The Impact of the Gross Book-to-Market Ratio in REITs, and Corporate Reactions to PBGC Variable Rate Premium Increases

by

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Abstract

The first two essays explore the usefulness of the gross book-to-market ratio in equity REITs. The first essay shows that the traditional calculation of the market-to-book (and book-to-market) ratio is flawed. We show that accumulated depreciation accounting leads to artificially high market-to-book ratios in REITs with highly depreciated assets, and this problem is exacerbated in REITs that utilize preferred equity. The three-tiered capital structure is employed by roughly half of the REITs, while only 12% of firms in a comparative non-REIT sample use preferred equity. We examine this effect in the context of capital structure studies and show that the gross book-to-market (where accumulated depreciation is added back to total assets and common equity) is superior to traditional metrics as a proxy for growth opportunities and stock valuations. We revisit a disagreement in the literature about the relationship between REIT market-to-book and leverage, and show additional support for pecking-order theory, while finding little evidence that market-timing drives capital structure decisions. We show that spurious relationships can yield T-statistics as high as 5 on the market-to-book, while the superior gross book-to-market is statistically insignificant. Our findings stress that future REIT researchers should use undepreciated balance sheet metrics, while also considering the three-tiered capital structure utilized by half of these firms.

The second essay shows the gross book-to-market to be among the best predictors of aggregate REIT returns. The gross book-to-market is unavailable prior to 1995 due to data limitations, but we show that the ratio of paid-in capital to market capitalization (paid-to-market) contains similar information, because it excludes the effects of accumulated depreciation. Paid-to-market is the single best predictor of REIT returns across our full sample time period, with out-of-sample R^2 statistics of 1.64% and 14.12% at the monthly and annual horizons, respectively. We show that REIT returns are predictable out-of-sample within an efficient market, as predictability stems from information connected to time varying risk aversion. Stripping accumulated depreciation from

the balance sheet substantially improves forecasting models, which can provide investors with significant utility gains and larger Sharpe ratios. Outperforming the total returns from a buy-and-hold strategy proves difficult though, as upside predictability is easier than downside predictability, especially during crises.

The third essay explores a separate topic in US corporate pension plans. The Pension Benefit Guarantee Corporation (PBGC) is often criticized for its mispriced pension insurance formula, and for creating risk-shifting incentives that could encourage bad behavior by pension plan sponsors. Beginning in 2014, the Variable Rate Premium (VRP) charged to underfunded pension plans began rising. The VRP rate, set by Congress, effectively penalizes firms that underfund their pension plans. We overcome challenges in the data sources to take a comprehensive look at firm reactions to the threat of VRP payments. When faced with larger VRP payments, firms make larger contributions to their pension plans and allocate more of their plan assets to equities. The VRP rate is so high that in recent years, firms may have realized cost savings by funding their pension plans using borrowed funds. While anecdotal evidence exists for borrow-to-fund, we do not find a statistically significant relationship between debt issuances and pension contributions. Nor do we find that VRP rate hikes were associated with additional plan freezes. Overall, VRP rate hikes likely had both positive and negative effects on pension risk, as corporations made higher contributions while also increasing the riskiness of plan assets.

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List of Abbreviations

AOCI	Accumulated Other Comprehensive Income
BTM	Book-to-market
EBIT	Earnings Before Interest and Taxes
EBITDA	Earnings Before Interest, Taxes, Depreciation and Amortization
FFO	Funds From Operations
GBE	Gross Book Equity
GFC	Global Financial Crisis
MTB	Market-to-book
NAV	Net Asset Value
NOI	Net Operating Income
OLS	Ordinary Least Squares
PAC	Preferred Apartment Communities
PBGC	Pension Benefit Guarantee Corporation
PIC	Paid-in Capital
RE	Retained Earnings

REIT	Real Estate Investment Trust
ROA	Return on Assets
ROE	Return on Equity
US	United States
VRP	Variable Rate Premium

Chapter 1

Biased Market-to-book Ratios and Implications for REIT Capital Structure Studies

1.1 Introduction

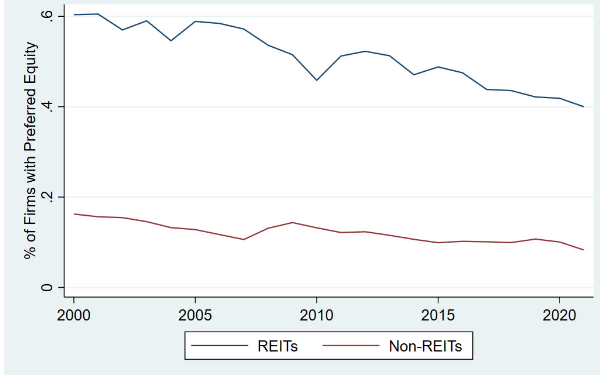
US REIT regulations provide researchers with a more ideal setting in which to test competing capital structure theories. Trade-off theory (Modigliani and Miller, 1958) predicts that firms will weigh the tax benefits of debt against the potential costs of financial distress. Trade-off theory predicts that REITs would maintain low levels of debt because they do not pay income taxes, but REIT tend to have high leverage ratios (Feng et al. 2007). The pecking order theory of Myers and Majluf (1984) predicts that adverse selection costs will discourage firms from issuing new common equity, and they will instead finance growth using retained earnings and debt (in that order) prior to issuing new shares. REITs are required to pay out at least 90% of net income as dividends, so their access to retained earnings is limited. The pecking order would therefore predict that REITs with more growth opportunities will increase their use of debt in subsequent years due to their need for external capital and their reluctance to issue common equity. So long as the market-to-book ratio is a proxy for growth opportunities, pecking order theory would predict that lagged market-to-book would be positively associated with increases in leverage. On the other hand, market timing theory (Baker and Wurgler, 2002) predicts that firms will opportunistically issue new equity when prices are high, so firms with high lagged market-to-book ratios will use less leverage. Feng et al. (2007) test these theories, and find market-to-book to be positively related to leverage, while Harrison et al. (2011) find the opposite.

In each study, the market-to-book ratio is distorted because the authors do not consider the impact of accumulated depreciation or the widespread use of preferred equity in REITs. Accumulated depreciation leads to artificially low book equity in REITs because the underlying properties are depreciated as if they were losing value, while in reality property prices tend to rise over time. Common book equity is traditionally calculated by subtracting debt and preferred equity from total assets, so any understatement of asset values ultimately flows through to common equity (leading to a high market-to-book ratio.)

This problem is accelerated in firms that finance only a small portion of their total assets using common equity. In REITs, "stockholder's equity" is often split between common equity and preferred equity, leading to small portions of common equity in the overall capital structure. Consider a REIT that finances apartment properties using a capital structure of 50% debt, 25% preferred equity, and 25% common equity. Apartments are depreciated over 27.5 years, so after only 7 years assets will have lost 25.4% of their book value. At that time the book value of common equity will be reduced below zero (all else equal.) In section 1.2 we provide an example of a REIT where this effect is exceedingly clear, and then illustrate how the market-to-book ratio can be corrected by adding back accumulated depreciation. Throughout this study we exclude mortgage REITs, as we see no reason that depreciation would cause similar distortions in their financial statements.

The three-tiered capital structure described above is not uncommon in REITs. Figure 1.1 shows the percentage of firms with preferred equity for both equity REITs and non-REITs listed in Compustat. Both samples show a downward trend over the last 20 years, while revealing the comparatively extensive use of preferred equity in REITs. REITs that use preferred equity tend to use less common equity, suggesting that they will have higher market-to-book ratios as the common equity base is quickly depreciated away. The widespread use of preferred equity also poses the question of how "leverage" in REITs should be defined. Common equity - to - assets should be assessed in addition to the traditional debt - to - assets.

Figure 1.1: Preferred Equity Usage in Equity REITs Versus Non-REITs



The academic literature ignores accumulated depreciation when calculating REIT common book equity, but outside of academia the reversal of depreciation charges is common. NAREIT offers Funds From Operations (FFO), which adds back depreciation expense to net income, as an alternative metric to more accurately assess REIT profitability. In *The Intelligent REIT Investor* (2016), Krewson-Kelly and Thomas advocate for assessing leverage using the gross debt-to-assets ratio (where accumulated depreciation is added back to total assets.) Alas, in academic REIT studies, common book equity is calculated by subtracting preferred equity and liabilities from net assets without adding back accumulated depreciation.

Biased REIT market-to-book ratios could impact a wide range of literature. Book-to-market is used to differentiate value firms from growth firms, with value firms showing significant outperformance in the cross section of stock returns (Fama and French, 1992.) Bond and Xue (2017), however, find book-to-market has little to no ability to explain the cross section of REIT returns. The book-to-market is also frequently used to forecast aggregate stock returns, as in Welch and Goyal (2008), Rapach et al. (2016), and many others. In our case study, we explore the implications for capital structure studies, where the market-to-book can proxy for both growth opportunities and equity valuations.

In this paper, we take a comprehensive look at the different balance sheet metrics that can be used to assess growth opportunities and market valuations. Potential proxies include Tobin's

Q, market-to-book, and book-to-market. We construct gross metrics for each by adding back accumulated depreciation, and show that the gross book-to-market outperforms its alternatives in both theoretical and empirical settings. We use the disagreement between Feng et al. (2007) and Harrison et al. (2011) as a case study to illustrate the impact of biased market-to-book ratios. Our results strongly indicate that the pecking order motivates REIT use of debt, while we find little evidence of market-timing. Firm size is the most likely driver of preferred equity usage in REITs, while market valuations and growth opportunities have an insignificant impact.

The remainder of this essay is organized as follows: Section 1.2 discusses the theoretical biases that result from REIT accumulated depreciation and capital structure, and shows a real world example of a misleading REIT market-to-book ratio. Section 1.3 reports our data and summary statistics, and explores the efficacy of various proxies for growth opportunities. Section 1.4 reports the results of our case study on the determinants of debt-to-assets. Section 1.5 explores the determinants of preferred equity usage in REITs. Section 1.6 concludes.

1.2 Proxies for Growth Opportunities

This paper was motivated in part by our observation of a REIT that financed large portions of its assets with preferred equity, while exhibiting an excessively high market-to-book ratio. Preferred Apartment Communities (henceforth, PAC) completed their initial public offering on April 5, 2011. Throughout their roughly 11 year existence, PAC relied heavily on preferred equity and debt to finance their rapid growth, while using very little common equity.

Panel A of table 1.1 presents PAC's balance sheet highlights from 2011-2018 using the Compustat database. Focusing on the time period of 2013-2016, we can see how accumulated depreciation and preferred equity work in tandem to create excessively high market-to-book ratios. As of 12/31/2013, PAC's capital structure consisted of 22.4% common equity, 26.2% preferred equity, and 51.4% debt, roughly in line with our example from the introduction. Over the next three years, PAC grew quickly by issuing preferred equity and debt. Common equity, defined as total assets minus liabilities and preferred equity, ended 2013 at roughly \$77 million before falling to

Table 1.1: Preferred Apartment Communities Financial Highlights

	12/31/2011	12/31/2012	12/31/2013	12/31/2014	12/31/2015	12/31/2016	12/31/2017	12/31/2018
Panel A: Balance Sheet Highlights				**$ (Millions)**				
Total Assets	$ 92.47	$ 123.29	$ 341.64	$ 696.41	$ 1,295.53	$ 2,420.83	$ 3,252.37	$ 4,410.96
Accumulated Depreciation	$ 2.70	$ 6.29	$ 11.41	$ 26.39	$ 53.99	$ 103.82	$ 172.76	$ 272.04
Total Liabilities	$ 57.85	$ 73.23	$ 175.58	$ 404.83	$ 770.08	$ 1,535.57	$ 1,971.60	$ 2,801.57
Preferred Stock (Redemption Value)	$ -	$ 19.76	$ 89.41	$ 192.85	$ 482.96	$ 914.42	$ 1,237.29	$ 1,652.00
Common Equity	$ 34.62	$ 30.30	$ 76.65	$ 98.73	$ 42.49	$ (29.16)	$ 43.48	$ (42.61)
				% of Total Assets				
Total Assets	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
Accumulated Depreciation	2.9%	5.1%	3.3%	3.8%	4.2%	4.3%	5.3%	8.4%
Total Liabilities	62.6%	59.4%	51.4%	58.1%	59.4%	63.4%	60.6%	86.1%
Preferred Stock (Redemption Value)	0.0%	16.0%	26.2%	27.7%	37.3%	37.8%	38.0%	50.8%
Common Equity	37.4%	24.6%	22.4%	14.2%	3.3%	-1.2%	1.3%	-1.3%
Panel B: Growth Opportunity Metrics								
Market Capitalization	$ 31.15	$ 41.19	$ 122.97	$ 194.78	$ 297.73	$ 395.09	$ 780.94	$ 587.37
Stock Price	$ 6.05	$ 7.79	$ 8.04	$ 9.10	$ 13.08	$ 14.91	$ 20.25	$ 14.06
Net Metrics								
Tobin's Q	0.96	1.09	1.14	1.14	1.20	1.18	1.23	1.14
Market-to-book	0.90	1.36	1.60	1.97	7.01	-13.55	17.96	-13.78
Book-to-market	1.11	0.74	0.62	0.51	0.14	-0.07	0.06	-0.07
Gross Metrics								
Gross Tobin's Q	0.96	1.08	1.13	1.13	1.19	1.17	1.22	1.13
Gross Market-to-book	0.83	1.13	1.40	1.56	3.09	5.29	3.61	2.56
Gross Book-to-market	1.20	0.89	0.72	0.64	0.32	0.19	0.28	0.39

Notes: Panel A reports balance sheet highlights for Preferred Apartment Communities (former ticker: APTS.) Panel B reports the growth opportunity metrics we study. Tobin's Q is market cap plus total liabilities and preferred stock, divided by total assets. Market-to-book is market cap divided by common book equity, and book-to-market is the inverse of market-to-book. "Gross" metrics are calculated by adding accumulated depreciation to the book values of total assets and common equity.

negative $29 million in 2016. Meanwhile, accumulated depreciation grew by a similar amount from $11 million to $104 million. By the end of 2016, PAC had negative common book equity, but shareholders did not retreat. In fact, market capitalization more than tripled while the stock price grew from $8.04 to $14.91. The negative common equity did not signal distress, and PAC was ultimately purchased by Blackstone Real Estate in 2022 with common shareholders receiving $25.00 per share.

Why would a firm with declining and ultimately negative book equity be rewarded by shareholders? The answer lies in accumulated depreciation accounting, which leads to a disconnect between the market value of assets and the book value of assets in REITs. Between 12/31/2013 and 12/31/2016, the Case-Shiller U.S National Home Price Index rose by 15.9% from 159.37 to 184.66. The market price of PAC's properties was likely increasing, while at the same time the balance sheet was treating those assets as if they were losing value. The highly aggressive capital structure caused PAC's common equity balance to quickly drop below zero, at which point it would be excluded from academic studies. In the common-sized balance sheet of table 1.1, we see that accumulated depreciation% generally rises over time. If accumulated depreciation rises to a level that exceeds the original common equity balance, book value could potentially drop below zero (absent changes retained earnings, which is legally close to zero in REITs, or changes in paid-in-capital.)

How should the market-to-book ratio be calculated for this firm? Tobin's Q (the market value of assets divided by the book value of assets) can be estimated as the market value of equity plus the book value of liabilities and preferred stock, divided by the book value of assets. This calculation is used in Harrison et al. (2011) as well as Feng et al. (2007) and referred to as the "market-to-book." Tobin's Q presents a problem for REITs such as PAC, as we do not observe the vast majority of changes in market value. Tobin's Q is defined as

$$Q \approx \frac{L + P + ME}{L + P + BE} \tag{1.1}$$

Where L is total liabilities, P is preferred equity, ME is market capitalization, and BE is common book equity. From equation 1.1, we can see that as the percentage of a firm's assets financed by common equity approaches zero, Q approaches 1. REITs are highly levered, especially when we consider common equity - to - assets, which averages only 37% in our sample. Accumulated depreciation accounting will generally lead to market capitalization that is higher than the book value of common equity, so we expect that the approximation of Tobin's Q will be biased towards an amount slightly higher than one in REITs that don't use much common equity. This is exactly what we see in Panel B of table 1.1: PAC's Tobin's Q hovers at an amount slightly larger than one.

The actual market-to-book ratio (market capitalization divided by common book equity) presents a different problem. As common book equity approaches zero, the market-to-book ratio approaches infinity. As REIT balance sheets depreciate away their common equity amounts, REIT market-to-book ratios will become excessively high. The book-to-market ratio is therefore preferable to the market-to-book ratio as it avoids the small denominator problem. The book-to-market may also be preferable to Tobin's Q, as we observe changes in both market capitalization and common book equity while the market values of debt and preferred equity are unobservable.

Regardless of which metric we consider, accumulated depreciation must be controlled for. We construct each of the three metrics again, but add back accumulated depreciation to total assets and common equity. Formally,

$$Gross\ Q = \frac{L + P + ME}{L + P + GBE} \tag{1.2}$$

$$Gross\ MTB = \frac{ME}{GBE} \tag{1.3}$$

$$Gross\ BTM = \frac{GBE}{ME} \tag{1.4}$$

Where GBE is gross book equity. Gross book equity is defined as total assets plus accumulated depreciation minus liabilities and preferred stock. The denominator of equation 1.2 is also simply total assets plus accumulated depreciation, or gross assets. In panel B of table 1.1, we report all six metrics that could be used to assess growth opportunities. The gross BTM is likely the best metric of all six options. All three of the net metrics fail to account for accumulated depreciation, gross Q is biased towards 1, and gross MTB suffers from the small denominator problem (firms often have small book equity amounts that turn negative, but never have negative share prices.)

While the gross BTM seems like the best choice theoretically, we still see a marked decline in PAC's gross BTM over time. This likely results from increasing property values, while the gross book value of those properties remains unchanged. The same problem remains for gross Q: if the market value of assets increases and book values remain unchanged, Q will be biased towards an amount slightly above one. The gross metrics should provide an improvement over the net metrics typically calculated in the academic literature, as the net metrics use over-depreciated (and thus, understated) asset values. We further explore the empirical properties of these metrics and verify their usefulness in section 1.3.

1.3 Data, Summary Statistics, and Empirical Demonstration of Market-to-Book Bias

We begin our data process with all US REITs listed in the Compustat database (SIC code 6798.) We use Mckay Price's list of REITs to identify REIT property types, as well as to eliminate mortgage REITs. Because Compustat's quarterly fields for preferred equity are largely unreliable, we focus our analysis on annual observations[1]. Annual observations are also used in Harrison et al. (2011) and Feng et al. (2007.) For firm-years without FFO data in Compustat, we use FFO data from Capital IQ. To mitigate the effects of outliers, we winsorize all variables at the 0.5th and the 99.5th percentiles. In our case study, we use the main control variables from Harrison et al. (2011), which we include in our summary statistics. Due to control variable availability in Compustat, we study the time period of 2001-2020.

Table 1.2 reports summary statistics on the equity REITs in our sample, organized into groups based on their amount of preferred equity as a percentage of total assets (preferred%.) REITs are sorted each year by preferred% and then placed into deciles. Because a considerable number of firms have no preferred equity, the category "$\leq$5, or 0%" includes all firms with preferred equity amounts less than or equal to the median in that year (in some years, the median is zero). The deciles contain different quantities of firms due to time-series variations in the percentage of REITs that use preferred equity (if only 30% of REITs used preferred equity in a year, no REITs would be assigned decile 6 or 7 in that year) as well as the arbitrary decision of which decile to place REITs in when their preferred% is exactly equal to the decile cutoff.

Table 1.2 reveals several noteworthy relationships. REITs that use more preferred equity tend to use less common equity as well as less debt. REITs in the 10th decile would be seen as using less leverage according to the traditional definition of "leverage" as debt-to-assets. If leverage is defined as common equity divided by assets, REITs with lots of preferred equity are highly levered. Relative to the lowest decile, REITs in the 10th decile have significantly higher market-to-book and Tobin's Q, along with lower book-to-market. However, if we recalculate each metric while adding

[1]Manually checking the quarterly preferred stock fields, we find many of them to be missing or to include the par value of $0.01 per share. The added benefit of more frequent updates in preferred equity amounts is outweighed by the additional noise created.

