*	0.231	-0.325
	(1.116)	(-0.710)	(1.484)	(-1.856)	(0.386)	(-1.767)	(-0.267)	(-0.739)	(1.675)	(1.812)	(1.109)	(-0.839)
Profitability	-1.007	-0.142	-1.079**	-3.897***	-0.367	-0.736	1.997*	0.465	0.260	0.977	-0.878	-0.671
	(-1.505)	(-0.083)	(-2.097)	(-2.998)	(-0.357)	(-0.948)	(1.759)	(0.263)	(0.253)	(1.022)	(-1.315)	(-0.936)
Earnings Volatility	0.800	-2.841	0.451	-0.648	-0.117	1.315	5.607**	0.147	2.072	-0.128	1.627	1.910
	(0.845)	(-0.813)	(0.552)	(-0.317)	(-0.068)	(1.467)	(2.241)	(0.064)	(1.432)	(-0.057)	(1.588)	(1.554)
Cash Holding	-0.449	-2.154	0.213	-2.359	-1.594	-0.483	-1.356	0.012	1.219	0.158	0.925	0.699
	(-0.699)	(-1.560)	(0.499)	(-1.117)	(-1.417)	(-0.935)	(-1.134)	(0.005)	(1.558)	(0.188)	(1.177)	(1.138)
Non-cash Working Capital	-0.048	0.423	0.167	2.043	-0.798	-0.310	1.423	0.362	0.334	-1.120	1.430*	0.090
	(-0.138)	(0.838)	(0.497)	(1.625)	(-1.200)	(-0.658)	(0.799)	(0.268)	(0.877)	(-1.113)	(1.756)	(0.191)
Capital Expenditure	-3.246	-5.117	1.147	-0.851	-1.286	-1.083	-2.963	0.797	0.642	0.549	-0.315	-0.660
	(-1.624)	(-1.307)	(1.004)	(-0.598)	(-0.466)	(-0.611)	(-1.407)	(0.601)	(0.356)	(0.170)	(-0.178)	(-0.640)
Constant	-5.160***	-5.269	-5.509***	-0.061	-0.044	-4.590***	-2.714***	-6.050	-5.830***	-4.861***	-1.483***	-5.554
	(-9.762)	(-0.126)	(-68.851)	(-0.070)	(-0.047)	(-9.768)	(-3.019)	(-0.720)	(-19.227)	(-11.086)	(-3.349)	(-0.304)
Number of Observations	1,651	689	3,767	674	1,024	1,275	600	1,968	1,468	618	3,223	1,336
Pseudo R^2	0.050	0.204	0.046	0.202	0.121	0.054	0.137	0.097	0.078	0.118	0.046	0.090

Notes: *, ** and *** denote significance at the 10, 5 and 1 percent level, respectively. The “Consumer NonDurables,” “Consumer Durables,” “Mfg,” “Enrgy,” “Chems,” “Business Equipment,” “Telcm,” “Utilities,” “Shops” “Hlth,” “Money” and “Other” represent Consumer NonDurables, Consumer Durables, Manufacturing, Energy, Chem.& Allied Prod, Business Equipment, Telecommunication, Utilities, Shops, Healthcare, Money and Other in the Fama-French 12-industry categories, respectively. Please refer to Footnote 14 for more details.

Table 15

INFLUENCE OF DE-RISKING ON FUNDING STATUS AND PENSION BETAS

	Pension Underfunding	Pension Deficit	Pension Asset Beta	Net pension
Post-De-risking Dummy	0.004***	0.014*	0.001	-0.006***
	(5.049)	(1.818)	(0.174)	(-3.287)
Total Assets	-0.002***	-0.016***	-0.015***	-0.011***
	(-11.687)	(-10.755)	(-7.836)	(-14.942)
Leverage	0.014***	0.117***	-0.022	-0.008
	(5.860)	(6.345)	(-1.034)	(-1.579)
Profitability	-0.046***	-0.152***	-0.027	-0.107***
	(-8.170)	(-2.933)	(-0.579)	(-4.315)
Earnings Volatility	0.004	0.282***	-0.121	0.009
	(0.364)	(3.225)	(-1.456)	(0.396)
Cash Holding	-0.007*	0.086**	-0.032	0.001
	(-1.867)	(2.285)	(-0.852)	(0.121)
Non-cash Working Capital	0.000	0.027	0.087***	0.022**
	(0.100)	(1.011)	(3.022)	(2.002)
Capital Expenditure	0.003	0.304***	0.142*	-0.097***
	(0.396)	(3.357)	(1.698)	(-3.558)
Constant	0.059***	0.519***	0.807***	0.197***
	(8.993)	(7.435)	(6.893)	(8.335)
Number of Obs.	15,892	17,114	12,073	18,293
Adjusted R^2	0.237	0.231	0.047	0.100