Table 1.2: Summary Statistics by Preferred% Decile

	≤5, or 0%	6	7	8	9	10	10 minus "≤5"
Number of REITs	1,295	188	244	252	247	256	
Capital Structure Metrics							
Preferred%	0.001	0.026	0.038	0.061	0.094	0.208	0.207***
Common Equity %	0.399	0.366	0.356	0.352	0.310	0.286	-0.113***
Debt-to-Assets	0.566	0.575	0.567	0.562	0.563	0.475	-0.091***
Gross Preferred%	0.001	0.022	0.033	0.053	0.080	0.170	0.169***
Gross Common Equity %	0.487	0.454	0.451	0.446	0.413	0.408	-0.079***
Gross Debt-to-Assets	0.481	0.494	0.483	0.479	0.477	0.398	-0.084***
Growth Opportunity Metrics							
Tobin's Q	1.364	1.328	1.324	1.277	1.251	1.414	0.049*
Market-to-Book	2.431	2.263	2.356	2.118	2.381	3.466	1.035***
Book-to-market	0.624	0.607	0.618	0.675	0.622	0.522	-0.103***
Gross Tobin's Q	1.151	1.136	1.118	1.091	1.066	1.159	0.008
Gross Market-to-book	1.385	1.399	1.341	1.264	1.240	1.445	0.06
Gross Book-to-market	0.916	0.879	0.946	1.077	1.048	0.986	0.07
Control Variables							
Profitability (FFO/ Assets)	0.053	0.047	0.045	0.048	0.042	0.047	-0.006***
Tangibility (Real Estate / Assets)	0.844	0.849	0.856	0.845	0.850	0.849	0.005
Total Assets	4,128.63	6,745.79	7,470.68	5,197.08	4,205.16	2,163.52	-1965.11***

Notes: REITs are sorted each year by their amount of preferred equity, scaled by total assets (preferred%) and then placed into deciles. REITs with zero preferred equity are automatically placed in decile "≤ 5, or 0%." The deciles contain different quantities of REITs due to time-series variations in the percentage of REITs that use preferred equity (If only 30% of REITs used preferred equity in a year, no REITs would be assigned decile 6 or 7 in that year) as well as the arbitrary decision of which decile to place REITs in when their preferred% is exactly equal to the decile cutoff. Preferred% is the redemption value of preferred equity divided by total assets. Debt-to-Assets is liabilities divided by total assets. Common Equity% is stockholder's equity minus preferred equity divided by total assets. "Gross" metrics divde by total assets plus accumulated depreciation, while Gross Common Equity % also adds accumulated depreciation to shareholder's equity.

back accumulated depreciation (the "gross" metrics), no statistically significant differences remain. This suggests that the use of gross valuation metrics mitigates any issues arising from preferred equity. The REITs in decile 10 are slightly less profitable, and are significantly smaller than the REITs in any other decile.

In table 1.3, we sort REITs according to their level of accumulated depreciation, scaled by total assets (accumulated depreciation%) and split them into deciles. When we consider net capital structure metrics, REITs with highly depreciated assets are highly levered according to debt-to-assets, common equity%, and preferred%. However, if we define leverage according to the gross metrics, we find that highly depreciated REITs have higher gross common equity% and lower gross debt-to-assets.

As we move from the left to the right (from decile 1 to 10) we see an almost monotonic increase in market-to-book and Tobin's Q, along with a corresponding decrease in book-to-market. Those differences are mostly eliminated when we consider the gross growth opportunity metrics. The magnitude of the difference between deciles 10 and 1 falls from 2.937 to 0.209 for the market-to-book, from 0.575 to 0.16 for Tobin's Q, and from -0.47 to 0.067 for the book-to-market. For the gross book-to-market, the difference between deciles 10 and 1 is statistically insignificant. Aside

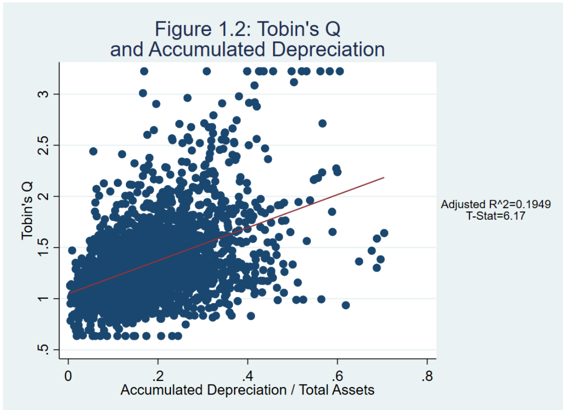
Table 1.3: Summary Statistics by Accumulated Depreciation% Decile

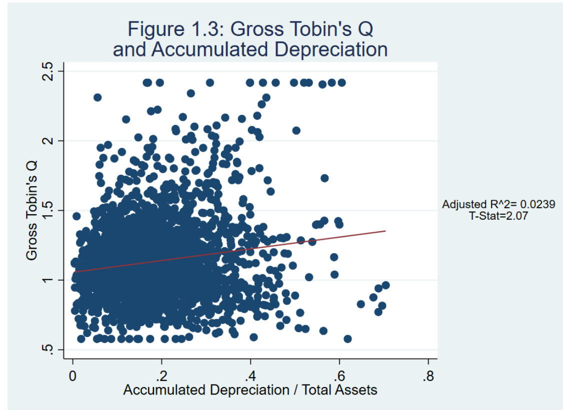
	1	2	3	4	5	6	7	8	9	10	10 minus 1
Number of REITs	238	249	250	247	252	246	245	252	247	256	
Accumulated Depreciation%	4.3%	7.9%	10.9%	13.2%	15.3%	17.8%	20.3%	23.4%	28.4%	39.4%	35.1%***
Capital Structure Metrics											
Preferred%	0.042	0.030	0.037	0.034	0.040	0.041	0.047	0.040	0.048	0.073	0.031***
Common Equity %	0.431	0.433	0.430	0.411	0.402	0.396	0.389	0.397	0.372	0.345	-0.086***
Debt-to-Assets	0.527	0.537	0.533	0.555	0.557	0.564	0.564	0.564	0.580	0.582	0.055***
Gross Preferred%	0.041	0.028	0.034	0.030	0.035	0.035	0.039	0.032	0.038	0.052	0.011
Gross Common Equity %	0.454	0.475	0.486	0.479	0.481	0.487	0.492	0.511	0.510	0.527	0.073***
Gross Debt-to-Assets	0.505	0.497	0.481	0.491	0.484	0.479	0.469	0.457	0.452	0.421	-0.084***
Growth Opportunity Metrics											
Tobin's Q	1.087	1.188	1.236	1.300	1.283	1.326	1.365	1.427	1.533	1.662	0.575***
Market-to-Book	1.523	1.961	1.804	2.103	1.941	2.228	2.532	2.682	3.487	4.459	2.937***
Book-to-market	0.902	0.723	0.695	0.646	0.652	0.601	0.542	0.510	0.478	0.432	-0.47***
Gross Tobin's Q	1.041	1.101	1.115	1.146	1.113	1.126	1.135	1.156	1.192	1.201	0.16***
Gross Market-to-book	1.210	1.369	1.334	1.410	1.317	1.345	1.354	1.380	1.464	1.419	0.209***
Gross Book-to-market	1.040	0.906	0.914	0.910	0.988	0.971	0.905	0.879	0.905	1.107	0.067
Control Variables											
Profitability (FFO/ Assets)	0.028	0.040	0.042	0.047	0.047	0.050	0.052	0.056	0.060	0.073	0.045***
Tangibility (Real Estate / Assets)	0.775	0.838	0.833	0.848	0.832	0.844	0.860	0.880	0.883	0.869	0.094***
Total Assets	3,136.11	4,109.51	5,219.59	5,478.43	5,452.90	5,058.87	4,234.57	5,010.15	3,925.35	3,999.60	863.486*
Gross Assets	3,281.43	4,456.01	5,813.03	6,237.25	6,317.38	5,962.96	5,129.98	6,231.42	5,085.54	5,716.15	2434.717***

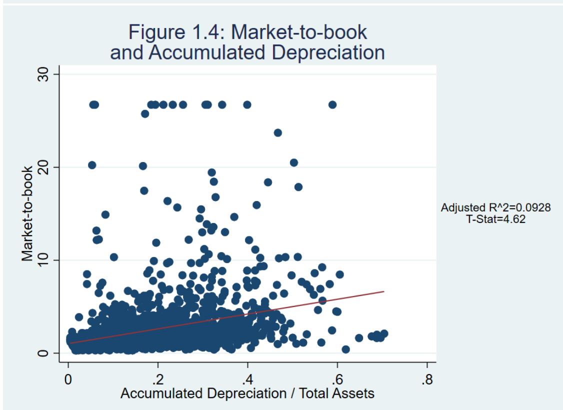
Notes: REITs are sorted each year by their amount of accumulated depreciation, scaled by total assets and then placed into deciles. Preferred% is the redemption value of preferred equity divided by total assets. Debt-to-assets is liabilities divided by total assets. Common equity% is stockholder's equity minus preferred equity divided by total assets. "Gross" metrics divde by total assets plus accumulated depreciation, while gross common equity % also adds accumulated depreciation to shareholder's equity.

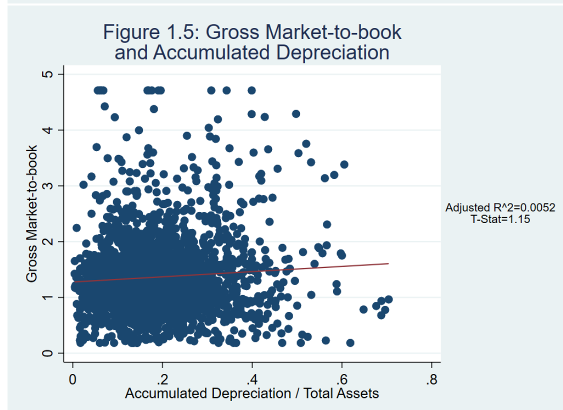
from our theoretical predictions, this provides the first empirical piece of evidence that the gross book-to-market may be the best metric out of the 6.

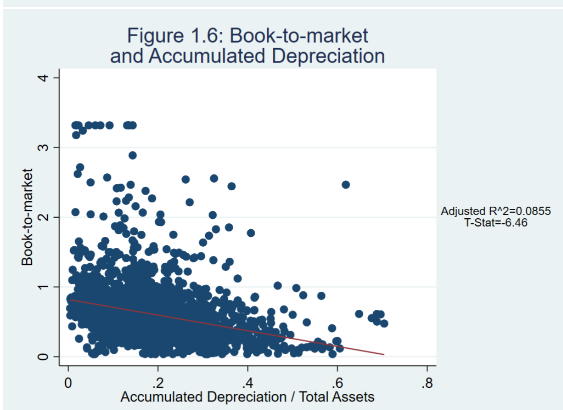
Next we consider scatter plots of growth metrics versus accumulated depreciation%. In figure 1.2, we plot accumulated depreciation% against net Tobin's Q, along with the best fit line. The T-Statistic of 6.17 is computed with standard errors clustered at the firm level. A staggering 19.49% of the variation in Tobin's Q can be explained by variation in accumulated depreciation% alone. Figure 1.4 plots accumulated depreciation% against market-to-book. The small denominator problem is clear, as even winsorized values of market-to-book are often higher than 20. In figures 1.4 and 1.6, we show that the market-to-book (book-to-market) is positively (negatively) related to accumulated depreciation%, with T-statistics of 4.62 (6.46) and adjusted R^2 statistics of 0.0928 (0.0855.)

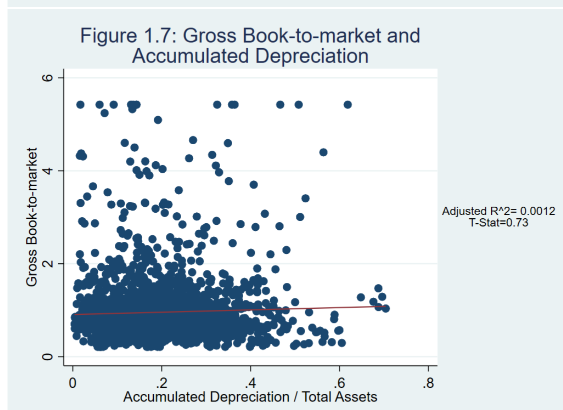












In figures 1.3, 1.5, and 1.7, we replace the net growth opportunity metrics with the corresponding gross metrics. In figure 1.3, the relationship between gross Tobin's Q and accumulated depreciation% is greatly reduced relative to figure 1.2. The T-statistic has dropped to 2.07 while the adjusted R^2 has fallen to 0.0239. In figures 1.5 and 1.7, there is no clear visual relationship or statistical significance between accumulated depreciation% and the gross MTB (or BTM),

Accumulated depreciation% is clearly associated with higher net market-to-book, and that relationship is greatly reduced when we consider gross market-to-book. In the interest of readability, throughout the rest of this paper we will tend to refer to “market-to-book” by default instead of repeatedly listing all three metrics (where appropriate.) If the over-depreciation of properties is the root cause, then we would expect for REITs with shorter depreciation schedules to have higher market-to-book. We therefore examine the differences between residential and non-residential REITs. Residential properties are depreciated over 27.5 years, while non-residential properties are depreciated over 39 years. We expect that residential REITs will have higher market-to-book, since their common equity is being depreciated away more quickly.

Table 1.4: Summary Statistics by Depreciation Schedule

	Non-Residential	Residential	Difference
Number of REITs	2,119	363	
Capital Structure Metrics			
Accumulated Depreciation%	0.176	0.217	0.041***
Preferred%	0.045	0.036	-0.008**
Common Equity %	0.375	0.322	-0.053***
Debt-to-Assets	0.548	0.604	0.056***
Gross Preferred%	0.037	0.031	-0.007*
Gross Common Equity %	0.465	0.440	-0.025***
Gross Debt-to-Assets	0.469	0.498	0.029***
Growth Opportunity Metrics			
Tobin’s Q	1.333	1.400	0.067***
Market-to-Book	2.370	3.129	0.759***
Book-to-market	0.640	0.480	-0.16***
Gross Tobin’s Q	1.131	1.145	0.014
Gross Market-to-book	1.356	1.393	0.037
Gross Book-to-market	0.975	0.821	-0.154***
Control Variables			
Profitability (FFO/ Assets)	0.051	0.044	-0.007***
Tangibility (Real Estate / Assets)	0.837	0.907	0.07***
Total Assets	4,558.00	4,515.31	-42.69

Notes: This table presents summary statistics for equity REITs, split out by property type. Residential properties are depreciated over 27.5 years, while non-residential properties are depreciated over 39 years.

Table 1.4 reports summary statistics with REITs separated into their residential versus non-residential property type status. Consistent with our prediction, the residential REITs have higher market-to-book and Tobin’s Q, along with lower book-to-market. The differences disappear when we consider the gross valuation metrics, with the exception of the gross book-to-market. For the gross book-to-market, the difference between the two groups as a percentage of the average is still smaller than for the net book-to-market. While this weakens our argument that the gross book-to-market is the best choice of the six, unobservable differences between residential and non-residential REITs may be driving the lower gross book-to-market in residentials. Table 1.4 is only one piece of evidence, and the larger body of evidence presented in this study suggests that the gross book-to-market is the best available proxy for REIT growth opportunities.

In capital structure studies, the market-to-book is intended to proxy for growth opportunities, but the summary statistics reveal that REIT market-to-book ratios may be biased by accumulated depreciation. This poses the question of whether or not market-to-book is actually related to future growth in REITs. We suspect that the gross metrics will likely outperform the net metrics in predicting future growth. In table 1.5, we again split the REITs into deciles, but this time we sort them based on their "growth opportunities" as measured by various market-to-book definitions. In panels A, B, C, and D, we sort the REITs by market-to-book, gross market-to-book, Tobin's Q, and gross Tobin's Q, respectively. We leave out the book-to-market and gross book-to-market, as the information would be redundant: a REIT in the first decile of book-to-market will always be in the 10th decile of market-to-book.

Table 1.5: Summary Statistics by Growth Opportunity Proxies

	1	2	3	4	5	6	7	8	9	10	10 minus 1
Panel A: Opportunities = Market-to-book											
Market-to-Book	0.824	1.143	1.321	1.489	1.678	1.903	2.157	2.497	3.085	6.800	5.976***
Asset Growth	0.132	0.146	0.126	0.120	0.109	0.116	0.106	0.117	0.150	0.130	-0.002
Gross Asset Growth	0.142	0.154	0.134	0.127	0.117	0.121	0.112	0.120	0.146	0.130	-0.013
Sales Growth	0.224	0.199	0.155	0.120	0.125	0.120	0.093	0.101	0.102	0.106	-0.118***
Panel B: Opportunities = Gross Market-to-book											
Gross Market-to-Book	0.580	0.823	0.955	1.075	1.193	1.315	1.439	1.590	1.829	2.642	2.062***
Asset Growth	0.056	0.085	0.089	0.124	0.134	0.149	0.133	0.139	0.159	0.180	0.124***
Gross Asset Growth	0.064	0.093	0.097	0.134	0.139	0.153	0.139	0.144	0.159	0.177	0.113***
Sales Growth	0.069	0.088	0.138	0.159	0.162	0.152	0.165	0.123	0.137	0.143	0.074***
Panel C: Opportunities = Tobin's Q											
Tobin's Q	0.888	1.019	1.086	1.145	1.217	1.299	1.371	1.464	1.620	2.089	1.201***
Asset Growth	0.143	0.112	0.119	0.117	0.114	0.125	0.097	0.115	0.155	0.154	0.011
Gross Asset Growth	0.154	0.123	0.127	0.124	0.121	0.130	0.103	0.120	0.153	0.148	-0.005
Sales Growth	0.214	0.197	0.143	0.127	0.138	0.104	0.100	0.102	0.102	0.116	-0.097***
Panel D: Opportunities = Gross Tobin's Q											
Gross Tobin's Q	0.779	0.888	0.946	1.000	1.053	1.115	1.175	1.244	1.340	1.671	0.892***
Asset Growth	0.081	0.085	0.088	0.107	0.123	0.141	0.147	0.150	0.137	0.189	0.108***
Gross Asset Growth	0.089	0.093	0.098	0.117	0.130	0.145	0.151	0.151	0.142	0.184	0.095***
Sales Growth	0.125	0.088	0.133	0.142	0.149	0.150	0.151	0.132	0.117	0.152	0.027

Notes: REITs are sorted each year by the lag of their corresponding growth metric and then placed into deciles. "Gross" metrics add accumulated depreciation to total assets and common equity. We only use market-to-book and Tobin's Q in this table, as the information contained in the book-to-market is redundant (a REIT in the first decile of book-to-market will always be in the 10th decile of market-to-book). Gross assets are defined as assets plus accumulated depreciation

After sorting the firms by their lagged metrics, we then report the averages of asset growth, gross asset growth, and sales growth for each decile. Lagging the market-to-book allows us to assess whether a firm with a high market-to-book actually experiences higher growth in the following year. In panel A, we find no relationship between asset growth and lagged market-to-book, and sales growth is *lower* in the high market-to-book group. Panel C reveals identical properties in Tobin's Q. However, if we consider the gross metrics in panels B and D, we see that high gross market-to-book (and Tobin's Q) is associated with higher growth. Gross Tobin's Q appears somewhat less reliable than gross market-to-book, as there is no statistically significant difference in sales growth between the 10th and 1st deciles of gross Tobin's Q.

Scatter plots of growth proxies against actual future growth reveal the gross metrics to be superior to the net metrics in predicting growth. In figures 1.8 and 1.10, we find no relationship between Tobin's Q (market-to-book) and gross asset growth. The only consistent finding from these two figures is that the extremely high-growth REITs (the winsorized values that are mostly in the top left) have low market-to-book, which is the exact opposite of what theory would predict. Figure 1.12 shows that the book-to-market outperforms market-to-book and Tobin's Q at predicting future growth, with a T-statistic of -1.90. Visually, the high growth REITs tend to have low book-to-market, consistent with their categorization as growth firms. However, the book-to-market doesn't capture much of the variation in growth, as shown by both the weak visual relationship and the adjusted R^2 of 0.0023.

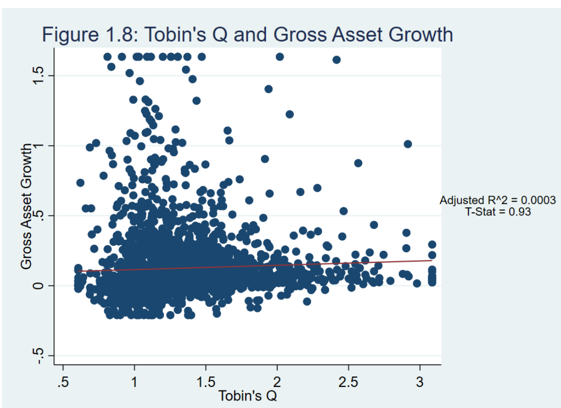


Figure 1.8: Tobin's Q and Gross Asset Growth

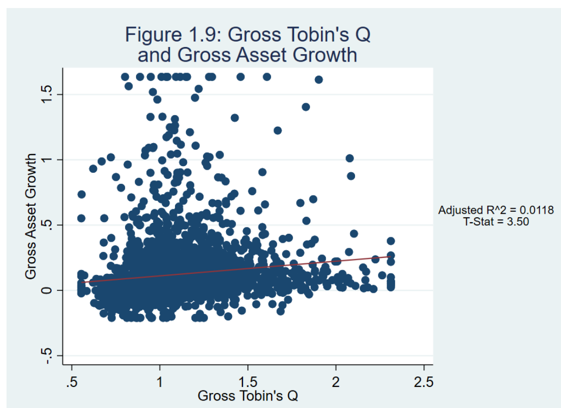


Figure 1.9: Gross Tobin's Q and Gross Asset Growth

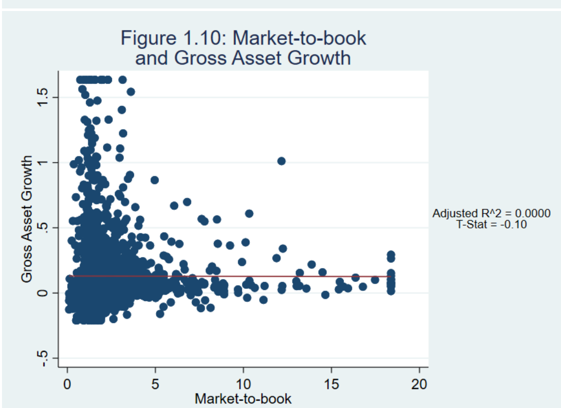


Figure 1.10: Market-to-book and Gross Asset Growth

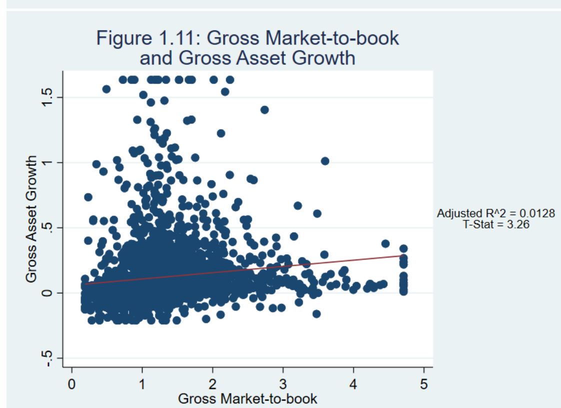


Figure 1.11: Gross Market-to-book and Gross Asset Growth

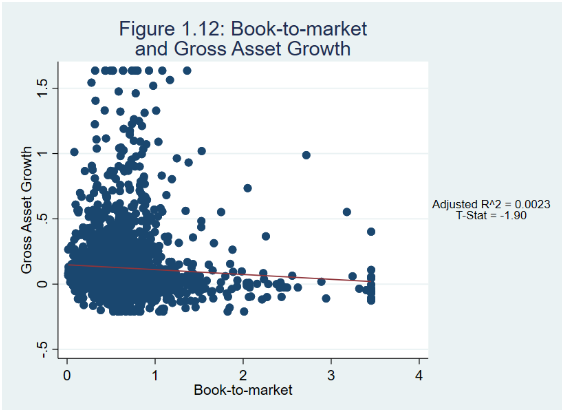


Figure 1.12: Book-to-market and Gross Asset Growth

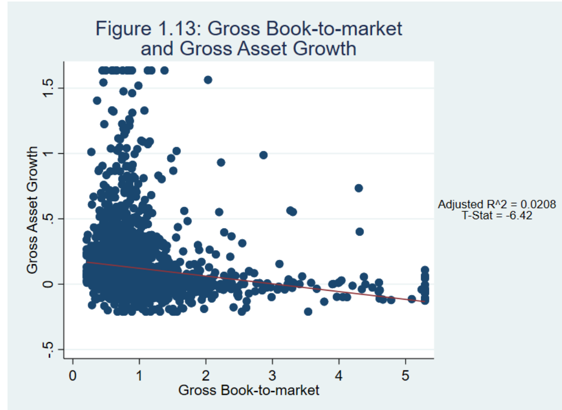


Figure 1.13: Gross Book-to-market and Gross Asset Growth

In figures 1.9, 1.11, and 1.13, we plot the lagged gross metrics versus gross asset growth, and find that the gross growth opportunity metrics outperform their corresponding net metrics at predicting growth. In each case, we see an improvement in the t-statistic and R^2. The gross market-to-book and gross Tobin's Q positively predict future gross asset growth, while a high gross book-to-market predicts low gross asset growth. Consistent with our theoretical prediction, the gross book-to-market performs the best at predicting future growth, as measured by both the t-statistic and R^2.

In all of our analysis thus far, we have relied on bivariate relationships without control variables. To more thoroughly establish the connection between accumulated depreciation and market-to-book, we decompose the market-to-book by conducting Fama-Macbeth regressions following Golubov and Konstantinidi (2019.) In their decomposition, they make use of the fact that the log of market cap divided by book equity is equal to the log of market cap minus the log of book equity. We utilize their setup and run the following cross-sectional regression each year:

$$
\begin{aligned}
log(MarketCap) = \beta_1 + \beta_2 * log(BookEquity) + \beta_2 * log(FFO)^{+} + \beta_3 * I * log(FFO)^{-} \quad (1.5) \\
+ \beta_4 * LEV + \beta_5 * Pref\% + \epsilon
\end{aligned}
$$

Where the dependent variable is the log of the market value of equity, $log(FFO)^{+}$ is the absolute value of the log of funds from operations, $log(FFO)^{-}$ is the absolute value of the log of funds from operations if it is negative, I is a dummy variable equal to one if the firm's funds from operations is negative, and LEV is book debt-to-assets. Our setup differs slightly from theirs, as we control for the log of FFO instead of the log of net income, and we include preferred% as a control in addition to debt-to-assets.

We model REIT market-to-book each year using equation 1.5, and then in table 1.6 we report the average cross-sectional coefficient along with the Fama-Macbeth t-statistic. Golubov and Konstantinidi find that leverage is negatively related to market-to-book for most industries, but model 1 shows that preferred equity and debt-to-assets are both positively related to market-to-book in REITs. From a theoretical standpoint, leverage should negatively impact market-to-book. All else equal, a firm with higher leverage is higher risk, so additional leverage should lead to lower market value (i.e. leverage should load positively on the "value" factor.) In REITs, we find that the opposite is true if we ignore the effects of accumulated depreciation.

Table 1.6: Determinants of REIT Market Value

	(1)	(2)	(3)
Preferred %	0.9090	0.2972	-0.0529
	(6.79)***	(2.35)**	(-0.47)
Book Leverage	0.5162	0.0287	-0.2726
	(3.35)***	(0.18)	(-1.72)*
Log (book value)	0.5224	0.4436	
	(14.27)***	(13.99)***	
Log (accumulated dep)		0.1817	
		(6.13)***	
Log (gross book value)			0.6621
			(12.31)***
Profitability (positive)	0.5082	0.4155	0.3872
	(15.67)***	(9.93)***	(8.15)***
Profitability (negative)	-0.0558	-0.0526	-0.0474
	(-1.66)*	(-1.57)	(-1.44)
Observations	2,482	2,482	2,482
Adjusted R2	0.8891	0.8981	0.9022

Notes: This table presents the average coefficients from cross-sectional OLS regressions run each year from 2001-2020, using equation 1.5. Fama-Macbeth t-stats are in parentheses. Preferred% is the value of preferred equity divided by total assets. Book Leverage is debt-to-assets. *** Indicates statistical significance at the 1% level; ** indicates statistical significance at the 5% level; * indicates statistical significance at the 10% level.

In model 2, we include the log of accumulated depreciation as an additional control variable, and find that accumulated depreciation is associated with higher market-to-book. The impact of preferred% and debt-to-assets are both greatly reduced in model 2, but preferred% remains positive and statistically significanct. However, model 2 is mis-specified. We should be making use of the fact that the log of market cap divided by gross book value is equal to the log of market cap minus the log of gross book value. The mathematically incorrect implicit assumption in model 2 is that

$$Log(\frac{Market\ Cap}{Book\ Equity + Accum\ Dep}) = Log(MarketCap) - Log(BookEquity) - Log(AccumDep) \tag{1.6}$$

We include model 2 for the sole purpose of illustrating that accumulated depreciation leads to higher market-to-book even while controlling for other determinants of market value. Model 3 does not explicitly control for accumulated depreciation, but instead replaces the net value of common book equity with the gross value of common book equity. The correctly specified model 3 reveals a negative relationship between leverage and market-to-book, as well as a negative but statistically insignificant relationship between preferred% and market-to-book.

Overall, the evidence in this section shows that REIT market-to-book ratios are biased by accumulated depreciation, and highly levered REITs (both those that use lots of debt and those that use lots of preferred equity) are disproportionately impacted. These findings are relevant to a wide range of REIT literature, but we choose to focus the remainder of our study on implications for capital structure studies. Is the bias large enough to cause problems with REIT capital structure studies, and what is the true relationship between market-to-book and leverage? We address these questions in the following section, where we use Harrison et al. (2011) as a case study.

1.4 Case Study: Market-to-book and Changes in Leverage

In light of the problems with REIT market-to-book ratios, we re-examine the capital structure debate posed by the disagreement between the findings of Harrison et al. (2011) and Feng et al. (2007). Harrison et al. found a negative relationship between market-to-book and leverage, while Feng et al. found a positive one. The market-to-book is of particular importance to capital structure theory due to its relation with growth opportunities and stock valuations. REITs have limited access to retained earnings, so under pecking order theory REITs with growth opportunities will finance that growth by issuing debt. If pecking order theory dominates market-timing theory, then the lagged market-to-book (book-to-market) ratio will be positively (negatively) related to changes in leverage. If market-timing motivations dominate pecking order theory, then we would expect to see the opposite. However, this setup only works if the market-to-book is a good proxy for growth opportunities, which it is not.

We replicate Harrison et al. (2011) with some slight adjustments to show how the definition of growth opportunities might impact results. As our dependent variable, we use book leverage instead of market leverage, since market leverage is mechanically linked to market-to-book. We test the main setup from their study using Tobin's Q, market-to-book, and book-to-market as our key variables of interest. We include the control variables from table 3, model 1, of their paper. The other specifications in their study used control variables that are unavailable in more widely used databases such as Compustat, but those models arrived at similar conclusions. The model uses debt-to-assets as the dependent variable, and includes the lag of debt-to-assets as a control variable, effectively modeling changes in leverage.

Table 1.7 reports the results, and then shows the sensitivities of the model to various definitions of market-to-book and leverage. In each model, we include year and property-type fixed effects. Models 1, 2, and 3 examine changes in debt-to-assets, while models 4, 5, and 6 model changes in gross debt-to-assets. The three-tiered capital structure employed by REITs suggests that not all changes in leverage are captured by debt-to-assets, so we include models 7, 8, and 9, which model changes in gross common equity%.

Table 1.7: Determinants of REIT Leverage

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable:	Debt-to-Assets			Gross Debt-to-Assets			Gross Common Equity%		
Growth Opportunity Defintion:	Q	MTB	BTM	Gross Q	Gross MTB	Gross BTM	Gross Q	Gross MTB	Gross BTM
"Growth Opportunities"	0.0238***	0.0043***	-0.0042	0.0337***	0.0166***	-0.0047*	-0.0266***	-0.0146***	0.0040
	(3.60)	(3.40)	(-1.06)	(4.83)	(5.76)	(-1.92)	(-3.58)	(-4.76)	(1.63)
Size	-0.0002	0.0001	0.0003	-0.0009	-0.0014	-0.0003	0.0020	0.0025	0.0015
	(-0.09)	(0.08)	(0.17)	(-0.54)	(-0.84)	(-0.20)	(1.17)	(1.46)	(0.85)
Profitability	-0.5188***	-0.4707***	-0.3771***	-0.5595***	-0.5759***	-0.4514***	0.5984***	0.6335***	0.5234***
	(-5.55)	(-5.82)	(-4.47)	(-7.17)	(-7.85)	(-5.94)	(6.54)	(7.01)	(5.99)
Tangibilty	0.0330*	0.0323*	0.0252	0.0149	0.0183	0.0056	-0.0026	-0.0064	0.0050
	(1.82)	(1.78)	(1.38)	(0.85)	(1.07)	(0.31)	(-0.14)	(-0.34)	(0.26)
Debt-to-Assets (t-1)	0.8736***	0.8568***	0.8806***						
	(53.75)	(45.48)	(54.48)						
Debt-to-Assets (gross, t-1)				0.8448***	0.8329***	0.8521***			
				(46.74)	(43.79)	(46.00)			
Common Equity% (gross, t-1)							0.8334***	0.8171***	0.8332***
							(43.50)	(41.34)	(43.43)
Constant	0.0418*	0.0686***	0.0681***	0.0585**	0.0812***	0.0956***	0.0649**	0.0601**	0.0325
	(1.67)	(2.88)	(2.65)	(2.35)	(3.44)	(3.87)	(2.48)	(2.35)	(1.24)
Observations	2,482	2,482	2,482	2,482	2,482	2,482	2,482	2,482	2,482
Adjusted R-squared	0.8506	0.8512	0.8487	0.8412	0.8424	0.8384	0.8489	0.8502	0.8474

Notes: This table reports the results of OLS regressions where the dependent variable is a leverage metric, and the lag of that same metric is included as a control variable. Size is the log of total assets. Profitability is FFO scaled by total assets. Tangibility is real estate assets divided by total assets. Gross debt-to-assets adds accumulated depreciation to total assets, while gross common equity% adds accumulated depreciation to total assets and common equity. Each model includes year and property-type fixed effects.

Models 1, 2, and 3 show how researchers might normally choose to set up this regression. That is, they examine how the net market-to-book (or book-to-market) impacts changes in the net debt-to-assets. A cynic could see the difference in significance between models 1 and 3 and think that previous research used Tobin's Q instead of the book-to-market in order to find statistically significant results, but previous studies likely used Tobin's Q simply because it represents larger growth opportunities. The book-to-market is less immediately intuitive, as a low book-to-market represents high growth opportunities. Equations 1 and 2 would indicate that pecking order theory motivates capital structure decisions in REITs, while equation 3 would indicate "no finding." Models 4, 5, and 6 confirm the findings of 1 and 2: REITs with more growth opportunities increase their usage of debt in the following year. Models 7, 8, and 9 generally confirm this, as the signs on the coefficients all flip as we switch the dependent variable from gross debt-to-assets to gross common equity%. However, model 9 shows a statistically insignificant relationship.

The book-to-market is superior to Tobin's Q and the market-to-book in terms of assessing growth opportunities, and the gross book-to-market is superior to the traditional book-to-market. Our preferred specifications for modeling debt usage are therefore models 3 and 6. Model 3 is insignificant, while model 6 is only statistically significant at the 10% level. The book-to-market is between 2 and 4 standard deviations less significant than Tobin's Q and market-to-book, depending on which models we compare. The large disagreement between specifications that are intended to model the same effect motivates further inquiry.

Is pecking order theory actually motivating REIT capital structure decisions, or is the relationship between changes in leverage and market-to-book spurious? In table 1.8, we dismiss with the proxies for growth opportunities and instead regress changes in capital structure on growth itself. For robustness we define growth as either asset growth, gross asset growth, or sales growth, depending on the model. Since growth is already included in the regression, the market-to-book now serves as a proxy for market-timing opportunities instead of growth opportunities. When the lagged market-to-book is high, stock prices were recently high and firms had the opportunity to raise equity capital at desirable prices. We therefore expect the market-to-book (book-to-market) to be negatively (positively) related to changes in leverage in table 1.8.

Table 1.8: Determinants of REIT Leverage

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent: Gross Debt-to-Assets	”Equity Valuation” = Gross Tobin’s Q			”Equity Valuation” = Gross MTB			”Equity Valuation” = Gross BTM		
Asset Growth	0.0479***			0.0465***			0.0523***		
	(5.65)			(5.43)			(6.11)		
Asset Growth (Gross)		0.0524***			0.0509***			0.0572***	
		(5.69)			(5.46)			(6.14)	
Sales Growth			0.0284***			0.0273***			0.0298***
			(4.53)			(4.34)			(4.64)
Equity Valuation (t-1)	0.0204***	0.0204***	0.0297***	0.0109***	0.0107***	0.0143***	0.0007	0.0010	-0.0020
	(2.93)	(2.93)	(4.26)	(3.70)	(3.67)	(5.00)	(0.32)	(0.42)	(-0.86)
Size	0.0001	0.0001	-0.0001	-0.0003	-0.0002	-0.0005	0.0008	0.0008	0.0006
	(0.07)	(0.08)	(-0.04)	(-0.18)	(-0.15)	(-0.30)	(0.50)	(0.53)	(0.38)
Profitability	-0.4132***	-0.4086***	-0.5015***	-0.4338***	-0.4279***	-0.5150***	-0.3110***	-0.3041***	-0.3873***
	(-5.54)	(-5.53)	(-6.79)	(-6.13)	(-6.09)	(-7.33)	(-4.30)	(-4.26)	(-5.39)
Tangibilty	0.0150	0.0134	0.0153	0.0175	0.0159	0.0180	0.0094	0.0076	0.0070
	(0.93)	(0.83)	(0.94)	(1.11)	(1.01)	(1.14)	(0.57)	(0.47)	(0.42)
Gross Debt-to-Assets (t-1)	0.8554***	0.8558***	0.8495***	0.8469***	0.8475***	0.8391***	0.8605***	0.8610***	0.8561***
	(49.14)	(49.41)	(49.21)	(46.35)	(46.57)	(46.05)	(49.03)	(49.30)	(48.53)
Constant	0.0474**	0.0473**	0.0474**	0.0616***	0.0615***	0.0681***	0.0611***	0.0605***	0.0753***
	(2.08)	(2.09)	(2.06)	(2.81)	(2.83)	(3.11)	(2.66)	(2.66)	(3.28)
Observations	2,482	2,482	2,482	2,482	2,482	2,482	2,482	2,482	2,482
Adjusted R-squared	0.8496	0.8498	0.8462	0.8502	0.8504	0.8470	0.8485	0.8487	0.8439

Notes: This table reports the results of OLS regressions where the dependent variable is gross debt-to-assets. Size is the log of total assets. Profitability is FFO scaled by total assets. Tangibility is real estate assets scaled by total assets. Gross debt-to-assets adds accumulated depreciation to total assets, while gross common equity% adds accumulated depreciation to total assets and common equity.

In table 1.8, all leverage and valuation metrics are gross, but the results are not sensitive to redefining leverage as net leverage. Models 1-3 use gross Tobin’s Q as the proxy for market-timing opportunities (labeled ”Equity Valuation”), while models 4-6 use the gross market-to-book, and models 7-9 use the gross book-to-market. In models 1-6, the relationship between equity valuation and leverage is the opposite of what we expected, and is highly significant. We find highly significant evidence in the opposite direction of market-timing when high equity valuations are measured by the MTB and Q, but the relationship is likely spurious. MTB suffers from the small denominator problem, while Q’s usefulness is reduced by our inability to observe the vast majority of changes in REIT market value. The superior gross BTM finds no relationship between equity prices and changes in leverage once growth is controlled for. The positive relationship between MTB and changes in leverage has no theoretical motivation once growth is controlled for, as high equity valuations would encourage managers to de-lever by issuing equity. Pecking order theory, on the other hand, is clearly present, as growth is associated with changes in leverage regardless of how we measure growth. The positive and statistically significant coefficients on market-to-book and Tobin’s Q are likely spurious, despite having t-statistics as high as 5.

1.5 Determinants of REIT Preferred Equity Usage

Empirical analysis of REIT capital structure is complicated by accumulated depreciation and the extensive use of preferred equity in REITs. The evidence in section 1.4 supports pecking order theory as it pertains to REIT debt issuances: high growth REITs tend to increase their use of leverage. What remains unclear is where preferred equity fits into the competing theories. Under pecking order theory, we could assume that preferred equity is used to finance growth opportunities in the same way as debt: it raises capital while avoiding the large adverse selection costs of common equity. This explanation assumes smaller adverse selection costs in preferred equity issuances, relative to common equity issuances. The pecking order view of preferred equity would lead to market-to-book being positively related to preferred equity issuances. However, if market-timing theory dominates, then we would expect MTB to be negatively related to changes in preferred%, as companies could simply issue common equity when their MTB was high.