Note: *, ** and *** denote significance at the 10, 5 and 1 percent level, respectively.

Table 16

INFLUENCE OF DE-RISKING ON FIRM'S STOCK PRICE AND VALUE

	Market-to-Book	Excess Equity Return
Post-De-risking Dummy	-0.002	0.038***
	(-0.155)	(4.482)
log(Total Assets)	0.022***	0.007***
	(6.021)	(3.108)
Leverage	-1.451***	-0.357***
	(-43.707)	(-10.808)
Profitability	5.129***	0.732***
	(26.293)	(10.910)
Earnings Volatility	1.782***	0.078
	(7.783)	(0.597)
Cash Holding	0.513***	0.007
	(5.567)	(0.141)
Non-cash Working Capital	-0.795***	-0.072**
	(-14.376)	(-2.190)
Capital Expenditure	0.067	-0.720***
	(0.389)	(-6.065)
Constant	1.112***	-0.102
	(12.405)	(-1.536)
Number of Obs.	18,293	15,416
Adjusted R^2	0.508	0.053

Note: *, ** and *** denote significance at the 10, 5 and 1 percent level, respectively.

H2d. Pension de-risking affects firms' financial leverage and operating performance.

We analyze whether firms' de-risking activities affected firms' financial leverage and operating performance in Table 17. The regressions still follow equation (12). The dependent variables considered in columns 2–6 are, respectively, profitability, earnings volatility, leverage, capital investment and sales growth. Only the coefficient of the post-de-risking dummy in the earnings volatility model is statistically significant. It indicates that pension de-risking activities increase firms' earnings volatility. However, since the impacts of de-risking on most of the investigated independent variables are statistically insignificant, we cannot support or reject H2d.

Table 17

INFLUENCE OF DE-RISKING ON FIRM'S OPERATING PERFORMANCE

	Profitability	Earning Volatility	Leverage	Capital Investment	Sales Growth
Post-De-risking Dummy	0.000	0.002**	0.004	-0.001	-0.001
	(0.357)	(2.177)	(1.460)	(-1.235)	(-0.138)
Total Assets	0.004***	-0.005***	0.002**	-0.002***	0.008***
	(9.442)	(-18.868)	(2.453)	(-10.340)	(5.309)
Leverage	-0.091***	0.010***		-0.009***	0.007
	(-23.766)	(4.019)		(-3.806)	(0.436)
Profitability	-0.138***		0.145***	0.051***	0.313***
	(-4.648)		(4.090)	(4.784)	(3.545)
Earnings Volatility	0.033***	0.056***	-0.455***	-0.057***	-0.063**
	(3.476)	(11.220)	(-33.589)	(-16.933)	(-2.076)
Cash Holding	0.012*	-0.010***	-0.171***	-0.033***	0.039*
	(1.825)	(-2.782)	(-14.746)	(-12.518)	(1.923)
Non-cash Working Capital	0.468***	0.056***	-0.145***		-0.124**
	(23.626)	(5.133)	(-3.772)		(-2.062)
Capital Expenditure		-0.048***	-0.466***	0.145***	0.438***
		(-4.980)	(-22.820)	(24.430)	(10.288)
Constant	0.071***	0.072***	0.372***	0.055***	-0.128*
	(4.837)	(6.995)	(7.280)	(8.213)	(-1.660)
Number of Obs.	18,293	18,293	18,293	18,293	18,293
Adjusted R^2	0.368	0.185	0.303	0.410	0.058

Note: *, ** and *** denote significance at the 10, 5 and 1 percent level, respectively.