We model the use of preferred equity using the same setup as in section 1.4, and replace debt-to-assets with preferred%. Preferred equity may also be used as a way of maintaining the debt-to-assets ratio. Since REITs may be motivated to finance growth with preferred equity when their debt-to-assets is high, we include the lagged debt-to-assets as a control variable, and expect it to be positively related to changes in preferred%. The results are reported in table 1.9, where "growth opportunities" is defined by each of the six possible metrics. Models 4 and 5, which use gross Tobin's Q and gross market-to-book, suggest that market timing motivations may dominate pecking order theory in REIT preferred equity usage: market-to-book is negatively related to preferred equity usage. However, model 6 suggests the relationship may be spurious. While we expected debt-to-assets would be positively related to changes in preferred%, we find no evidence of this in table 1.9.

The analysis in table 1.9 suffers from the same problem as in table 1.7: MTB, Q, and BTM are all imperfect proxies for growth opportunities, even when we consider their gross values. To further investigate preferred equity's relationship to the pecking order, we include actual growth as

Table 1.9: Determinants of Preferred%

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent = Net Preferred%			Dependent = Gross Preferred%		
Growth Opportunity Defintion:	Q	MTB	BTM	Gross Q	Gross MTB	Gross BTM
"Growth Opportunities"	-0.0041*	-0.0005	0.0021	-0.0045*	-0.0017*	0.0007
	(-1.77)	(-1.22)	(1.10)	(-1.87)	(-1.66)	(0.76)
Debt-to-Assets (t-1)	-0.0001	0.0014	-0.0006	0.0008	0.0019	-0.0004
	(-0.02)	(0.18)	(-0.09)	(0.10)	(0.22)	(-0.05)
Size	-0.0021***	-0.0022***	-0.0021***	-0.0021***	-0.0020***	-0.0021***
	(-2.79)	(-2.82)	(-2.70)	(-3.08)	(-3.04)	(-3.01)
Profitability	-0.0511	-0.0663*	-0.0669*	-0.0523	-0.0546	-0.0665**
	(-1.42)	(-1.87)	(-1.76)	(-1.58)	(-1.56)	(-2.01)
Tangibility	-0.0129*	-0.0123	-0.0115	-0.0128*	-0.0128*	-0.0116
	(-1.69)	(-1.60)	(-1.52)	(-1.80)	(-1.79)	(-1.63)
Preferred% (t-1)	0.9107***	0.9111***	0.9099***	0.9003***	0.9009***	0.8989***
	(37.66)	(37.95)	(38.36)	(34.99)	(34.93)	(34.99)
Constant	0.0394***	0.0351***	0.0327***	0.0380***	0.0348***	0.0332***
	(3.37)	(3.11)	(2.65)	(3.48)	(3.23)	(2.87)
Observations	2,482	2,482	2,482	2,482	2,482	2,482
Adjusted R-squared	0.8421	0.8420	0.8420	0.8193	0.8193	0.8191

Notes: This table reports the results of ordinary least square regressions where the dependent variable is preferred equity, scaled by total assets (preferred%.) Size is the log of total assets. Profitability is FFO scaled by total assets. Tangibility is real estate assets divided by total assets.

a control variable in table 1.10. Controlling for growth, the gross MTB, gross Q, and gross BTM are now proxies for equity valuations. In the context of pecking order theory and market-timing theory, we would expect growth to be positively related to changes in preferred%, while we expect lagged equity valuation would be negatively (positively) related to preferred% when we measure equity valuation with MTB (BTM.) They key variables of interest (growth and equity valuation) are mostly insignificant. Specifications 3, 6, and 9 find the theorized relationship with respect to sales growth, with statistical significance around the 5% threshold. However, asset growth is not related to changes in preferred%. Spcifications 3 and 6 also find the theorized relationship with respect to equity valuations: REITs issue less preferred equity when their MTB is high. However, the finding is not robust to multiple specifications. Our most consistent finding is that small REITs are more likely to issue preferred equity than large REITs.

Overall, we find that small and less profitable REITs are more likely to issue preferred equity than large profitable REITs. There is also some evidence that REITs use preferred equity when their sales growth is high and equity valuation is low, which would support both pecking order theory and market timing theory, but the findings are not robust to multiple specifications. The tendency for small REITs to issue more preferred equity could be explained by larger adverse selection costs in common equity issuances by small firms. Taken together with the finding that REITs issue less preferred equity when they are profitable, it seems that REITs issue preferred

Table 1.10: Determinants of Preferred%

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	”Equity Valuation” = Gross Tobin’s Q			”Equity Valuation” = Gross MTB			”Equity Valuation” = Gross BTM		
Asset Growth	-0.0030			-0.0030			-0.0036		
	(-0.76)			(-0.78)			(-0.92)		
Gross Asset Growth		-0.0022			-0.0022			-0.0028	
		(-0.50)			(-0.51)			(-0.65)	
Sales Growth			0.0042*			0.0043**			0.0041*
			(1.95)			(1.99)			(1.88)
Equity Valuation	-0.0036	-0.0039	-0.0051**	-0.0013	-0.0015	-0.0021**	0.0003	0.0004	0.0011
	(-1.38)	(-1.49)	(-2.11)	(-1.22)	(-1.33)	(-2.01)	(0.33)	(0.42)	(1.13)
Gross Debt-to-Assets (t-1)	-0.0000	0.0002	0.0018	0.0008	0.0012	0.0033	-0.0011	-0.0009	0.0004
	(-0.00)	(0.03)	(0.22)	(0.09)	(0.13)	(0.37)	(-0.13)	(-0.11)	(0.05)
Size	-0.0021***	-0.0021***	-0.0019***	-0.0021***	-0.0021***	-0.0019***	-0.0022***	-0.0022***	-0.0020***
	(-3.22)	(-3.19)	(-3.00)	(-3.21)	(-3.18)	(-2.94)	(-3.14)	(-3.11)	(-2.90)
Profitability	-0.0618*	-0.0588*	-0.0431	-0.0644*	-0.0613*	-0.0441	-0.0763**	-0.0739**	-0.0572*
	(-1.88)	(-1.77)	(-1.28)	(-1.85)	(-1.75)	(-1.24)	(-2.33)	(-2.24)	(-1.70)
Tangibility	-0.0128*	-0.0127*	-0.0127*	-0.0128*	-0.0127*	-0.0129*	-0.0118	-0.0117	-0.0114
	(-1.78)	(-1.77)	(-1.82)	(-1.76)	(-1.76)	(-1.82)	(-1.65)	(-1.63)	(-1.63)
Gross Preferred % (t-1)	0.8993***	0.8996***	0.9022***	0.8997***	0.9001***	0.9032***	0.8980***	0.8982***	0.9006***
	(34.43)	(34.41)	(34.98)	(34.32)	(34.29)	(34.85)	(34.63)	(34.59)	(34.98)
Constant	0.0388***	0.0385***	0.0362***	0.0362***	0.0357***	0.0324***	0.0356***	0.0350***	0.0301**
	(3.52)	(3.50)	(3.34)	(3.30)	(3.27)	(3.01)	(2.99)	(2.93)	(2.59)
Observations	2,482	2,482	2,482	2,482	2,482	2,482	2,482	2,482	2,482
Adjusted R-squared	0.8194	0.8193	0.8197	0.8193	0.8193	0.8197	0.8192	0.8191	0.8195

Notes: This table reports the results of ordinary least square regressions where the dependent variable is preferred equity, scaled by total assets (preferred%.) Size is the log of total assets. Profitability is FFO scaled by total assets. Tangibility is real estate assets divided by total assets.

equity as a substitute for common equity when common equity is unavailable (low profitability) and unattractive (low market valuations, high adverse selection costs.) However, we do not find evidence that REITs issue preferred equity as a substitute for debt, as there is no relationship between lagged debt-to-assets and changes in preferred%.

1.6 Conclusion

We show that market-to-book ratios in REITs are biased by accumulated depreciation, and that the effect is accelerated by the three-tiered capital structure employed by many REITs. Tobin’s Q, market-to-book, and book-to-market all serve as poor proxies for growth opportunities, with book-to-market performing the best. Gross metrics, constructed by adding accumulated depreciation to total assets (and consequently, common equity) serve as far better indicators of future growth, with the gross book-to-market performing the best out of the 6 options.

Re-examining the debate of pecking order theory versus market-timing theory, we find significant evidence that the pecking order motivates REIT use of leverage. High growth REITs tend to increase their usage of debt. Controlling for growth, the MTB serves as a proxy for market-timing opportunities, and we find very little evidence that market-timing drives capital structure decisions. The relationship between MTB and future debt usage can be positive and statistically significant with t-statistics as high as 5, despite having no theoretical motivation. The gross book-to-market in the same setup shows no statistical significance, suggesting the relationship between MTB and debt-to-assets may be spurious.

These findings stress the need for future REIT studies to use the gross book-to-market as a proxy for market valuations and growth opportunities, and also we encourage researchers to consider the three-tiered capital structure employed by many REITs.

Chapter 2

Time-Varying Risk Premiums in Real Estate: Evidence from REIT Return Forecasts

2.1 Introduction

Existing asset pricing research finds evidence of return predictability in multiple asset classes, potentially suggesting that risk premiums are time-varying (Cochrane 2011[1].) Nonetheless, the reliability of return forecasts and whether investors can benefit from forecasting in real-time are still ongoing questions (Pesaran, 1995; Welch and Goyal, 2008), particularly for the real estate market. Real estate investment trusts (REITs) are unique because they are required to invest at least 75% of their assets in real estate (or cash), generate at least 75% of their gross income from real estate sources, and distribute 90% of their income as dividends. As such, REIT market returns are largely a reflection of the performance of their collective real estate portfolio, which amounts to roughly $4.5 trillion as of mid-2022.[2] Identifying predictors of REIT returns not only sheds light on economic factors that drive risk premiums in REITs, but also offers potential to improve financial decision-making for both corporations and investors.

In this study, we perform a rigorous examination of the predictability of equity REIT market returns. We implement both in-sample and out-of-sample forecasting tests, paying close attention to the consistency and reliability of predictors, and then assess the benefits of using forecasting models in asset allocation decisions. Notably, we find that the traditional predictors of broad stock

[1]An inexhaustive list includes the bond market (Fama and Bliss, 1987; Campbell, 1991; Cochrane and Piazzesi, 2005; Diebold and Li, 2006), the U.S. stock market (Fama and French, 1988; Goyal and Welch, 2003; Lewellen, 2004; Ang and Bekaert, 2007; Cochrane, 2008; Welch and Goyal, 2008, international stock markets (Hjalmarsson 2010), and foreign currency exchange markets (Hansen 1980; Fama, 1984; Bekaert and Hodrick,1992)

[2]See NAREIT's "REITs by the Numbers" report: https://www.reit.com/data-research/data/reits-numbers

market returns, such as the dividend yield, exhibit little forecasting power for REIT returns. Instead, we document substantial predictive power in several REIT-specific valuation and profitability ratios, as well as select economic indicators. In particular, we introduce a novel valuation metric called “paid-to-market”, defined as the ratio of REITs’ paid-in capital to equity market capitalization (market cap), and find it to be the single best predictor of equity REIT market returns. Not only does it outperform 36 other popular predictor variables at both the monthly and annual horizons, it also manages to predict returns consistently over time. Welch and Goyal (2008) show that many suggested forecasting variables fail to predict returns out-of-sample and/or across multiple horizons. We follow their procedure to assess consistent versus sporadic return predictability.

The results show that while the paid-to-market ratio performs exceptionally well immediately following REIT bear markets, it also consistently predicts returns throughout the sample period. Furthermore, we show that using the paid-to-market ratio to forecast the REIT risk premium enables a mean-variance investor to optimally time their exposure to risk, yielding annualized positive net utility gains of 188 basis points.[3]

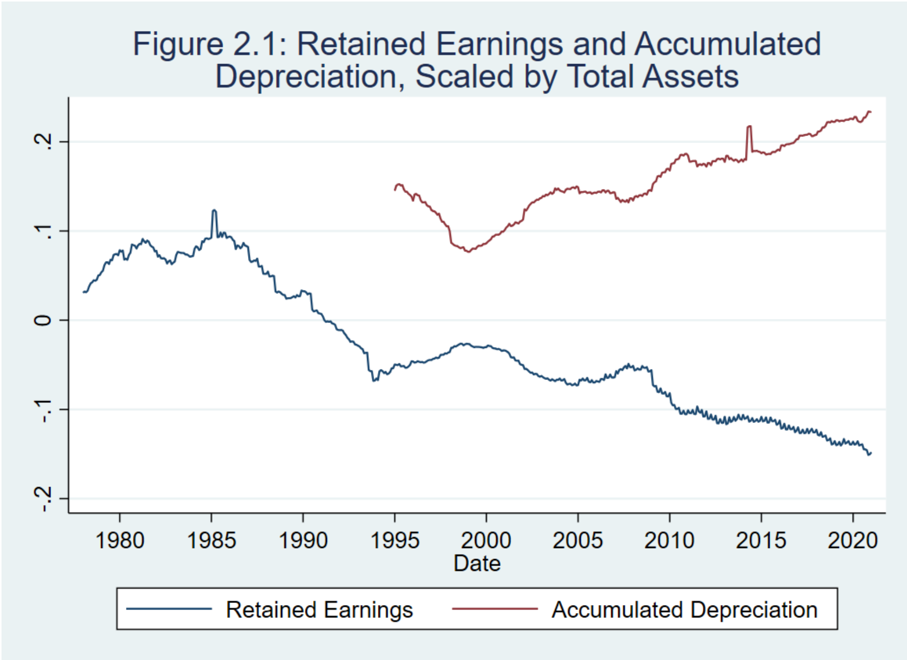
The paid-to-market ratio resembles the traditional book-to-market, but is more informative about future returns. Importantly, it avoids the bias of accumulated depreciation in the book value of equity, which is so large that many REITs report negative retained earnings and maintain payout ratios exceeding one. The mean (median) payout ratio of REITs in our sample is 1.48 (1.08), with REIT retained earnings becoming increasingly negative over time.

Figure 2.1 plots aggregate REIT retained earnings and accumulated depreciation, scaled by aggregate REIT assets[4]. As the REIT market aged, retained earnings became increasingly negative, not because REITs were losing money, but because their profits vastly understate their cash flows. This is widely recognized in industry practice, as Funds From Operations (FFO), which

[3]Net utility gains are derived from computing the certainty equivalent return following Neely et al. (2014) and Rapach et al. (2016).

[4]Compustat data for accumulated depreciation begins in 2001. We hand-collect additional data back to 12/31/1994 using the SEC’s Edgar. Note that in Figure 2.1, the spike in accumulated depreciation in the first quarter of 2014 is due to a data error in Compustat’s accumulated depreciation amount for GVKEY 138743. The spike in retained earnings in 1985 results from a data error with the retained earnings in GVKEY 005056.

adds back depreciation expense, is used as an alternative metric to net income. We observe accumulated depreciation beginning on 12/31/1994, after which it shows a clear relationship with retained earnings. Accumulated depreciation generally rises over time as properties age, and the rise in accumulated depreciation is almost perfectly offset by a reduction in retained earnings.



As depreciation expense ultimately flows through to retained earnings, we can remove its effects by calculating paid-in capital as book equity minus retained earnings and accumulated other comprehensive income (AOCI). The paid-to-market and the gross book-to-market (where accumulated depreciation is added back to book equity) contain similar information, but paid-to-market can be calculated across our entire sample time period. Because depreciation is a non-cash expense, paid-to-market represents a more fundamental-focused valuation ratio than book-to-market. Furthermore, any time variation in the risk premium will naturally be reflected in fluctuations of the paid-to-market ratio. As new equity is issued, it is recorded as paid-in capital. If risk premiums rise, then the market value of equity will fall relative to existing paid-in capital, causing an increase in the paid-to-market ratio. Therefore, an exceptionally high paid-to-market ratio may signal a high risk premium, thus predicting large future returns.

While Akinsomi et al (2016) argue that "successful return forecasting questions market efficiency," our results are consistent with an efficient market in which predictors reveal information about time-varying risk premiums. In general, we find that predictive power is greatest immediately after market sell-offs, particularly when the sell-off coincides with an economic recession. Our most successful forecasting models predict higher returns precisely when one might expect investors to be the most risk-averse and *require* high rates of return. For example, we find that high unemployment forecasts high REIT returns, suggesting that risk premiums become elevated when investors are especially concerned about broad economic conditions and/or their own individual livelihood and well-being. Furthermore, we find that paid-to-market fails to anticipate earnings surprises, which suggests that its predictability stems from a risk premium channel rather than a cash flow channel. From a practical perspective, our forecasts provide utility to investors by producing higher risk-adjusted returns, but fail to generate higher gross returns than a buy-and-hold strategy.

We contribute to the existing literature in several ways. To our knowledge, this is the first paper to analyze the paid-to-market ratio and highlight its potential as the single best predictor of equity REIT market returns. We show that it greatly improves on the traditional book-to-market ratio, yielding a notable annual out-of-sample R^2 statistic of 14.26%. For comparison, Rapach et. al. (2016) argue that aggregate short interest is the greatest predictor of stock returns with an annual out-of-sample R^2 of 13.24%. More broadly, this study adds to the growing literature on forecasting REIT returns. Relative to existing studies, our analysis considers a far greater number of predictor variables. Ling et al (2000) find predictability in REIT returns that would allow an investor to outperform a buy-and-hold strategy, but only in the absence of transaction costs. Patel et al. (2009) find that REIT prices tend to revert towards a discounted NAV, a phenomenon they attribute to time-variant risk premia in both private and public real estate markets. Serrano et al. (2009) study daily securitized real estate returns and find that REIT returns are generally more predictable than non-REIT stock returns. Akinsomi et al. (2016) find predictability in REIT returns that would allow an investor to outperform a buy-and-hold strategy. Their paper tests several multivariate model selection processes and finds dynamic model selection to be the preferred method of forecasting REIT returns.

Our study also contributes to the long-standing literature on return forecasting in other asset classes. Welch and Goyal (2008) take a comprehensive look at forecasting the risk premium in the broad stock market. They find that most popular predictors, such as dividend ratios, fail to predict returns *consistently* in out-of-sample forecasts. Moreover, the statistical significance of successful predictors are often driven by a select handful of years, such as the 1974 oil crisis. They conclude that stock returns are largely unpredictable. More recently, several papers have found evidence of stock return predictability. Neely et al. (2014), Lin (2018), and Dai et al. (2020) perform return forecasts using technical indicators. Rapach et al. (2016) argue that short interest is the single best predictor of aggregate stock returns. Jiang et al. (2019) find that management sentiment negatively predicts stock returns. We bridge the gap between market efficiency and return predictability, and show that returns are predictable because risk premiums vary over time.

The remainder of this paper is organized as follows: Section 2.2 discusses our data and variable selection. Section 2.3 presents the in-sample and out-of-sample results. Section 2.4 presents the utility gain results of our asset allocation exercise. Section 2.5 focuses on interpretations of the results and the implications for market efficiency. Section 2.6 concludes.

2.2 Introduction

We begin our analysis of the predictability of equity REIT returns by constructing a comprehensive dataset of predictor variables. Our dependent variable is the excess return of the NAREIT Equity REIT index. We incorporate economic, bond market, stock market, and REIT market variables, including all available variables from Welch and Goyal (2008). In constructing our REIT-specific variables, we rely on Compustat when aggregate data is not available from NAREIT. We begin with all firms in Compustat with an SIC code of 6798 and then narrow the sample to equity REITs using the list of equity REITs compiled by Feng et al. (2011.) The NAREIT return data starts in 1972, but REIT data in Compustat is sparse in the early 1970s. To avoid issues of small sample size, we begin our study in 1978, which is the first year in which the Compustat data provides at least 30 usable equity REITs. Our in-sample analysis covers the entire time period of 1978-2020. For our out-of-sample analysis, we train the model for 120 months and then make our first forecast in 1988. Table 2.1 presents detailed definitions of all variables used in this study, while table 2.2 reports summary statistics.

Table 2.1: Variable Definitions

i. REIT and Real Estate Variables

Variable Name	Description	Source
Paid-to-Market	Aggregate REIT paid-in-capital divided by aggregate REIT market capitalization. Paid-in-capital is common book equity minus retained earnings and AOCI	Compustat/Capital IQ
Gross Book-to-Market	Aggregate REIT common book equity plus accumulated depreciation divided by aggregate REIT market capitalization. Common book equity is total equity minus Preferred Stock.	Compustat/Capital IQ
Book-to-Market	Aggregate REIT common book equity divided by aggregate REIT market capitalization. Common book equity is total equity minus Preferred Stock.	Compustat/Capital IQ
Return on Equity	Aggregate REIT Net Income divided by aggregate REIT common equity	Compustat/Capital IQ
Net Margin	Aggregate REIT Net Income divided by aggregate REIT Revenue	Compustat/Capital IQ
REIT Return Variance	The variance of all available historical monthly returns on the NAREIT equity REIT index	CRSP, Computations
Equity Multiplier	Aggregate REIT assets divided by aggregate REIT common equity	Compustat/Capital IQ
Retained-to-Market	Aggregate REIT retained earnings divided by aggregate REIT market capitalization	Compustat/Capital IQ
Asset Turnover	Aggregate REIT revenue divided by aggregate REIT assets	Compustat/Capital IQ
Mortgage Rate	Current interest rate on 30-year mortgages	FRED
Dividend/Price	The log of total equity REIT dividends paid over the last 12 months minus the log of equity REIT prices	NAREIT
REIT Short Interest	REIT short interest, detrended and normalized following Rapach et al. (2016)	Compustat, Calculations
Housing Starts	The number of housing starts	FRED
Housing Starts per Capita	Housing starts divided by US population	FRED, Census Bureau
REIT Payout Ratio	Aggregate REIT dividends paid over the last 12 months divided by aggregate REIT net income, winsorized at top/bottom 1%	Compustat

ii. Stock Market Variables

Variable Name	**Description**	**Source**
Book-to-Market	The ratio of equity book value to market value for the Dow Jones Industrial Average	Amit Goyal
Shiller P/E ratio	The Cyclically Adjusted Price to Earnings Ratio	Robert Shiller
Net Equity Expansion	The ratio of net equity issuances to market capitalization (NYSE stocks only)	Amit Goyal
Dividend/Price	The log of total dividends paid over the last 12 months minus the log of total equity prices	Robert Shiller
Dividend/Yield	The log of total dividends paid over the last 12 months minus the log of total lagged equity prices	Robert Shiller
Percent Equity Issuing (1980-2008)	The ratio of equity issuances to total issuances	Jeffrey Wurgler
VIX Volatility Index (1990-2020)	S&P 500 option-implied volatility index (VIX)	CBOE
Dividend Payout Ratio	The log of total dividends paid over the last 12 months minus the log of total earnings	Robert Shiller
Return Variance	Sum of squared daily returns on the S&P 500	Amit Goyal
Investor Sentiment	The sentiment index comes from Jeffrey Wurgler's website	Jeffrey Wurgler

iii. Economic Variables

Variable Name	**Description**	**Source**
Long-term Treasury Return	The return on long-term US treasuries	Amit Goyal
Unemployment Rate	The number of unemployed persons as a percentage of the labor force	FRED
Term Spread	The difference in yields between long-term government bonds and the Treasury bills	FRED
Cay - post (1980-2019)	The consumption, wealth, income ratio	Martin Lettau
Cay - ante (1980-2019)	Following Welch and Goyal (2008), *cay*-ante is constructed to eliminate look-ahead bias	Calculated from Martin Lettau's data
Treasury Bill Rate	The annualized yield on three-month treasury bills	Amit Goyal
Consumer Confidence Index	The University of Michigan Consumer Sentiment Index	FRED
Long-term Yield	The yield on long-term US government bonds	Amit Goyal
Inflation Rate	The percent increase in the Consumer Price Index	Amit Goyal
Default Yield Spread	The difference in yields between Baa and AAA bonds	Amit Goyal
Default Return Spread	The default return spread is the difference in returns between long-term corporate bonds and long term government bonds	Amit Goyal

Table 2.2: Summary Statistics

This table presents the summary statistics and correlation matrix of variables used in this study. Data are monthly from 1978 and 2020, unless otherwise noted. See Table 2.1 for a detailed definition of each variable.

	Mean	Min	Max	StDev	Dates
Dependent Variable					
Excess Equity REIT Return	0.726	-31.82	31.00	4.921	1978-2020
REIT-Specific Variables					
Paid-to-Market	0.607	0.305	1.204	0.164	1978-2020
Gross Book-to-Market	0.705	0.446	2.388	0.172	1995-2020
Book-to-Market	0.532	0.303	1.116	0.150	1978-2020
Return on Equity	0.072	-0.004	0.195	0.030	1978-2020
Net Margin	0.120	-0.009	0.251	0.067	1978-2020
Return Variance	23.86	7.876	93.60	23.19	1978-2020
Equity Multiplier	2.769	2.176	4.188	0.422	1978-2020
Retained-to-Market	-0.032	-0.222	0.184	0.104	1978-2020
Asset Turnover	0.283	0.131	0.637	0.167	1978-2020
Mortgage Rate	7.804	2.670	18.44	3.479	1978-2020
Dividend/Price	-2.808	-3.481	-1.620	0.393	1978-2020
Cap Rate	0.066	0.032	0.112	0.021	1978-2020
REIT Short Interest	0.000	-1.831	2.929	1.000	1978-2020
Housing Starts	1375	478.0	2273	394.6	1978-2020
Housing Starts per Capita	0.005	0.002	0.010	0.002	1978-2020
REIT Payout Ratio	1.480	0.404	10.53	1.624	1978-2020
Stock Market Variables					
Book-to-Market	0.420	0.121	1.207	0.262	1978-2020
Shiller P/E Ratio	21.89	6.640	44.19	8.765	1978-2020
Net Equity Expansion	0.004	-0.056	0.046	0.020	1978-2020
Dividend/Price	-1.609	-1.955	-1.205	0.185	1978-2020
Dividend/Yield	-1.606	-1.958	-1.204	0.185	1978-2020
Percent Equity Issuing	0.161	0.021	0.635	0.109	1980-2008
VIX Volatility Index	19.57	9.510	59.89	7.720	1990-2020
Dividend Payout Ratio	-0.343	-0.540	0.599	0.149	1978-2020
Return Variance	0.003	0.000	0.073	0.006	1978-2020
Investor Sentiment	0.129	-1.547	2.933	0.714	1978-2020
Economic Variables					
Long-term Treasury Return	0.007	-0.112	0.152	0.032	1978-2020
Unemployment Rate	6.232	3.500	14.800	1.734	1978-2020
Term Spread	0.021	-0.037	0.046	0.015	1978-2020
Cay-post	0.003	-0.045	0.038	0.018	1980-2019
Cay-ante	0.002	-0.035	0.065	0.025	1980-2019
Treasury Bill Rate	0.043	0.000	0.163	0.036	1978-2020
Consumer Confidence Index	99.93	95.58	103.2	1.676	1978-2020
Long-term Yield	0.064	0.006	0.148	0.032	1978-2020
Inflation Rate	0.003	-0.019	0.015	0.004	1978-2020
Default Yield Spread	0.011	0.006	0.034	0.005	1978-2020
Default Return Spread	0.000	-0.098	0.074	0.016	1978-2020

We define paid-in-capital (PIC) as REIT common equity (CEQ) minus retained earnings (RE) and accumulated other comprehensive income (AOCI), as follows:

$$\text{Paid-in Capital (PIC)} = \text{CEQ} - \text{RE} - \text{AOCI}. \tag{2.1}$$

We calculate common equity as total equity minus the redemption value of preferred stock. In the quarterly Compustat file, the preferred stock amounts are often filled with the par value (usually \$0.01 per share) as opposed to the redemption value. We therefore only update the quarterly preferred stock amount if it does not contradict the beginning and end-of-year preferred stock amounts. We calculate aggregate paid-in-capital and aggregate market capitalization each month using only information available to the investor as of that month. While paid-in capital is available on a quarterly basis, we observe market capitalization on a monthly basis using CRSP data. We then calculate the ratio of paid-in capital to equity market capitalization (ME), "paid-to-market", as follows:

$$\text{Paid-to-Market (PTM)} = \frac{\text{PIC}}{\text{ME}}. \tag{2.2}$$

Because retained earnings are negative on average, paid-to-market is generally larger than book-to-market. We also include the standard book-to-market, the gross book-to-market (where accumulated depreciation is added to common equity), as well as retained earnings-to-market, as explanatory variables.

In addition to paid-to-market, we include several variables that potentially have predictive power for equity REIT returns. Because NAV is of interest to investors, and because REIT prices tend to revert towards a discounted NAV (Patel et al. 2009), we include several variables related to NAV estimation. We also include return on equity (ROE), as Bond and Xue (2017) find profitability (measured by return on equity) to have substantial predictive power in explaining the cross-section of REIT returns. A Dupont-style decomposition of return on equity allows us to study its pieces as well as their relation to NAV and REIT returns.

NAV is generally estimated by attaching an assumed capitalization rate (cap rate) to a property's Net Operating Income to back out an estimated asset value. In that spirit, we explore whether the Dupont composition of return on equity has predictive power for REIT returns. ROE can be decomposed into three pieces relevant to our analysis:

$$\text{ROE} = \frac{\text{Net Income}}{\text{Common Equity}} = \frac{\text{Net Income}}{\text{Revenue}} \times \frac{\text{Revenue}}{\text{Total Assets}} \times \frac{\text{Total Assets}}{\text{Common Equity}}. \tag{2.3}$$

The first two components, net profit margin and asset turnover, give us ROA:

$$\text{ROA} = \frac{\text{Net Income}}{\text{Total Assets}} = \frac{\text{Net Income}}{\text{Revenue}} \times \frac{\text{Revenue}}{\text{Total Assets}}. \tag{2.4}$$

Cap rates are calculated as net operating income divided by assets, so ideally we would test

$$\text{Cap Rate} = \frac{\text{Net Operating Income}}{\text{Total Assets}} = \frac{\text{Net Operating Income}}{\text{Revenue}} \times \frac{\text{Revenue}}{\text{Total Assets}}. \tag{2.5}$$

However, we do not directly observe Net Operating Income in our data. Instead, we proxy for net operating income using the most closely related Compustat item that is available. We set net operating income equal to $\hat{\text{NOI}}$, where $\hat{\text{NOI}}$ is either EBITDA, EBIT, or Net Income, in that order based on availability. We construct the cap rate as

$$\text{Cap}\hat{\text{Rate}} = \frac{\hat{\text{NOI}}}{\text{Total Assets}}. \tag{2.6}$$

We ultimately include return on equity, net margin, leverage, asset turnover, and $\text{Cap}\hat{\text{Rate}}$ as REIT-specific explanatory variables. Because depreciation accounting could cause problems in equity REIT net income, we test the return on equity, net margin, and earnings yield twice, once using net income and once using $\hat{\text{NOI}}$ in place of net income. While we report the metrics using net income, the unreported results using $\hat{\text{NOI}}$ are qualitatively similar in that these variables fail to serve as good predictors of equity REIT returns. Balance sheet bias from accumulated depreciation is a larger concern than income statement bias from depreciation expense, as annual expenses will occur each year. Net income would be understated relative to cash flows on a relatively consistent level every year. Accumulated depreciation, on the other hand, is the sum of all previous depreciation charges, and will decrease asset values by greater amounts in later years than in early ones (as shown in figure 2.1.)

Other notable variables include the dividend/price ratio and the dividend payout ratio. Equity REIT returns are largely tied to future dividends, so investors may expect future returns to be higher when the dividend/price ratio is high. We follow the literature in defining the dividend/price ratio as the log of dividends minus the log of prices. We define the dividend payout ratio as total dividends divided by total income. This definition allows us to verify that payout ratios average more than 100% in equity REITs. The median and mean payout ratios are 1.08 and 1.48, respectively. We also include equity REIT short interest, as Rapach et al. (2016) find short interest to be the single best predictor of stock returns. We follow their work in assuming a linear trend over time in the log of short interest, and then creating a normalized short interest index for equity REITs. By construction, normalized short interest has a mean of zero. Equity REIT short interest is generally lower than the aggregate stock short interest reported in Rapach et. al. (2016.) In our sample, REIT short interest peaks at 6.23% in 2008, while stock short interest peaks at 8.93% in their sample. The final dataset allows us to study the predictive power of 37 different variables. While the large number of explanatory variables enables to us to thoroughly examine potential predictors, it also raises concerns of data mining, which we address in Section 2.3.

2.3 Forecasting REIT Returns

In this section, we analyze the predictability of future equity REIT returns using various REIT market, stock market, and economic variables as predictors. Subsection 2.3.1 reports our in-sample results, and Subsection 2.3.2 provides our out-of-sample results.

2.3.1 In-Sample Results

For each forecasting variable, we regress the time series of future excess equity REIT returns on the contemporaneous predictor. We use the following standard predictive regression model:

$$r_{t:t+h} = \alpha + \beta x_t + \epsilon_{t:t+h}, \tag{2.7}$$

where $r_{t,t+h} = (1/h) \times (r_{t+1} + r_{t+2} + ... + r_{t+h})$, r_t is the excess return on the NAREIT equity REIT index, and x_t is the value of the forecasting variable observed at time t. Statistical inference in forecasting models is complicated by the Stambaugh (1999) bias and the use of overlapping observations. We therefore compute t-statistics using Newey-West (1987) standard errors and p-values using the wild bootstrapping procedure of Rapach et al. (2013). In choosing a lag length for the Newey-West standard errors, we follow Avino et al. (2020) as well as Rangvid (2006) and Ang and Bekaert (2007), all of whom use a lag length of $(h + 1)$, where h is the forecasting horizon in months. The statistical significance according to the bootstrapping procedure is largely in line with the Newey-West t-statistics.

Table 2.3 reports the results of Equation (2.7) over the sample period from 1978 to 2020 (except for the variables noted as having shorter time periods). Columns 1 to 4 present the results forecasting monthly returns, and columns 5 to 8 present the results forecasting annual returns. All of the stock market variables fail to predict equity REIT returns. Several of the failures are notable, given previous findings in the literature. While Rapach et al. (2016) find short interest to be the single best predictor of aggregate stock returns, short interest in REITs exhibits no ability to predict aggregate REIT returns. Welch and Goyal (2008) find that percent equity issuing predicts stock returns both in- and out-of-sample, but it fails to predict REIT returns. They also find the consumption, wealth, income ratio (*Cay*) successfully predicts stock returns, but only when look ahead bias is allowed (*cay*-post). In our equity REIT sample, *Cay* fails to predict REIT returns even when look ahead bias is allowed (*cay*-post and *cay*-ante both fail). In Welch and Goyal, the dividend/price ratio, dividend yield, and book-to-market all predict stock returns in-sample

Table 2.3: In-Sample Predictability of REIT Returns

This table reports in-sample estimates from the predictive regression model $r_{t:t+h} = \alpha + \beta x_t + \epsilon_{t:t+h}$, where $r_{t:t+h} = (1/h)(r_{t+1} + r_{t+2} + ... + r_{t+h})$, and r_t is the excess return on the NAREIT equity REIT index. Newey-West t-statistics are calculated using a lag length equal to the forecasting horizon plus one. P represents bootstrapped p-values, computed following Rapach et al. (2013). The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Monthly Return Forecasting				Annual Return Forecasting			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	β	R^2	T	P	β	R^2	T	P
REIT and Real Estate Variables								
Paid-to-Market	4.143	0.017	2.685***	0.002***	3.491	0.166	3.245***	0.001***
Gross Book-to-Market	6.261	0.025	2.351**	0.005***	5.275	0.242	3.213***	0.002***
Book-to-Market	3.274	0.008	2.152**	0.016**	2.917	0.095	2.724***	0.006**
Return on Equity	-12.268	0.004	-2.176**	0.023**	-10.773	0.056	-1.852*	0.054
Net Margin	-5.435	0.004	-1.748*	0.064	-4.571	0.045	-1.789*	0.091
REIT Return variance	0.018	0.005	1.864*	0.039*	0.015	0.063	2.363**	0.024**
Equity Multiplier	-0.196	-0.002	-0.422	0.304	-0.196	0.001	-0.484	0.277
Retained-to-Market	-2.649	0.001	-1.221	0.12	-1.981	0.019	-1.220	0.107
Asset Turnover	0.052	-0.002	0.043	0.492	-0.062	-0.002	-0.065	0.413
Mortgage Rate	-0.040	-0.001	-0.691	0.33	-0.016	0.000	-0.362	0.409
Dividend/Price	0.521	0.000	0.957	0.16	0.390	0.010	0.877	0.201
REIT Short Interest	-0.047	-0.002	-0.132	0.475	-0.040	-0.001	-0.134	0.469
Cap Rate	-2.998	-0.002	-0.292	0.402	-0.419	-0.002	-0.054	0.459
Housing Starts	0.000	-0.002	0.106	0.482	0.000	0.001	-0.368	0.304
Housing Starts per Capita	16.587	-0.002	0.107	0.473	-35.946	0.000	-0.341	0.295
REIT Payout Ratio	-0.014	-0.001	-2.609***	0.027*	0.009	0.005	4.868***	0.034*
Stock Market Variables								
Book-to-Market	0.415	-0.001	0.525	0.205	0.595	0.010	1.049	0.108
Shiller P/E Ratio	-0.003	-0.002	-0.139	0.152	-0.022	0.017	-1.328	0.024**
Net Equity Expansion	10.891	0.000	0.688	0.206	14.283	0.039	1.225	0.11
Dividend/Price	0.638	-0.001	0.595	0.224	0.702	0.007	0.865	0.164
Dividend/Yield	0.806	-0.001	0.757	0.332	0.667	0.006	0.823	0.328
Percent Equity Issuing	-1.903	0.000	-0.893	0.156	-0.068	-0.003	-0.044	0.448
VIX Volatility Index	-0.021	-0.002	-0.283	0.403	0.036	0.028	1.227	0.048*
Dividend Payout	1.176	-0.001	0.373	0.282	2.413	0.064	2.04**	0.034*
Return Variance	-45.760	0.001	-0.447	0.383	32.138	0.011	1.598	0.063
Investor Sentiment	-0.200	-0.001	-0.804	0.179	-0.238	0.013	-1.132	0.098
Economic Variables								
Long-term Treasury Return	25.959	0.027	3.06***	0.000***	2.717	0.002	1.817*	0.004***
Unemployment Rate	0.341	0.013	2.741***	0.008**	0.296	0.117	3.119***	0.003***
Term Spread	23.778	0.003	1.583	0.025**	31.480	0.106	3.085***	0.000***
Cay-post	-14.000	0.000	-1.333	0.133	-2.208	-0.001	-0.298	0.452
Cay-ante	-5.759	-0.001	-0.811	0.289	-1.268	-0.002	-0.234	0.454
Treasury Bill Rate	-7.431	0.001	-1.252	0.159	-5.741	0.020	-1.320	0.131
Consumer Confidence Index	-0.112	0.000	-0.606	0.184	-0.175	0.042	-1.510	0.032*
Long-term Yield	-4.581	-0.001	-0.716	0.417	-0.715	-0.002	-0.147	0.447
Inflation Rate	-71.115	0.001	-0.977	0.449	-34.650	0.006	-1.168	0.384
Default Yield Spread	25.257	-0.001	0.274	0.388	62.871	0.039	1.549	0.093
Default Return Spread	-1.263	-0.002	-0.037	0.467	7.259	0.004	1.275	0.134

over their full time period; however, all of these metrics fail to predict REIT returns in-sample. This suggests the determinants of REIT returns may be independent of the determinants of stock returns. This finding is of particular interest to practitioners that view REITs as alternative assets. The failure to predict REIT returns using traditional stock market indicators also motivates further analysis into usage of REIT-specific predictors.

Paid-to-market proves to be one of the most statistically significant variables in-sample. The positive coefficient suggests future REIT returns are high when the paid-to-market is high. This is consistent with the notion that investors pay capital into a REIT with the expectation of receiving a certain rate of return. If required rates of return increase, the market value of REIT shares will fall, and investors will experience higher future returns. A high paid-to-market indicates that the risk premium has risen since investors initially purchased shares from the REIT. Paid-to-market is a far superior metric to the book-to-market, as it reduces the noise in book values created by accumulated depreciation. Accumulated depreciation ultimately flows through to retained earnings, which has no ability to predict REIT returns (as evidenced by the near-zero R^2 on retained-to-market). The book-to-market has roughly half the predictive power of paid-to-market (as measured by R^2). Gross book-to-market, calculated by adding accumulated depreciation to book equity, has even better predictive power than the paid-to-market, but is used over a shorter time period due to data availability. The success of gross book-to-market suggests that paid-to-market's improvement over book-to-market results from its connection to accumulated depreciation.