Table 18

IMPACT OF MACROECONOMIC VARIABLES ON PENSION DE-RISKING

	Without Time-Fixed Effect					With Time-Fixed Effect				
	[1]	[2]	[3]	[4]	[5]	[1]	[2]	[3]	[4]	[5]
Equity Market Return	-0.032***				-0.018	-0.061				-0.037
	(-3.016)				(-1.579)	(-1.552)				(-0.895)
10-Y Treasury Yield		-0.075***			-0.111***		0.001			0.026
		(-6.591)			(-6.501)		(0.008)			(0.209)
Treasury Yield Spread			-0.003		-0.153***			-0.286**		-0.314**
			(-0.135)		(-5.659)			(-2.215)		(-2.320)
Credit Risk Spread				0.238***	0.158**				0.316	0.321
				(5.377)	(2.280)				(1.609)	(1.459)
log(Total Assets)	0.027**	0.014	0.027***	0.020*	0.013	0.010	0.010	0.011	0.010	0.011
	(2.537)	(1.285)	(2.588)	(1.897)	(1.182)	(0.952)	(0.936)	(0.968)	(0.924)	(0.969)
Leverage	-0.009	0.073	0.014	0.019	0.046	0.137	0.140	0.143	0.137	0.138
	(-0.082)	(0.668)	(0.124)	(0.173)	(0.422)	(1.241)	(1.271)	(1.299)	(1.248)	(1.258)
Profitability	-0.812***	-0.730***	-0.823***	-0.746***	-0.745***	-0.735***	-0.738***	-0.735***	-0.740***	-0.736***
	(-3.483)	(-3.102)	(-3.516)	(-3.190)	(-3.186)	(-3.126)	(-3.132)	(-3.119)	(-3.144)	(-3.126)
Earnings Volatility	0.923**	0.852**	0.949**	0.833**	0.909**	1.107***	1.110***	1.113***	1.106***	1.107***
	(2.430)	(2.256)	(2.511)	(2.186)	(2.401)	(2.980)	(2.987)	(2.992)	(2.978)	(2.981)
Cash Holding	0.221	0.132	0.226	0.167	0.138	0.069	0.068	0.074	0.068	0.075
	(1.172)	(0.671)	(1.189)	(0.868)	(0.700)	(0.341)	(0.339)	(0.370)	(0.338)	(0.374)
Non-cash Working Capital	0.229	0.239	0.223	0.228	0.235	0.174	0.175	0.177	0.174	0.177
	(1.509)	(1.547)	(1.475)	(1.486)	(1.526)	(1.109)	(1.109)	(1.127)	(1.105)	(1.127)
Capital Expenditure	-0.379	-0.009	-0.383	-0.202	-0.164	-0.126	-0.116	-0.111	-0.123	-0.124
	(-0.763)	(-0.020)	(-0.763)	(-0.412)	(-0.337)	(-0.263)	(-0.243)	(-0.232)	(-0.258)	(-0.260)
Constant	-2.347***	-1.919***	-2.368***	-2.540***	-1.685***	-2.015***	-2.077***	-1.514***	-2.296***	-1.714**
	(-5.862)	(-4.695)	(-5.908)	(-6.257)	(-3.930)	(-3.973)	(-3.622)	(-2.672)	(-4.381)	(-2.414)
Number of Observations	18,293	18,293	18,293	18,293	18,293	18,293	18,293	18,293	18,293	18,293
Adjusted R^2	0.017	0.022	0.016	0.020	0.029	0.044	0.044	0.045	0.044	0.045

Note: *, ** and *** denote significance at the 10, 5 and 1 percent level, respectively.

3.3 HYPOTHESIS 3

Macroeconomic variables significantly affect firms' pension de-risking decision.

In this section, we study the impact of macroeconomic variables on pension de-risking activities. The independent variable is the de-risking dummy and the regressions follow equations (9) and **(10)**. Our candidate macroeconomic variables include equity market premium, yield of 10-year Treasury security, yield spread between 10-year and 2-year Treasury securities and credit risk spread measured as the difference of yields between Moody's Baa-rated and Aaa-rated corporate bonds with maturities 20 years and above. We conduct the experiments without and with time-fixed effects[19]. The results are reported in Table 18. More variables are statistically significant in the experiments that do not control for time-fixed effect, although the pseudo R^2s for the experiments with time-fixed effect are higher. In the regressions without time-fixed effect, when all the four macroeconomic variables are considered together, the equity market return becomes insignificant, while the other three variables are all statistically significant. The coefficients keep the same signs no matter if they are considered jointly or separately.

The equity market premium is the market return net of risk-free rate from the Fama-French 3-factor model on Kenneth French's website at Dartmouth College[20]. It reflects the opportunity cost of investing in a well-diversified market equity portfolio. In both types of regressions, an increase in equity market premium will reduce pension de-risking. This might be because pension assets will increase in a bull stock market, which improves a plan's funding status and makes pension de-risking less compelling.

The 10-year Treasury yield measures long-term base interest rate with the minimum default and liquidity risk. The variable is statistically negatively significant at the 1% level in the experiments without time-fixed effect, indicating a lower long-term rate may drive more de-risking activities. This is consistent to the trend analysis in Section 2.3.1 De-risking Dataset. In a declining interest rate environment, liabilities will increase, and if there isn't the same level of increase in the plan assets, it will deteriorate the financial position of the plan, making de-risking strategies more attractive.

Both the treasury yield spread and credit risk spread are indicators of economic activities and counter-cyclical. That means when the spread widens (reduces), the economy is contracting (expanding). These two variables are therefore inversely correlated to the business cycle and business activities. In the experiments without time-fixed effect, the coefficient of treasury yield spread is statistically insignificant, while the coefficient of credit risk spread is statistically positively significant at the 1% level. It indicates that when the credit spread increases, firms are more likely to de-risk their pension plans. Due to the counter-cyclical feature of the credit risk spread, a larger spread suggests an upcoming recession and the market downturn pushes firms to take pension de-risking.

[19] Controlling for variables that are constant across entities but vary over time can be done by including time-fixed effects (Hanck et al., 2019). The rationale of including the time-fixed effect is the presence of unobservable factors. If we conjecture that our model has included all important factors of de-risking, there is no need to add time-fixed effect. But if there is a lack of theories to establish a structure model or the existing research has little empirical evidence to specify the factors, a time-fixed effect should be considered. In this study, we run the baseline regression to look for the possible determinants of de-risking. Although we largely believe that our model specification is reliable, we also report the results with the control of time-invariant characteristics.

[20] More details can be found at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/. The market return is the value-weight return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ. The risk-free rate is the one-month Treasury bill rate from Ibbotson Associates.

Our result supports H3 as most of the risk premia variables (equity market premium, yield spread and credit spread) and long-term interest rate variable (10-year Treasury yield) significantly affect firms' de-risking activities.

3.3 SUMMARY OF HYPOTHESIS TESTS:

HYPOTHESIS 1

- *H1a.* DB plan sponsors with higher pension underfunding ratio are more likely to de-risk pension plans: Supported.
- *H1b.* DB plan sponsors with lower pension asset beta are more likely to de-risk pension plans: Supported.
- *H1c.* DB plan sponsors with higher default probability are more likely to de-risk pension plans: Rejected.
- *H1d.* DB plan sponsors with lower profitability are more likely to de-risk pension plans: Supported.
- *H1e.* DB plan sponsors with higher return volatility are more likely to de-risk pension plans: Supported.
- *H1f.* Industry features affect firms' decision on pension de-risking: Supported.

HYPOTHESIS 2

- *H2a.* Pension de-risking improves firms' funding status: Rejected.
- *H2b.* Pension de-risking reduces firms' pension beta: Supported.
- *H2c.* Pension de-risking increases stock price and value: Supported.
- *H2d.* Pension de-risking affects firms' financial leverage and operating performance. Unconcluded.

HYPOTHESIS 3

Macroeconomic variables significantly affect firms' pension de-risking decision: Supported.

4. Future Work

This study builds a DB de-risking database that identified six typical pension risk transferring strategies. We present new empirical findings that either meet or deviate from prior expectations. The work is only a starting step towards more comprehensive and systematic analysis of U.S. DB pension de-risking. Below we list the major limitations of the project, which also provide research opportunities for future work. We hope we can address some of these limitations in future study.