The term spread successfully predicts REIT returns at the annual horizon, but not at the monthly horizon. This result parallels the findings of Rapach et al. (2016) for aggregate stock returns. An inverted yield curve has long been a harbinger of an economic recession, and the positive relationship between term spread and future REIT returns confirms that a steep yield curve is associated with higher future returns.

Other variables that are successful in-sample predictors of equity REIT returns include return on equity, the long-term Treasury return, and the unemployment rate. Low return on equity is associated with high future returns. Larger long-term Treasury returns forecast higher future REIT returns. Given that we are testing 37 potential predictor variables, some may present as statistically significant by mere chance. To address potential data-mining issues, we perform out-of-sample forecasts in Section 2.3.2. Note that the return on equity and long-term treasury results are not robust to out-of-sample forecasting tests.

The coefficient on the unemployment rate is positive and statistically significant. That is, a high unemployment rate forecasts high future excess REIT returns. This may initially seem counter-intuitive, as we tend to associate bull markets with a healthy economy. However, this phenomenon can be explained by a time-varying risk premium. At times when the unemployment rate is high, investors lack job security, and they are only willing to take risk in the REIT market if they are compensated with higher expected returns. In Section 2.3.2, we show that the predictive power of the unemployment rate is entirely contained to the Global Financial Crisis (GFC) and the Covid-19 crisis. This might indicate that risk premiums become elevated at times when investors are worried about the stability of their livelihood or general well-being (i.e., risk aversion is high). In this view, forecasting success comes not from market inefficiencies but rather predictor variables, like the unemployment rate, that reflect rational time-varying risk premiums.

2.3.2 Out-of-Sample Results

Table 2.4 reports our out-of-sample forecasting results. We begin our out-of-sample analysis in 1988, allowing for 10 years of previous data to be used in estimating parameters. In each month t, the log excess return for the following period is forecast to be

$$\hat{r}_{t:t+h} = \hat{\alpha}_t + \hat{\beta}_t x_t, \tag{2.8}$$

where $\hat{\alpha}_t$ and $\hat{\beta}_t$ are estimated using all data available through time t. The out-of-sample R^2 is calculated as

$$R^2 = 1 - \frac{MSE_f}{MSE_h}, \tag{2.9}$$

where MSE_f is the mean squared error of the forecasting model and MSE_h is the mean squared error of the historical mean model. In the historical means model, the next month excess return is expected to be the mean of all previous excess returns.

We additionally report the mean squared forecasting error (MSFE) as well as MSFE-adjusted. MSFE-adjusted is the Clark and West (2007) t-statistic used for testing the null hypothesis that the forecasting model is no better at predicting returns than the historical mean. Because we are interested in knowing whether the prediction model provides a *better* forecast than the historical mean, the significance levels for this test are one-sided. The MSFE-adjusted t-statistic is constructed by first computing the time series variable f, as follows:

$$f_t = (r_{t:t+h} - \bar{r}_{t:t+h})^2 - (r_{t:t+h} - \hat{r}_{t:t+h})^2 + (\bar{r}_{t:t+h} - \hat{r}_{t:t+h})^2. \tag{2.10}$$

We then regress f on a constant and compute the t-statistic using Newey-West standard errors. We report the Clark and West (2007) t-statistic along with statistical significance in columns 3 and 6 of Table 2.4.

At the monthly horizon, six variables have positive out-of-sample R^2 and are statistically significant at the 10% level: paid-to-market, gross book-to-market, book-to-market, return on equity, long-term Treasury returns, and the unemployment rate. At the annual horizon, the long-term Treasury return fails to predict REIT returns whereas the term spread succeeds. Again, paid-to-market is the single best predictor of REIT returns, with out-of-sample R^2 statistics of 1.64% and 14.12% at the monthly and annual horizons, respectively. The gross book-to-market has a slightly higher monthly R^2 but a lower Clark and West (2007) t-statistic. The gross book-to-market suffers from an incomplete time period, leading to a higher mean squared forecasting error over the more volatile 1995 to 2020 period, as well as a lower t-statistic. Across the full sample period, the overall next-best predictor is the unemployment rate, with monthly and annual out-of-sample R^2 statistics of 1.06% and 8.13%, respectively.

Table 2.4: Out-of-Sample Predictability of REIT Returns

This table reports out-of-sample forecasting results for potential predictors of REIT returns. MSFE is the mean squared forecast error. MSFE-adj is the Clark and West (2007) test statistic used for testing whether the forecasting model produces smaller squared forecasting errors than the historical means model. The critical values for this one-sided test statistic are 1.28, 1.65, and 2.33. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Monthly Return Forecasting			Annual Return Forecasting		
	(1)	(2)	(3)	(4)	(5)	(6)
	R^2	$MSFE$	$MSFE\text{-}Adj$	R^2	$MSFE$	$MSFE\text{-}Adj$
REIT and Real Estate Variables						
Paid-to-Market	0.0164	26.2182	2.317**	0.1412	2.0349	2.285**
Gross Book-to-Market	0.0189	39.9729	1.874**	0.1104	3.0821	1.6*
Book-to-Market	0.0069	26.4710	1.555*	0.0526	2.2449	1.688**
Return on Equity	0.0046	26.5330	1.69**	0.0442	2.2648	2.043**
Net Margin	0.0003	26.6471	0.9017	-0.0624	2.5175	-0.5909
REIT Return Variance	-0.0437	27.8190	-0.2550	-0.1558	2.7388	1.443*
Equity Multiplier	-0.0035	26.7479	0.0471	-0.0686	2.5322	-0.4799
Retained-to-Market	-0.0046	26.7776	0.0484	-0.1055	2.6197	-1.3944
Asset Turnover	-0.0052	26.7931	-0.5313	-0.1059	2.6204	-2.7385
Mortgage Rate	-0.0051	26.7907	-1.0822	-0.0635	2.5201	-2.6378
Dividend/Price	-0.0052	26.7918	-0.2083	-0.0938	2.5917	-2.1390
Cap Rate	-0.0056	26.8033	-1.3093	-0.0900	2.5829	-2.3582
REIT Short Interest	-0.0090	26.8955	-0.9431	-0.1609	2.7508	-2.4289
Housing Starts	-0.0140	27.0269	-0.4227	-0.1071	2.6234	-0.8845
Housing Starts per Capita	-0.0147	27.0471	-0.4318	-0.1196	2.6530	-1.0193
REIT Payout Ratio	-0.0886	29.0172	-0.8121	-2.8989	9.2388	0.9812
Stock Market Variables						
Book-to-Market	-0.0029	26.7318	0.0605	-0.0563	2.5029	0.0974
Shiller P/E Ratio	-0.0054	26.7984	-0.2348	-0.1331	2.6851	0.0292
Net Equity Expansion	-0.0073	26.8502	-0.7063	-0.0444	2.4749	-0.2584
Dividend/Price	-0.0076	26.8561	0.2417	-0.1250	2.6657	-0.0680
Dividend/Yield	-0.0079	26.8638	0.4657	-0.1224	2.6596	-0.1109
Percent Equity Issuing	-0.0084	14.8115	-0.9038	-0.0344	2.5589	-2.8060
VIX Volatility Index	-0.0305	36.3521	-0.5247	-0.0614	3.0528	-0.9491
Payout Ratio	-0.0316	27.4956	-0.7570	-0.0311	2.4433	-0.1759
Return Variance	-0.0312	27.4859	-0.6072	0.0011	2.3669	0.7727
Investor Sentiment	-0.0019	26.7058	-1.2404	-0.0066	2.3851	-0.3254
Economic Variables						
Long-term Treasury Return	0.0135	26.2959	1.661**	-0.0042	2.3796	0.3807
Unemployment rate	0.0106	26.3727	2.117**	0.0813	2.1769	2.238**
Term Spread	0.0020	26.5998	0.9104	0.1022	2.1274	2.746***
Cay-post	-0.0002	25.8635	0.8750	-0.0349	2.4523	-0.8999
Cay-ante	-0.0038	25.9573	-1.1769	-0.0662	2.5263	-2.4092
Treasury Bill Rate	-0.0063	26.8210	-0.0086	-0.0276	2.4349	-0.2815
Consumer Confidence Index	-0.0057	26.8065	-0.4749	0.0069	2.3532	0.7748
Long-term Yield	-0.0081	26.8715	-0.9729	-0.0792	2.5574	-2.5001
Inflation Rate	-0.0075	26.8539	-0.1957	-0.0059	2.3837	-0.6735
Default Yield Spread	-0.0137	27.0191	-1.0908	0.0045	2.3589	0.5396
Default Return Spread	-0.0322	27.5140	-1.8077	-0.0038	2.3786	0.3393

Welch and Goyal (2008) show that statistical significance in forecasting often results from a single event. In their study, the 1974 oil crisis explained the entire statistical significance of several predictor variables. They propose graphing the time series difference between the cumulative squared prediction error of the forecasting model and that of the historical means model. Positive out-of-sample R^2 and t-statistics occur when the model provides lower forecasting errors than the historical mean, and these graphs allow researchers to visually examine precisely when this goal is achieved. The line drifts upward (downward) when the forecast provides better (worse) predictions than the historical mean. A variable may be considered a good predictor when the line consistently drifts upward over time. The visual depiction makes it apparent which variables exhibit statistical significance solely due to a single event and enables us to address concerns of spurious results and data mining.

In Figures 2.2 to 2.13, we present the graphs of the time series difference in cumulative squared prediction error (labeled *PE diff*) for each forecasting variable that has statistically significant out-of-sample performance (at the 10% level). To highlight how the forecasts perform through market cycles, bear market periods are shaded in blue and recessions in grey. For the purposes of this graph, bear markets are defined as months in which excess return in the previous one, two, three, four, five, or six months is less than negative 20%. Additionally, we plot the out-of-sample return forecast minus the historical mean. The red line is greater than zero when excess returns are predicted to be higher than the historical mean. We scale *PE diff* by dividing it by 100 in order to avoid the need for a secondary y-axis. The numeric value of *PE diff* is not immediately interpretable or relevant. The relevance of *PE diff* lies in its direction: the line drifts upwards when the model is performing well. Because *PE diff* represents the cumulative predictive power of a model, a predictor variable with negative out-of-sample R^2 will have negative *PE diff* at the end of the time period.

Figure 2.2: Return on Equity Squared Prediction Error, Monthly Horizon

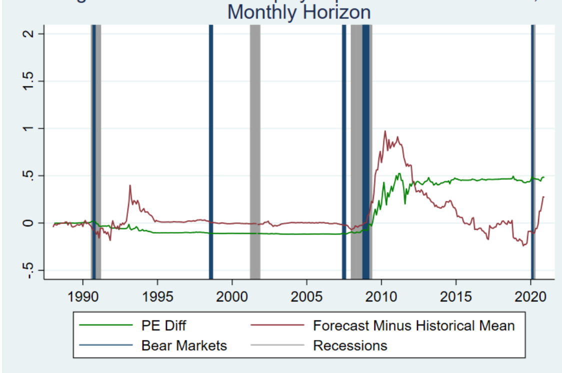
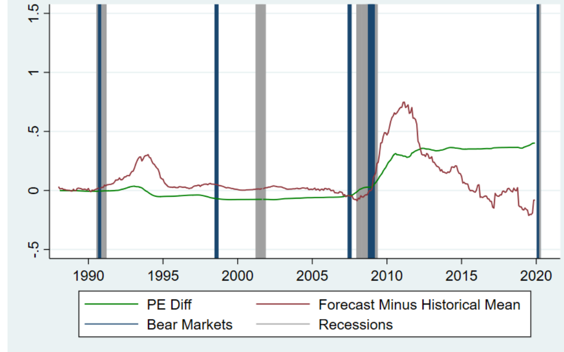


Figure 2.3: Return on Equity Squared Prediction Error, Annual Horizon



We begin our presentation of the Welch and Goyal (2008) style graphs by showing how they can reveal misleading statistical significance, and then move on to the more successful forecasting variables. Figures 2.2 and 2.3 present various aspects of the forecasting performance when using the return on equity as a predictor variable. While return on equity is statistically significant at the 5% level at both the monthly and annual horizons, the figures show that its predictive power is driven entirely by the 2009 to 2013 time period. Prior to 2009, the metric is largely useless, as it forecasts returns roughly equal to the historical mean. Therefore, one may reasonably conclude that return on equity is not a consistent predictor of REIT returns.

Figure 2.4: Long Term Treasury Return Squared Prediction Error, Monthly Horizon

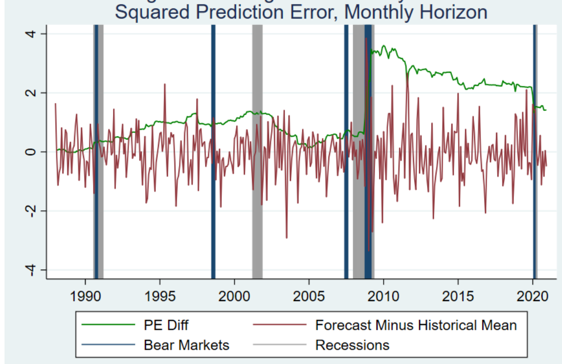


Figure 2.4 illustrates the failure of long-term Treasury returns to consistently forecast REIT returns. *PE diff* drifts downward for almost the entirety of the 2002 to 2020 time period, with the exception of the GFC. Furthermore, the predictions of the long-term treasury return are sporadic: return forecasts are highly positive in one month and then highly negative in the next month, depending on the size and sign of long-term treasury returns.

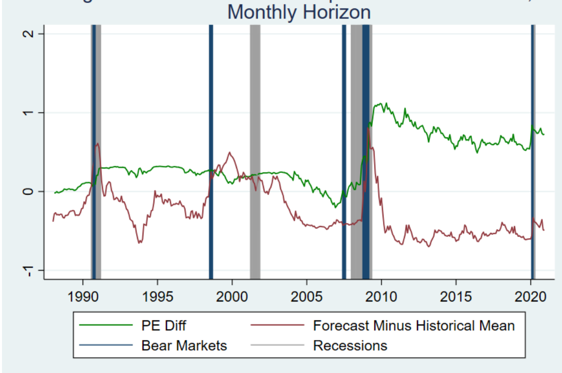


Figure 2.5: Book-to-market Squared Prediction Error, Monthly Horizon

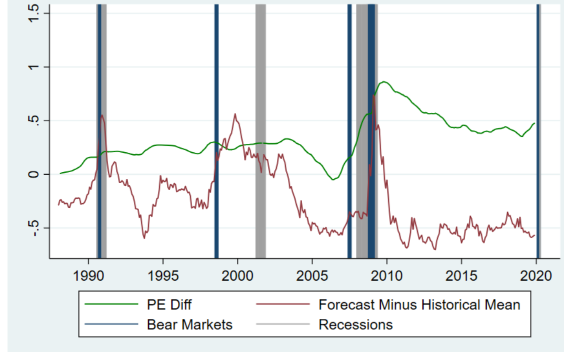


Figure 2.6: Book-to-market Squared Prediction Error, Annual Horizon

Figures 2.5 and 2.6 show the forecasting performance when using the book-to-market ratio as a predictor. Book-to-market performs well until 2010, after which it underestimates future REIT returns. The failure of the book-to-market in later years is potentially caused by noise in retained earnings (through accumulated depreciation.) Figure 2.1 shows the negative retained earnings in REITs averaging over 10% of assets after 2010. This leads the book-to-market in REITs to be biased downward, particularly in the later years of our sample, causing the book-to-market to underestimate future returns in later years.

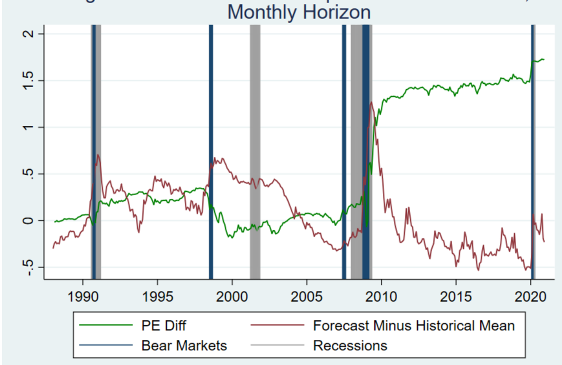


Figure 2.7: Paid-to-market Squared Prediction Error, Monthly Horizon

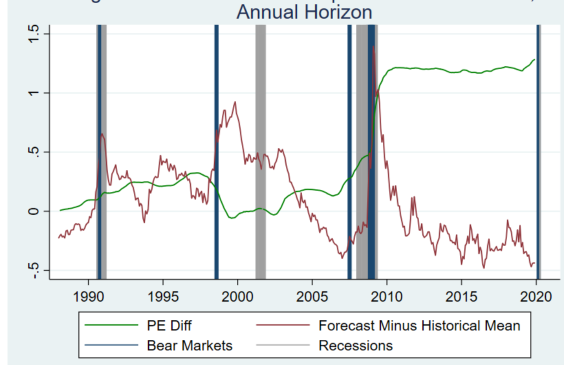


Figure 2.8: Paid-to-market Squared Prediction Error, Annual Horizon

In Figures 2.7 and 2.8, we show the performance when using the paid-to-market ratio as a predictor of REIT returns. An ideal forecasting variable is one that exhibits consistency in predictive power over time, which is what we find with the paid-to-market. At the monthly forecasting horizon in particular, *PE diff* rises steadily throughout the entire sample period, with the exception of the 1998 to 2000 period. Notably, the paid-to-market ratio generally performs well immediately after bear markets. Following the 1990 market decline, paid-to-market correctly predicts higher-than-average future returns. While the signal predicts high returns following the August 1998 bear market, these returns do not materialize, perhaps because the REIT market decline occurred more than 2 years prior to the early 2000s recession. Apart from the failed buy signal in 1998 and 1999, *PE diff* has an almost exclusively positive trend, indicating that the predictions of the paid-to-market consistently outperform the historical mean. Following the bear markets of 2007 and late 2008 to early 2009, we observe paid-to-market forecasting high future excess returns. These predictions were successfully realized as REIT prices swiftly recovered, leading to a dramatic jump in *PE diff*. The model continues to perform well throughout the 2010s. The quantitative results of our test statistics, combined with the evidence in Figures 2.7 and 2.8, strongly suggest that paid-to-market is the single best predictor of REIT returns yet documented in the literature. That is, it predicts returns consistently, across multiple time periods, and with high out-of-sample R^2.

Figure 2.9: Gross Book-to-Market Squared Prediction Error, Monthly Horizon

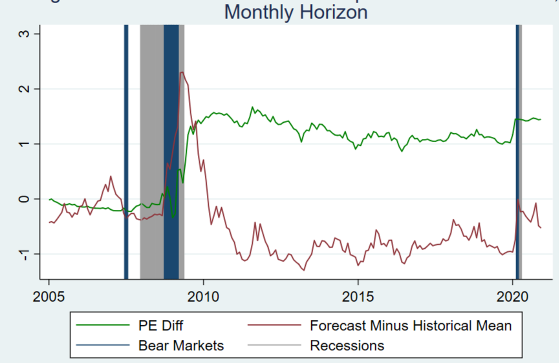
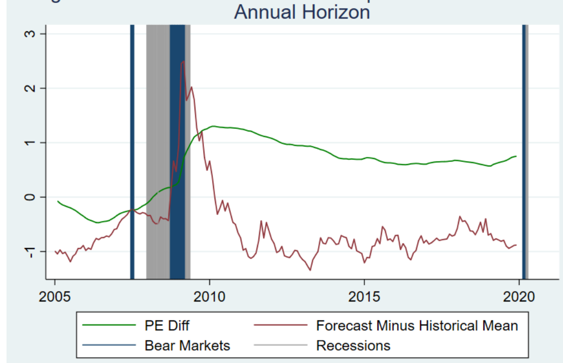


Figure 2.10: Gross Book-to-Market Squared Prediction Error, Annual Horizon



By comparison, the gross book-to-market also performs well as a predictor of REIT returns; however, the analysis is based on a shorter time period due to data constraints. As shown in Figures 2.9 and 2.10, the predictive power of gross book-to-market is largely driven by the GFC and COVID-19 crisis.