First, we employed innovative web crawling, text mining and machine learning techniques in data collecting and processing. Some techniques could be better designed to make the process more efficient and reduce errors. Would a more robust data set produce different results? This would be a possible future work product.

Second, these univariate and hypothesis tests do not consider data post 2014. In the study, the conclusions are made by pulling all de-risking cases together. Considering most of DB pension buyouts and buy-ins took place in the last five years, adding data for 2015–2018 will make it possible for us to investigate the impact of an individual de-risking strategy. Results from individual strategies will bring more valuable information to firms with DB plans, actuaries and other stakeholders.

Third, the firm-level financial data are from the Compustat database. It would be more reliable if we could instead use data from Form 5500 for regression-based analysis. For example, the "funding target reported on Schedule SB," an attachment to Form 5500, is a good source of actuarial information about DB plans' funding requirements and whether employers met minimum funding.

Fourth, our de-risking data were collected from SEC EDGAR, a database that focuses on public companies. It would be of interest to also investigate the de-risking activities of private companies. In addition, since the SEC EDGAR data are not available before 1993 and we did not include post 2014 data in this study, the period considered in the study (1994–2014) may not include an adequate number of full economic cycles. For example, in the studied period, the interest rate level kept a general decreasing trend although the rates slowly climbed after the Great Recession. Therefore, it's hard to show causation if the rates haven't cycled up yet.

Fifth, in the before-after comparison in Section 2.3.2 Univariate Tests, we compared the key features of the de-risking firms one-year before and one-year after de-risking. Will a longer time horizon comparison lead to different conclusions? In addition, for those firms that conducted pension de-risking in recent years, we may need to wait for a longer time period to observe the influences on the firms and plan sponsors. It's worthwhile to revisit these firms five or even 10 years later to check the long-term impacts of pension de-risking.

Sixth, in this study, we excluded the de-risking cases that target pension plans for directors, executives, or highly compensated employees. It would be interesting to examine the managerial incentives of pension de-risking activities by including or even focusing on the executive-based de-risking activities. Furthermore, does a single company or a few companies skew the results? This is also worth further investigation.

5. Conclusion

DB pension de-risking, as an avenue to manage the imbalance between pension assets and liabilities, has drawn more and more attention to pension providers, pensioners and a broader group of market participants in the new millennium. Few studies examine the determinants of de-risking strategies and the subsequent influence on firms, which, however, is of considerable interest in this study.

This study starts to fill the gap of pension de-risking literature by providing empirical evidences from the U.S. market. Considering six pension de-risking strategies that include shift (from DB to DC), freeze, termination, buyout, buy-in and longevity hedge, we built a U.S. pension de-risking database based on firms' filings from the SEC EDGAR database through web crawling, text mining, machine learning and manual judgment. The de-risking database is compiled with the Compustat database for empirical analysis.

The de-risking data across various industries show that firms operating in different business sectors have remarkable heterogeneity in their de-risking decisions. Firms from the "manufacturing" industry are more likely to de-risk their DB plans. In the univariate tests, we found that de-risking firms have higher stock return volatility, higher earnings volatility and lower S&P credit rating, suggesting that the market does not perceive pension de-risking as an effective risk-reducing mechanism to improve a firm's credit rating. However, the lower net pension beta of the de-risking firms (significant at the 1% level) shows that the net effect of de-risking truly contributed to a reduction of firm risk. This indicates that pension de-risking did successfully de-risk pension risks. In addition, we observe that the funding ratio of de-risking firms is typically lower than that of non-de-risking firms, at a significance level of 5%. This may be related to the long-term feature of a de-risking strategy and its short-term cost. Since de-risking strategies are long-term strategies, they do not directly improve pension funding status right after de-risking. In addition, short-term costs of de-risking may deteriorate plans' funding status in the short run.

Through probit and OLS regressions, we tested three hypotheses. First, we explored what drives those firms that initially adopted a DB plan to de-risk. Our results show that low profitability, poor pension funding status, high pension asset beta, or high earnings /stock volatility are associated with a higher probability of DB de-risking. Second, we evaluate the outcomes of adopting a de-risking strategy. Consistent with the univariate tests, we reject the hypothesis that pension de-risking improves firms' funding status but support the hypothesis that de-risking improves net pension beta, both significant at a level of 1%. We also find evidence that the long-term shareholder value is created by implementing de-risking strategies. Third, we examine the impact of macroeconomic variables on firms' pension de-risking decisions. We find that DB plan sponsors' pension de-risking choices are sensitive to the economy's activities and interest rate level. Economic downturns and lower interest rates are the driving factors of pension de-risking.

Taken together, this research contributes to the extant literature of pension management by exploring empirical evidence about the functions and outcomes of de-risking strategies. Given the nature of our research and the fact that the U.S. de-risking market continued being active after our observation period (post-2014), our results warrant further study and attention to evaluate the structure of pension plans and the optimal design of benefit contracts among employees, shareholders and other stakeholders. New and extensive web crawling, text mining and machine learning techniques were employed in this research. We believe that more work is needed to make the process more efficient and reduce the error rate. In addition, these techniques may be employed in the future for more robust data sets and more generally for other financially focused research projects.

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Appendix A: Glossary

Buy-in: a process by which a DB pension plan purchases an annuity contract as an investment to match some or all of its future obligations to retirees.

Buyout: a DB plan de-risking strategy that transfers all or part of the pension obligations and assets to an insurer using a bulk annuity contract.

Deferred Income Annuity (DIA): a type of annuity contract which guarantees lifetime income that begins at a pre-determined future date, up to forty years later in some cases.

Defined benefit (DB) plan: an employer-sponsored retirement plan where employee benefits are computed using a formula that considers several factors, such as length of employment and salary history.

Defined contribution (DC) plan: a retirement plan in which employees contribute a fixed amount or a percentage of their paychecks to an account that is intended to fund their retirements, such as 401(k) or 403(b).

Freeze: in a DB pension plan, benefits of some or all employees stop accruing, but the plan continues to exist and the assets remain in the plan.

Liability-driven Investment (LDI): an investment strategy of DB pension sponsors that aims at aligning a plan's assets with its liabilities.

Longevity Hedge: financial products that allow a DB pension plan to transfer the risk of retirees living longer than expected to a third party.

Ordinary Least Squares (OLS): a method to estimate the unknown parameters in a linear regression model. OLS determines the parameters of explanatory variables in a linear function by minimizing the sum of the squares of the differences between the observed and predicted values of the dependent variable.

Probit model: a regression model where the dependent variable is binary that can take only two values, 0 or 1. The model uses the cumulative Gaussian normal distribution to calculate the probability of being in one category or not.

Shift: a sponsor transfers its retirement plan from DB to DC, shifting investment risk from the corporate sector to households.

Termination: a DB pension plan stops operating. Employees participating in a pension when it is terminated are generally offered a monthly annuity payment during retirement or a lump sum payment to be made at the time of the termination of the plan.

Univariate: Mathematically, univariate refers to an expression, equation, function or polynomial of only one variable.

Appendix B: Web Crawling and Text Mining

To construct our de-risking database, we conducted a two-layer keyword search on the SEC EDGAR website. The Level 1 keywords included "defined benefit(s)," "pension(s)" and "retirement." The Level 2 keywords target the six considered de-risking strategies (i.e., shift, freeze, termination, buyout, buy-in, and longevity hedge) individually. As we explained in Section 1.1.7 Liability-driven Investment (LDI), we did not collect data for LDI solutions since LDI strategies are hard to identify from available data sources. In Table 19, we present the keywords or combination of keywords for the Level 2 web crawling. Specifically, the following three steps were utilized to identify firms' de-risking activities from the SEC EDGAR database:

- Step 1: Conduct the first-round search based on the Level 1 keywords "defined benefit(s)," "pension(s)" and "retirement."
- Step 2: Conduct the second-round search. We searched Level 2 keywords (de-risking keywords) that appeared in the same sentences as any of the Level 1 keywords and then extracted those sentences.[21] Please refer to Table 19 for the Level 2 keywords.
- Step 3: Conduct manual judgment to identify DB pension plans' de-risking activities, based on the extracted sentences that contain both Level 1 and Level 2 keywords.