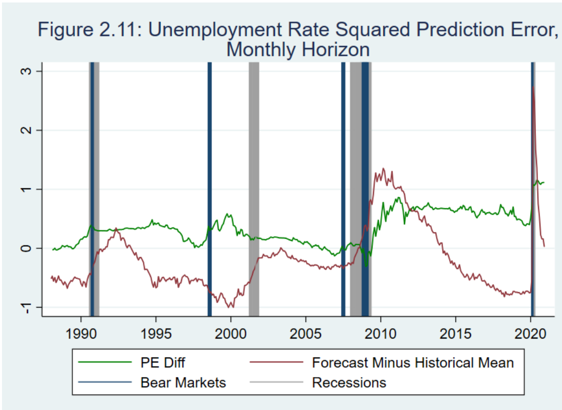


Figure 2.11: Unemployment Rate Squared Prediction Error, Monthly Horizon

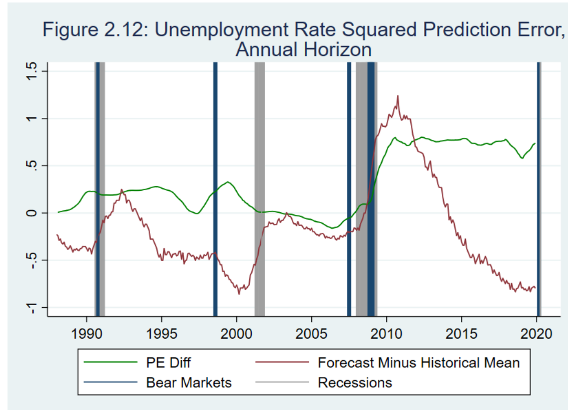
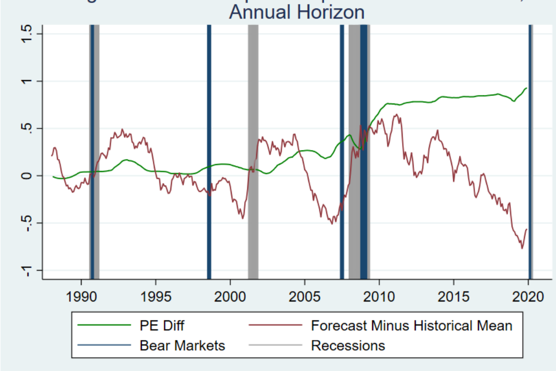


Figure 2.12: Unemployment Rate Squared Prediction Error, Annual Horizon

Figures 2.11 and 2.12 present the results of using the unemployment rate as a predictor of REIT returns. We find that its predictive power is driven entirely to two time periods: immediately following the Global Financial Crisis and immediately after the COVID-19 bear market. In both cases, increases in the unemployment rate forecast higher future returns. This finding may reflect the importance of labor markets for time-varying risk premiums in real estate. At times when investors are worried about losing their jobs (or with COVID-19, their lives) the risk premium is understandably high. During times of crisis, predictive regression models based on the unemployment rate or paid-to-market ratio anticipate high future returns, which is consistent with an efficient market with time-varying risk premiums. During the peak frenzies of the Global Financial Crisis and COVID-19 crisis, a predictive regression model would have indicated to investors that future returns would be high. Armed with this information, an investor may have simply responded, “they better be!”, for without higher expected returns, such an investor would likely prefer the comfort of holding the risk-free asset. We further explore the utility of our forecasting models in Section 2.4.

Figure 2.13: Term Spread Squared Prediction Error, Annual Horizon



Finally, figure 2.13 graphs the benefit of using the term spread as a predictor variable. Because an inverted yield curve has long been considered a harbinger of recession, one might expect the predictive power of the term spread to be driven by recession events. However, the model performs well throughout the entire 2002 to 2020 period (at the annual horizon). The term spread correctly predicts lower-than-average returns at the onset of the Great Financial Crisis and continues to perform well after the crisis is over. The success of the term spread model at the annual, but not monthly, horizon is consistent with the findings of Rapach et al. (2016) for aggregate stock returns.

2.4 Asset Allocation and Certainty Equivalent Return

In this section, we analyze the economic gains to a forecaster who uses each of the predictor variables to inform asset allocation decisions. Following Rapach et al. (2010) and Neely et al. (2014), we consider an investor that allocates her portfolio between equity REITs and risk-free treasuries while using a predictive regression model to forecast REIT returns. At the end of each month t, the investor allocates a percentage of her portfolio w_t to REITs, where the weight is determined as

$$w_t = 1 - \frac{1}{\gamma}\frac{\hat{r}_{t+1}}{\hat{\sigma}^2_{t+1}}, \tag{2.11}$$

where γ is the investor's coefficient of relative risk aversion, $\hat{r}_{t+1}$ is the expected excess return from the forecasting model, and $\hat{\sigma}^2_{t+1}$ is the expected variance of the excess return. We assume the portion of assets not invested in REITs earns the risk-free rate. We allow the investor to rebalance her portfolio monthly and rely on monthly forecasts. We assume the coefficient of relative risk aversion is 3. The expected variance of the excess return is calculated using a rolling 60-month window of past excess returns. We restrict w_t to values between -0.5 and 1.5.

The investor realizes an average utility, or certainty equivalent return (CER) of

$$CER = \bar{R}_p - 0.5\gamma\hat{\sigma}_p^2, \tag{2.12}$$

where $\bar{R}_p$ and $\hat{\sigma}_p^2$ are the mean and variance of the investor's portfolio, respectively. The CER represents the risk-free rate that an investor would be willing to accept instead of the risky portfolio. Higher CERs are associated with better portfolios that provide the investor with more utility. The CER penalizes portfolios that experience high volatility, and the weight that an investor places into risky assets is lower when past volatility is high. These characteristics assuage concerns that the paid-to-market may only provide utility by instructing an investor to take more risk during economic crises when volatility is high. To assess utility gains, we forecast $\hat{r}_{t+1}$ using each forecasting variable and then repeat the procedure while forecasting $\hat{r}_{t+1}$ using the historical means model. CER gains are calculated as the difference between the CER using the forecasting variable and the CER using the historical means model.

Column 1 of Table 2.5 presents the gross annualized CER gain of a forecasting model based on each predictor variable. The historical mean model has a CER of 5.52%, while the CER of the paid-to-market model is 7.44%, imputing a gross CER gain of 1.92%. Column 2 reports the Sharpe ratio for each portfolio, while column 3 reports the average monthly turnover of the portfolio. The paid-to-market portfolio has the highest Sharpe ratio of any variable with availability during the full sample period. The gross book-to-market performs well, but its results are based on the shorter time period.

Column 4 reports the CER gain after we incorporate transaction costs of 25 basis points. Portfolios with higher turnover than the historical mean model portfolio will have lower net CER gains relative to their gross CER gains. Most portfolios using predictive regression forecasts

Table 2.5: Portfolio Performance Results

This table presents the performance statistics for a strategy that allocates to a combination of US treasuries and REITs using either a predictive regression or a historical mean model. The ΔCER reports the CER of a predictive regression in excess of the historical mean model. The ΔCER^T is the ΔCER less transaction costs (25 basis points). Sharpe is the average monthly return over monthly standard deviation. The relative risk-aversion coefficient is set to three.

	(1)	(2)	(3)	(4)
	CER	Sharpe	Turnover	CER^T
Historical Mean Model	0.0552	0.1224	0.0213	0.0531
	ΔCER	Sharpe	Turnover	ΔCER^T
REIT and Real Estate Variables				
Paid-to-market	0.0192	0.1509	0.0374	0.0188
Gross Book-to-Market	0.0328	0.1080	0.1214	0.0312
Book-to-market	0.0119	0.1394	0.0490	0.0114
Return on Equity	0.0036	0.1277	0.0360	0.0032
Net Margin	-0.0071	0.1010	0.0721	-0.0087
Return Variance	-0.0114	0.1094	0.0712	-0.0123
Equity Multiplier	-0.0001	0.1205	0.0455	0.0012
Retained-to-Market	-0.0072	0.1105	0.0510	-0.0079
Asset Turnover	-0.0137	0.0945	0.0731	-0.0153
Mortgage Rate	-0.0014	0.1230	0.0166	-0.0013
Dividend/Price	-0.0009	0.1145	0.0446	-0.0017
Cap Rate	-0.0024	0.1164	0.0423	-0.0030
REIT Short Interest	-0.0022	0.1197	0.0277	-0.0024
Housing Starts	0.0109	0.1370	0.0470	0.0102
Housing Starts per Capita	0.0086	0.1327	0.0615	0.0074
REIT Payout Ratio	-0.0033	0.1166	0.0517	-0.0042
Stock Market Variables				
Book-to-Market	-0.0118	0.0942	0.0548	-0.0123
Shiller P/E Ratio	-0.0156	0.0913	0.0684	-0.0167
Net Equity Expansion	0.0003	0.1205	0.0439	-0.0003
Dividend/Price	-0.0288	0.0599	0.0679	-0.0290
Dividend/Yield	-0.0279	0.0588	0.0685	-0.0282
Percent Equity Issuing	0.0049	0.1764	0.0143	0.0051
VIX Volatility Index	0.0095	0.1435	0.1203	0.0061
Dividend Payout	-0.0055	0.1125	0.0477	-0.0063
Return Variance	-0.0087	0.1108	0.0770	-0.0104
Investor Sentiment	0.0004	0.1233	0.0242	0.0003
Economic Variables				
Long-term Treasury Return	0.0076	0.1352	0.6979	-0.0129
Unemployment Rate	0.0047	0.1242	0.0872	0.0034
Term Spread	-0.0121	0.1028	0.0520	-0.0131
Cay-ante	-0.0062	0.1260	0.0435	-0.0070
Cay-post	0.0044	0.1435	0.0372	0.0039
Treasury bill rate	-0.0115	0.1140	0.0092	-0.0112
Consumer Confidence Index	-0.0212	0.0884	0.0618	-0.0225
Long-term Yield	-0.0027	0.1226	0.0095	-0.0024
Inflation Rate	-0.0130	0.1096	0.1485	-0.0169
Default Yield Spread	-0.0317	0.0708	0.0740	-0.0334
Default Return Spread	-0.0362	0.0753	0.1040	-0.0391

have higher turnover than the historical mean model. This results from the historical mean model providing a less volatile estimate of future returns. After accounting for transaction costs, the CER gain of paid-to-market is 1.88%. In economic terms, an investor would be willing to pay 1.88% per year to have access to a predictive regression forecast based on paid-to-market. The results of this exercise show that the paid-to-market ratio contains valuable information to investors, as a mean-variance optimizing investor can obtain substantial increases in utility through forecasting.

2.4.1 A Note on Multivariate Models

One potential next step in our study would be to combine predictor variables into multivariate models. Multivariate model selection processes generally involve testing every possible model and then selecting the best performing one, or a combination of the best ones, based on some criteria. In REITs, Ling et al. (2000) select the best model as the one with the highest in-sample R^2, while Akinsomi et al. (2016) test a variety of model selection processes and largely find dynamic model selection performs well. In both studies, the authors begin by testing every possible combination of variables. Ling et al. use a set of 16 predictor variables while Akinsomi et al. use 13. Given k predictor variables, the number of potential models is 2^k. In our study, we analyze 37 potential predictors of REIT returns over an out-of-sample period of 396 months. Implementing a model selection process would require running $396 \times 2^{37} \approx 54.4$ trillion regressions. This task is computationally infeasible, particularly when we consider an investor wishing to use such a process to forecast returns as early as the 1980s.

An obvious way to lighten the computational load would be to reduce the number of predictor variables. However, this leads to an ethical dilemma for researchers. How can one objectively choose which variables to include when one has prior knowledge about specific variables that perform well out-of-sample? In unreported results, we find that a forecasting model using paid-to-market, return on equity, long term treasury returns, and the unemployment rate has large predictive power and can significantly outperform a buy-and-hold investor by entering and exiting the REIT market at optimal times. However, we chose these four variables to include in the multivariate model precisely because they perform the best *out-of-sample*. A skilled trader would have no such ex-post knowledge and would likely not have chosen to use these forecasting variables. Deciding which variables to include in a model selection process will always be problematic, as the researcher can easily select variables to include based on their univariate out-of-sample performance. We don't directly take issue with the results of Ling et al. (2000) or Akinsomi et al. (2016), but we do urge caution for future studies. The variable inclusion problem is endemic to every study utilizing a model selection process, just as the data-mining issue is problematic in this study.

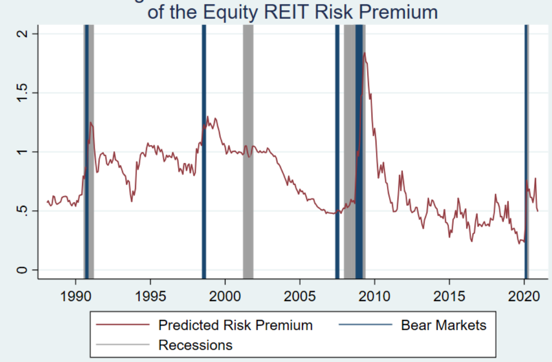
2.5 Prediction with the Paid-to-Market Ratio: Risk Premium Channel or Cash Flow Channel?

In an efficient market, the stock price represents discounted future cash flows. We explore whether the evidence indicates that the predictive power of paid-to-market comes through the risk premium channel (discount rate) or cash flow channel. If the paid-to-market ratio successfully forecasts returns because it contains timely information about REIT risk premiums, then we should find that predicted returns are high precisely when one might expect investors to *require* higher returns. The results generally support this view. Figure 2.7 shows that paid-to-market correctly anticipates larger returns immediately after bear markets, especially when the bear market coincides with a recession. The predictions of both the paid-to-market ratio and the unemployment rate are similar: when investors lack job security, their risk aversion is high, which leads to high risk premiums and high expected excess returns on real estate assets.

Through the cash flow channel, paid-to-market may predict returns by accurately forecasting earnings news. If this is this case, then we should observe that predicted returns are high at times when cash flows exhibit high growth potential. We examine this later in this subsection.

The ability to beat a buy-and-hold investor using a forecasting model may also point to market inefficiency. In our asset allocation exercise in Section 2.4, we showed that information contained in the paid-to-market has substantial value to a mean-variance optimizing investor. By adjusting the aggressiveness of their portfolio up and down over time, an investor can experience higher risk-adjusted returns through use of a forecasting model. However, CER exercises do not necessarily indicate that an active investor could experience larger total returns than a passive one over a long period of time. Long-term total return outperformance over a buy-and-hold investor would only be possible if a forecaster could enter and exit the market at optimal times to avoid losses. The paid-to-market offers no such opportunity. A forecasting model would only instruct an investor to exit the market if it predicted negative future returns. Figure 2.14 graphs the predicted risk premium according to the paid-to-market. At no time does the prediction ever become negative. Over the last decade, predicted returns have gradually fallen—but never below zero. If offered a binary choice between investing in REITs and investing in the risk-free asset, a return-maximizing investor would always be advised to invest in REITs.

Figure 2.14: Paid-to-market's Prediction of the Equity REIT Risk Premium



The recently low forecasted returns are in-line with several other predictors that have received attention in the news media. Aggregate Price/Earnings as well as the Shiller P/E have been elevated for years, but investors have continued realizing positive returns (notwithstanding 2022). Warning signs are too mild and too early to enable an investor to simply walk away from risky assets. Such is the challenge for the return forecaster: time in the market still beats timing the market when it comes to total returns, as we cannot predict exactly when prices will fall. Robert Shiller published the third edition of *Irrational Exuberance* in 2015, warning once again of potential bubbles. A long-term investor would have been sorely mistaken to divest completely from risky assets at that time. As of this writing, the S&P 500 has roughly doubled its 2015 average. Yet our model's predictions are largely in line with that of the Shiller P/E: we predict that future returns will be smaller on average, but not necessarily negative. The challenge in outperforming the passive investor is determining when to sell, and we find that predicting large positive returns is far easier than predicting large negative returns.

We do not view return predictability as a sign of irrationality, but instead argue that it is a sign of time-varying risk premia. Several studies have explored time-varying risk aversion as well as its connection to expected returns and investor sentiment. Guiso et al. (2018) examine portfolio and survey data and find risk aversion increased as a result of fear following the GFC. Cohn et al. (2015) conduct experiments in which they prime financial professionals with boom and bust scenarios, and find evidence for countercyclical risk aversion. Greenwood et al. (2014) find that investor expectations are positively correlated with past returns and negatively related to future expected returns. This relates to our findings, as paid-to-market successfully predicts high future returns when past returns have been poor.

If the paid-to-market simply indicates a higher required risk premium, then we would expect it to be correlated with other indicators of risk aversion. We might also expect it not to have much ability to predict earnings surprises. Table 2.6 reports correlations between statistically successful predictor variables and the other independent variables examined in this study. In the interest of readability, we do not report the full correlation table, but instead focus on the seven variables that showed predictive power in our out-of-sample tests. We view the unemployment rate, default yield spread, consumer confidence index, and sentiment index as containing information about levels of risk aversion. The paid-to-market is uncorrelated with the unemployment rate and default yield spread, but negatively correlated with the consumer confidence index and investor sentiment. The two significant negative correlations both support predictability through the risk aversion channel: when investors are pessimistic and lack confidence, the paid-to-market ratio and required risk premium is high. Moving to the gross-book-to-market we find additional, but admittedly incomplete, support for the risk aversion channel. The gross book-to-market is positively correlated with the

Table 2.6: Correlations Among Successful Predictors of REIT Returns

	PTM	GBTM	BTM	ROE	LTTR	UR	TS
Statistically-Significant Predictors							
Paid-to-Market (PTM)	1.000	0.983***	0.688***	-0.520***	-0.004	-0.076	0.072
Gross Book-to-Market (GBTM)	0.983***	1.000	0.961***	-0.238***	0.017	0.161**	0.325***
Book-to-Market (BTM)	0.688***	0.961***	1.000	-0.093*	-0.004	0.105*	-0.127**
Return on Equity (ROE)	-0.520***	-0.238***	-0.093*	1.000	0.061	-0.150***	-0.271***
Long-term Treasury Return (LTTR)	-0.032	0.017	-0.004	0.061	1.000	0.058	-0.061
Unemployment Rate (UR)	-0.075	0.161**	0.105*	-0.150***	0.058	1.000	0.386***
Term Spread (TS)	0.072	0.325***	-0.127**	-0.271***	-0.061	0.386***	1.000
REIT and Real Estate Variables							
Net Margin	0.022	-0.297***	-0.405***	0.233***	-0.015	-0.611***	-0.286***
Return Variance	0.119**	-0.034	-0.152***	-0.496***	-0.028	0.540***	0.304***
Equity Multiplier	-0.068	0.092	0.203***	-0.026	0.022	0.156***	0.105*
Retained-to-Market	-0.313***	-0.057	0.460***	0.567***	0.029	0.190***	-0.278***
Asset Turnover	-0.377***	0.256***	0.361***	0.488***	0.061	0.370***	-0.049
Mortgage Rate	-0.217***	0.486***	0.478***	0.512***	0.051	0.274***	-0.197***
Dividend/Price	0.174***	0.847***	0.655***	0.385***	0.039	0.130**	-0.082
Cap Rate	-0.164***	0.523***	0.522***	0.523***	0.040	0.230***	-0.152***
REIT Short Interest	0.214***	0.114**	0.100**	-0.136***	-0.004	0.205***	0.159***
Housing Starts	-0.011	0.094	0.185***	0.389***	-0.049	-0.410***	-0.160***
Housing Starts per Capita	-0.052	0.189***	0.376***	0.448***	-0.033	-0.220***	-0.159***
REIT Payout Ratio	0.161***	0.076	-0.082	-0.636***	-0.003	0.388***	0.364***
Stock Market Variables							
Book-to-Market	-0.165***	-0.382***	0.501***	0.308***	0.027	0.441***	-0.211***
Shiller P/E Ratio	0.318***	0.113*	-0.285***	-0.279***	-0.046	-0.586***	-0.082
Net Equity Expansion	0.310***	0.377***	0.369***	-0.433***	-0.041	0.129**	0.152***
Dividend/Price	-0.292***	-0.150**	0.394***	0.355***	0.050	0.479***	-0.076
Dividend/Yield	-0.297***	-0.164**	0.390***	0.355***	0.043	0.479***	-0.075
Percent Equity Issuing	-0.196***	0.239***	0.241***	0.206***	-0.084	0.649***	-0.193***
VIX Volatility Index	0.528***	0.529***	0.423***	-0.0391	0.154***	0.275***	0.053
Dividend Payout Ratio	0.201***	0.520***	0.209***	-0.0191	0.001	0.314***	0.336***
Return Variance	0.122**	0.232***	0.038	-0.00271	0.162***	0.179***	0.059
Investor Sentiment	-0.263***	0.133*	-0.119**	0.359***	0.076	0.019	0.053
Economic Variables							
Cay-ante	-0.301***	0.432***	0.347***	0.523***	0.045	0.234***	-0.022
Cay-post	0.068	0.502***	0.285***	0.2151***	0.044	-0.087**	0.150***
Treasury Bill Rate	-0.197***	0.186***	0.483***	0.523***	0.023	0.078	-0.494***
Consumer Confidence Index	-0.120**	0.021	-0.250***	0.260***	-0.016	-0.630***	-0.085
Long-term Yield	-0.192***	0.492***	0.493***	0.472***	-0.002	0.269***	-0.099*
Inflation Rate	0.031	-0.009	0.353***	0.100*	-0.196***	0.004	-0.286***
Default Yield Spread	-0.074	0.306***	0.176***	0.301***	0.093*	0.561***	0.057
Default Return Spread	0.032	0.049	0.011	-0.046	-0.471***	0.037	0.095*

unemployment rate and default yield spread, while relatively uncorrelated with sentiment and consumer confidence. The picture is somewhat muddied by gross book-to-market's incomplete time period.