Table 19

LEVEL 2 DE-RISKING KEYWORDS

Strategy	Keywords
Shift	shift/shifts/shifting + defined benefit/DB + defined contribution/DC switch/switches/switching + defined benefit/DB + defined contribution/DC defined benefit/DB + to + defined contribution/DC from + defined benefit/DB + to to + defined contribution/DC
Freeze	freeze/freezes/froze/frozen/freezing + pension freeze/freezes/froze/frozen/freezing + plan/plans freeze/freezes/froze/frozen/freezing + defined benefit/DB benefit/ benefits + accruals/accrued + frozen benefit/ benefits + frozen
Termination	Terminate/terminates/termination/terminated + pension Terminate/terminates/termination/terminated + defined benefit/DB Terminate/terminates/termination/terminated + plan wind-up/winds-up + pension wind up/winds up/winding up + pension wind up/winds up/winding up + DB scheme wind up/winds up/winding up + defined benefit
Buyout	Pension + buyout/buy-out/buyouts/buy out/buy outs defined benefit/DB + buyout/buy-out/buyouts/buy out/buy outs plan/plans + buyout/buy-out/buyouts/buy out/buy outs
Buy-in	Pension + buyin/buy-in/buyins/buy in/buy ins defined benefit/DB + buyin/buy-in/buyins/buy in/buy ins plan/plans + buyin/buy-in/buyins/buy in/buy ins
Longevity Hedge	longevity swap/swaps longevity hedge/hedging/hedges longevity reinsurance hedge/hedging/hedges + longevity risk longevity-hedging longevity risk transfer

Note: *, ** and *** denote significance at the 10, 5 and 1 percent level, respectively.

[21] If more than one sentence (for different de-risking strategies) in an SEC filing is found, all the matched sentences are extracted and reported.

Appendix C: Description of The Machine Learning Process

To help improve the efficiency and accuracy of manual judgement, we applied machine learning techniques to the data collected from the EDGAR database. Two de-risking strategies have been examined in the model development process—termination and freeze. For both types of cases, the data contains five columns: year, quarter, document link, extracted sentences from the document that include both Level 1 and Level 2 keywords, and a label indicating if it's a true or false termination/freeze case based on prior manual judgment ("label 0" for false case and "label 1" for true case).

We use a group of machine learning methods called supervised learning for text classification to build a model that automatically identifies true and false cases by analyzing the extracted sentences in the dataset. The model has been developed in RapidMiner and comprises of the following steps:

1. Read data from .xlsx file and perform basic attribute selection and transformation
2. Process text data (tokenize, remove stopwords, stem, and generate n-gram) and create a term frequency–inverse document frequency (TF-IDF) vector
3. Divide the sample set into a training set and a testing set
4. Run a classification algorithm on the training set to build a predication model
5. Apply the prediction model on the testing set
6. Perform parameter tuning and optimization
7. Generate and output performance results

Three popular text classification algorithms were used and compared based on accuracy measures (recall and precision): K-Nearest Neighbors (KNN), Naïve Bayesian, and Support Vector Machine (SVM). Using the 1994-1995 termination dataset and 1997 freeze dataset for training and testing, the results show that SVM achieves the highest recall and precision (92.38% +/- 1.95%), closely followed by KNN (88.38% +/- 2.44%). Therefore, we have applied both the SVM and KNN models to the unknown dataset and are currently in the process of manually validating the results.

Appendix D1: Variable Construction I

Variables	Variable Definitions
De-risking Variables	
Pension De-risking Dummy	An indicator variable that takes the value of one when the corresponding de-risking strategy is adopted, and zero otherwise.
Pension De-risking	An indicator variable that takes the value of one when a firm adopts any of the six de-risking strategies, and zero otherwise.
Post-de-risking	An indicator variable that takes the value of one for the year and all the years after a firm's first de-risking activity, and zero otherwise.
Pension-Related Characteristics	
Pension Assets (PA)	Before 1997, pension plan assets equal to the sum of overfunded (Compustat item PPLAO) and underfunded (Compustat item PPLAU) pension assets; after 1997, pension plan assets equal to pension plan assets (Compustat item PPLAO).
Pension Liabilities (PL)	Before 1997, projected pension benefit obligations equal to the sum of overfunded (Compustat item PBPRO) and underfunded (Compustat item PBPRU) pension benefit obligations; after 1997, projected benefit obligations equal to projected benefit obligations (Compustat item PBPRO).
Pension Deficit Ratio	Calculated as (PA-PL) divided by firms' total market value (the sum of equity market value (E) and debt book value (D)).
Pension Underfunding Ratio	Calculated as (PA-PL) divided by pension assets (PA).
Pension Funding Ratio	The ratio of pension assets to pension liabilities (PA/PL).
Pension Asset Beta	Estimated by following the method of Jin et al. (2006) and An et al. (2013). For the firms with multiple plans, we calculate the weighted average of all plans' pension asset beta with the plan assets as weights.
Net pension beta	Calculated as pension asset beta minus pension liability beta, adjusted by value of pension assets and pension liabilities as a percentage of the firm's total market value (the sum of equity market value (E) and debt book value (D)).
Firm-Related Characteristics	
Total Assets	Measured by CPI-adjusted book value of total assets. The logarithm of total assets is finally used in regressions.
Leverage	Total debt divided by total market value of assets, where market value of assets is the sum of total debt and market value of equity.
Profitability	The ratio of EBITDA (earnings before interest, tax, depreciation, and amortization) to total assets.
Earnings Volatility	The standard deviation of the first difference in EBITDA scaled by book value of assets over the period of 4 years preceding a given fiscal year.
Cash Holding	The ratio of cash plus marketable securities to total assets.
Non-cash Working Capital	The ratio of working capital net of cash to total assets.
Tangible Assets	A ratio of book value of tangible assets to book value of total assets.
Private Debt	The proportion of private debt capital to market value of assets. We extract private debt from the balance sheet by subtracting the amount of notes, subordinated debt, debentures and commercial papers from total debt.

Appendix D2: Variable Construction II

Variables	Variable Definitions
Firm-Related Characteristics	
Altman's Z-score	It's computed as: Z = 1.2×(Working Capital/Total Assets) + 1.4×(Retained Earnings/Total Assets) + 3.3× (EBIT/Total Assets) + 0.6×(Market Value of Equity/Total Liabilities) + 0.999×(Sales/Total Assets).
Stock Return Volatility	The standard deviation of monthly stock returns over up to preceding 24-month period.
Firm Return Volatility	The standard deviation of monthly asset returns over up to preceding 24-month period. We first compute equity return based on monthly stock returns, and then convert it to assets return according to Hamada's equation.
Earnings Volatility	The standard deviation of the first difference in EBITDA scaled by book value of assets over the period of 4 years preceding a given fiscal year.
S&P Credit Rating	S&P long term rating and we follow a similar conversion process from Klock et al. (2005) to assign numbers to rating categories.
Distance-to-default Probability	The 12-month moving average of monthly distance to default by following KMV–Merton methodology described in Crosbie and Bohn (2003).
Capital Expenditure	Capital expenditure divided by total assets.
R&D Expenses	Research and development expenses divided by total assets.
Market-to-book	The ratio of market value of assets to book value of assets.
Equity Excess Return	Follows the method in Faulkender and Wang (2006) to estimate a firm's annualized stock returns subtracted by the benchmark returns of Fama and French (1993) size and book-to-market matched portfolios during the same time period.
Macroeconomic Variables	
Equity Market Premium	Calculated as the market return net of risk-free rate from the Fama-French 3-factor model on Kenneth French's website at Dartmouth College. The market return is the value-weight return of all CRSP firms incorporated in the U.S. and listed on the NYSE, AMEX, or NASDAQ. The risk-free rate is the one-month Treasury bill rate from Ibbotson Associates.
10-year Treasury Yield	10-Year Treasury Constant Maturity Rate from the Federal Reserve Bank at St. Louis.
Treasury Yield Spread	The yield spread between 10-year and 2-year Treasury securities.
Credit Risk Spread	Calculated as the difference of yields between Moody's Baa-rated and Aaa-rated bonds with maturities 20 years and above.

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