The correlation table, the forecasting power of the unemployment rate, and the timing of paid-to-market's success all support the risk aversion explanation over the market irrationality explanation. We further rule out market irrationality by testing paid-to-market's ability to predict analysts' forecast errors. If paid-to-market forecasts REIT returns because it can better predict growth in firm fundamentals, then we would expect positive earnings surprises when the paid-to-market is high. If the paid-to-market only signals a high required risk premium, then paid-to-market should fail to forecast earning surprises.

We begin our analysis by compiling analyst forecasts of FFO in the I/B/E/S database. We begin our analysis in 2000, as this is the first year when data is widely available. We focus on FFO instead of earnings per share, as FFO estimates are more common and applicable in REITs. We calculate forecasting error FE as

$$FE_{j,t} = \frac{ActualFFO_{j,t} - \overline{E(FFO_{j,t})}}{SharePrice_{j,t}}, \tag{2.13}$$

where $\overline{E(FFO_{j,t})}$ is the mean analyst forecast of FFO per share for firm j during quarter t. We construct FE so that a positive (negative) FE indicates a positive (negative) earnings surprise. We then calculate the mean of FE across all REITs in a given month. Because earnings announcements are quarterly, we ultimately test paid-to-market's ability to predict average forecasting errors over the next quarter and year in addition to the next month.

Analyst forecasting errors have been shown to be predictable (Boudt et al. 2015). If FE is predictable, then our analysis should also control for its determinants so that we can assess paid-to-market's ability to predict unexpected analyst errors. We start by modeling analyst forecasting errors as

$$\begin{aligned} FE_{j,t} =& \beta_0 + \beta_1 FEpos_{j,t-1} + \beta_2 FEneg_{j,t-1} + \beta_3 DISP_{j,t-1} + \beta_4 COV_{j,t-1} \\ &+ \beta_5 Size_{j,t-1} + \beta_6 Ret6_{j,t-1} + \beta_7 Ret12_{j,t-1} + \beta_8 EP_{j,t-1} + \epsilon_{j,t} \end{aligned}, \tag{2.14}$$

where $FEpos_{j,t-1}$ and $FEneg_{j,t-1}$ are the lagged positive and negative earnings surprises. $DISP_{j,t}$ is analyst dispersion, calculated as the standard deviation of analyst estimates. $COV_{j,t}$ is the log of the number of analysts covering the firm at time t, $Size_{j,t}$ is the log of market capitalization, $Ret6_{j,t}$ and $Ret12_{j,t}$ are previous 6- and 12- month stock returns, and $EP_{j,t}$ is the earnings-to-price ratio. The control variables come from Boudt et al. (2015), with some slight modifications (we use FFO in place of earnings). The lags of FE are motivated by findings of autocorrelation in analyst errors. Larger firms with greater analyst coverage tend to have lower forecast errors, while dispersion is positively related to forecasting errors. Firms with high past stock returns tend to have positive earnings surprises, and the earnings-to-price ratio is argued by Boudt et al. to contain characteristics of growth versus value firms.

We model expected analyst forecast errors as the predicted values from estimating Equation (2.14) and then calculate the cross sectional means $\overline{FE}$ and $\overline{\widehat{FE} - FE}$ at each month t. We then test paid-to-market's ability to predict forecast error using the following models:

$$\overline{FE}_{t:t+h} = \alpha_0 + \alpha_1 \times PTM_t + \epsilon_{t:t+h} \tag{2.15}$$

and

$$\overline{\widehat{FE} - FE}_{t:t+h} = \alpha_0 + \alpha_1 \times PTM_t + \epsilon_{t:t+h}, \tag{2.16}$$

where $\overline{FE}_{t:t+h}$ and $\overline{\widehat{FE} - FE}_{t:t+h}$ are the sums of $\overline{FE}$ and $\overline{\widehat{FE} - FE}$ over the future h months. We test monthly, quarterly, and annual horizons. Analysts' forecasting errors can contain extreme outliers, so we winsorize FE at the top and bottom 1% of its distribution, and utilize a least absolute deviations model in addition to an ordinary least squares model. The results of this exercise are presented in Table 2.7.

Table 2.7: Does Paid-to-Market Forecast Earnings Surprises?

This table reports results from a predictive regression model where FE is the analyst forecast error of FFO per share divided by share price. Models 1-3 predict mean forecast error and mean unexpected forecast error in the following month, while models 4-6 predict mean error over the following 3 months and models 7-9 predict over the following year. Models 2, 5, and 8 predict analyst forecast error using ordinary least squares, while models 3, 6, and 9 predict analyst error using least absolute deviation. Newey-West t-statistics are in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$\overline{FE}$	$\overline{\widehat{FE}\text{-}FE}$	$\overline{\widehat{FE}\text{-}FE}$	$\overline{FE}$	$\overline{\widehat{FE}\text{-}FE}$	$\overline{\widehat{FE}\text{-}FE}$	$\overline{FE}$	$\overline{\widehat{FE}\text{-}FE}$	$\overline{\widehat{FE}\text{-}FE}$
Paid-to-Market	-0.0019	-0.0006	-0.0013	0.0001	0.0049	0.0020	-0.0001	0.0053	0.0022
	(-1.03)	(-0.38)	(-0.75)	(0.01)	(0.77)	(0.25)	(-0.02)	(0.84)	(0.27)
Constant	0.0008	0.0002	0.0004	-0.0055	-0.0056	-0.0066	-0.0053	-0.0061	-0.0068
	(0.70)	(0.19)	(0.37)	(-1.17)	(-1.34)	(-1.26)	(-1.10)	(-1.43)	(-1.28)
Model Type	—	OLS	LAD	—	OLS	LAD	—	OLS	LAD
Forecast Horizon	1Mon	1Mon	1Mon	3Mon	3Mon	3Mon	1Yr	1Yr	1Yr
Observations	252	252	252	249	249	249	241	241	241
Adjusted R^2	0.0142	-0.0019	0.0049	0.006	-0.0017	-0.0027	-0.0042	0.0169	-0.0018

The results of Table 2.7 shows that the paid-to-market ratio does not forecast aggregate earnings surprises, suggesting that its ability to predict REIT returns lies outside of the cash flow channel.

2.6 Conclusion

We document in-sample and out-of-sample predictability of excess equity REIT market returns using a large set of economic, stock market, and REIT market variables. We introduce a valuation ratio called paid-to-market, defined as paid-in-capital divided by equity market capitalization. We find it to be the most powerful predictor of equity REIT market returns that has yet been documented in the literature. Paid-to-market eliminates the bias of accumulated depreciation in the traditional book-to-market ratio. A high paid-to-market ratio predicts high REIT returns. It consistently predicts returns over time with large out-of-sample R^2 statistics of 1.64% and 14.12% at the monthly and annual horizons, respectively. We also find in-sample and out-of-sample evidence of REIT return predictability using the REIT gross book-to-market ratio, REIT book-to-market ratio, REIT return on equity, and the unemployment rate.

A forecasting model based on the paid-to-market ratio enables an investor to optimally time their exposure to risk, providing an annualized net utility gain of 188 basis points. In general, the model anticipates lower returns at the peak of bull markets and higher returns following bear markets and recessions. However, while the model anticipates lower-than-average future returns with some success, the precise timing of market selloffs proves rather difficult. The paid-to-market forecasting model provides investors with higher risk-adjusted returns but does not necessarily generate higher total returns than a buy-and-hold investor. As for the reasons underlying the model's predictive ability, our results point to predictable time-varying risk premiums in the REIT market rather than inefficiencies in prices.

Chapter 3

Corporate Responses to PBGC Variable Rate Premium Increases

3.1 Introduction

Mispriced defined benefit pension insurance creates moral hazard incentives for plan sponsors. In the US, corporate pension plan sponsors with at least 25 employees are required to have insurance with, and pay premiums to, the Pension Benefit Guarantee Corporation (PBGC). If a pension sponsor enters financial distress, it may terminate its pension plan by transferring all assets and liabilities to the PBGC[1]. The "trusteed plan" benefits are then paid by the PBGC up to a maximum guaranteed amount (in 2023, \$6,750 per month for a 65 year old.) Sharpe (1976) and Treynor (1977) show that PBGC insurance acts as a put option, the value of which can be maximized by underfunding the pension plan and maximizing the riskiness of plan assets. By shifting risk onto the pension plan and the PBGC, managers can increase the expected wealth of shareholders. Love et al. (2011) show that correctly priced insurance would eliminate the incentive for risk-shifting, while underpriced insurance encourages more risk taking.

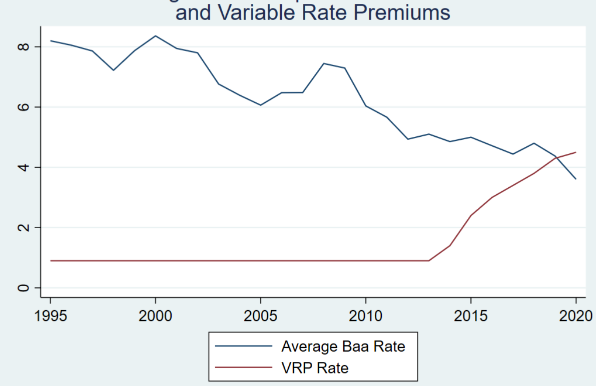
Prior to 2014, PBGC insurance was clearly mispriced, particularly for underfunded plans. Bodie (2006), Wilcox (2006), and Brown (2008) argued that the PBGC insurance was mispriced, since premiums at the time were mostly unrelated to pension funded status, and completely unrelated to firm health or pension asset allocation. Beginning in 2014, the variable-rate premium

[1]The firm must file a distress termination application with the PBGC and prove to the it, or to a bankruptcy court, that the firm cannot continue to operate without terminating the plan

charged to underfunded pension plan sponsors began rising, so that the cost of underfunding a pension increased. The Variable Rate Premium (VRP) rate charged to pension sponsors was gradually raised through a series of Congressional budget provisions from 0.9% of unfunded liabilities in 2013 to 5.2% starting in 2023. Firms that fully fund their pension plans by maintaining pension assets at least as large as pension liabilities pay zero VRP. Underfunded firms will pay an insurance premium to the PBGC equal to the VRP rate times pension liabilities minus pension assets. VRP rate hikes likely encouraged larger contributions by underfunded pension plan sponsors who wish to minimize costs. In recent years, the cost of underfunding a pension was larger than the average cost of investment grade debt, creating an incentive for firms to borrow-to-fund and eliminate their funding deficits entirely.

Figure 3.1 shows the Variable Rate Premium charged on unfunded pension liabilities over time, as well as the average cost of Baa debt. In 2019 and 2020, the typical cost of debt was lower than the variable rate premium, creating an incentive for firms to borrow-to-fund. In 2020, for example, a firm could have potentially borrowed a dollar by issuing a bond with a 4% interest rate (or even less at certain times during the year), then placed that dollar into their underfunded pension plan to avoid a VRP penalty of 4.5%. This would reduce costs even before considering tax benefits and expected return on pension assets (which we explore further in section 3.3). Firms with low costs of capital could easily eliminate their pension deficit while those with high costs of capital may be the only ones willing to shoulder the higher premium.

Figure 3.1: Corporate Bond Rates
and Variable Rate Premiums



While many papers have focused on how PBGC insurance creates opportunities for moral hazard and risk-shifting towards the pension, the effects of penalizing pension sponsors for underfunding remains largely unstudied. A decrease in the mispricing of pension insurance could have led to significant changes in risk-shifting behavior by firms. When the VRP is high, firms likely contribute more to their pension plans. Additionally, it may be possible that they shift risk away from the pension rather than towards it, since the cost of issuing debt can be lower than the benefits of contributing to the pension.

In this study, we take a comprehensive look at corporate reactions to PBGC VRP increases. We contribute to the literature by being the first to investigate actions taken by corporations to avoid paying larger VRP. We find that increases in the VRP were associated with higher pension contributions (both voluntary and involuntary) but that firms faced with higher VRP payments also took more risk in their pension asset allocations. We illustrate how the VRP is now so high that a new different type of risk shifting may be justified, where optimal corporate policy would shift risk out of the pension and onto debtholders. We further explore whether VRP increases influenced plan freeze decisions. Overall, we find that underfunded firms made larger pension contributions and chose more aggressive pension asset allocations, but do not find widespread evidence that firms financed pension contributions through debt issuances, or that VRP increases led to additional plan freezes. The evidence is consistent with VRP rate hikes having increased the cost of sponsoring an underfunded pension plan, so that only firms with a high cost of capital would still be willing to underfund.

The remainder of this paper is organized as follows: Section 3.2 discusses the PBGC as well as the related literature. Section 3.3 discusses the hypotheses tested and empirical setup. Section 3.4 discusses our data process. Section 3.5 discusses our empirical results. Section 3.6 reports robustness checks. Section 3.7 concludes.

3.2 PBGC Background Information and Related Literature

The Pension Benefit Guarantee Corporation PBGC was founded in 1974 upon the passage of the Employee Retirement Income Security Act (ERISA), and acts as an insurance entity for US corporate pensions, guaranteeing defined benefit retirement payments to over 33 million American workers and their families. While the Federal Government makes decisions pertaining to the PBGC's operations, the PBGC itself operates without the support of tax revenues. It is instead financed by insurance premiums paid by pension plan sponsors, as well as through trusteed plan assets. In the event of a sponsor's bankruptcy, the pension plan assets and liabilities are transferred to the PBGC, and beneficiaries will continue to receive their promised payments up to a maximum guarantee.

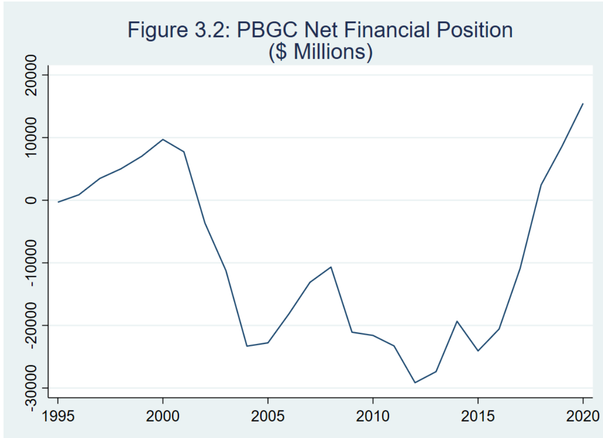
PBGC insurance largely ignored the financial health of pension plans prior to 2014, creating significant moral hazard incentives for plan sponsors. By raising the VRP rate, Congress reduced the extent of insurance mispricing, and may have changed risk shifting and risk management dynamics of pension plan sponsors. Plans covered by the PBGC pay flat-rate premiums based on the number of plan participants as well as variable-rate premiums based on the size of any unfunded pension liability. Table 1 shows the flat-rate and variable-rate premium rates over time. Variable Rate Premiums were raised starting in 2014, when a cap on total premiums was also introduced. Table 3.1 summarizes PBGC Premiums by year:

The PBGC reported that in 2017 and 2018, only 8.2% and 7.7% of plans had their VRP capped by the per participant cap. This figure is unavailable for other years. In recent years, the VRP is higher than the market rate of investment grade corporate debt, so borrowing to fund would be profitable even if the firm doesn't earn anything on pension assets. While the borrow-to-fund hypothesis is most strongly motivated by recent years, our sample ends in 2018 due to data availability from the PBGC. We ultimately study the period from 2009-2018, giving us 5 years of data before the VRP was increased, and 5 years after.

Table 3.1: PBGC Premium Rates

	Flat Rate Premium	Variable Rate Premium	Per Participant Cap
2009	$ 34	0.9%	N/A
2010	$ 35	0.9%	N/A
2011	$ 35	0.9%	N/A
2012	$ 35	0.9%	N/A
2013	$ 42	0.9%	$ 400
2014	$ 49	1.4%	$ 412
2015	$ 57	2.4%	$ 418
2016	$ 64	3.0%	$ 500
2017	$ 69	3.4%	$ 517
2018	$ 74	3.8%	$ 523
2019	$ 80	4.3%	$ 541
2020	$ 83	4.5%	$ 561
2021	$ 86	4.6%	$ 582
2022	$ 88	4.8%	$ 598
2023	$ 96	5.2%	$ 652

The VRP rate hikes began at a time when concerns mounted over the financial health of the PBGC. Figure 3.2 shows the PBGC's net financial position (trusteed assets minus trusteed liabilities) over time. In the 2000s, low interest rates and poor asset returns deteriorated pension funded status. This effect, combined with several large bankruptcies, drove PBGC trusteed liabilities to exceed assets by over $20 billion. In response to the poor financial health of the PBGC, as well as to criticism of the mispriced insurance formula, Congress began raising PBGC premiums in 2008, with the first increase in the variable rate portion beginning in 2014. In the past few years, the net financial position of the PBGC has significantly improved.



Clearly the financial position of the PBGC has improved as it has collected larger premiums, but were higher VRP rates associated with better behavior by corporate pension plan sponsors? If management's goal was to minimize the risk in the pension plan, firms would invest pension assets in debt securities (to hedge against interest rate risk) and fully fund their plans. But if the goal was to maximize shareholder wealth, firms may shift risk onto the PBGC by choosing more aggressive asset allocations and underfunding their plans.

The PBGC's impact on asset allocation and pension funding has a rich history in the literature. Shortly after the creation of the PBGC, Sharpe (1976) and Treynor (1977) studied the potential for risk shifting incentives resulting from pension insurance. They showed PBGC insurance to be a put option on the pension plan, the value of which can be maximized by underinvesting in the pension plan and allocating pension assets to equities. Under this view, firm value would be maximized using a min-max strategy where pension funding is minimized while the pension asset allocation to equities is maximized. The theory is similar to that of Jensen and Meckling (1976), where managers can increase shareholder value by increasing the volatility of firm assets when there is a significant risk of default.

Much of the incentive to engage in risk-shifting arises from mispriced pension insurance. Bodie (2006) and Wilcox (2006), and Brown (2008) argued that the PBGC insurance is mispriced, as premiums at the time were mostly flat and unrelated to firm health or pension asset allocation.

While the VRP has increased in recent years, firm risk and pension asset allocation remain unpriced. The mispriced PBGC insurance creates incentives for poorly funded firms to shift risk, and also encourages less risky pension sponsors to drop out of the system entirely. Love et al. (2011) model pension sponsor decisions and find that in the absence of pension insurance and regulatory constraints, firms would fully fund their pension and invest in bonds. They also show that correctly priced insurance would eliminate the incentive for risk-taking, while underpriced insurance would encourage more risk taking.

Considerable attention has been brought to the degree of PBGC insurance mispricing, particularly before VRP began rising. Boyce and Ippolito (2002) calculated that PBGC premiums should be twice as high as they were at the time, while Lewis and Pennacchi (1999) and VanDerHei (1990) estimated even higher values of the fair premium level. More recently, Binsbergen et al. (2014) found PBGC insurance to be underpriced, and estimated the value of PBGC insurance to be $358 billion, net of the present value of PBGC premiums. Chen and Uzelac (2014) criticized the PBGC's use of primarily flat-rate premiums and praised increases to the VRP, but point out that a fair insurance premium would also reward overfunded plans with lower premiums. Many papers expressing concerns about underpriced PBGC insurance were published in the last 20 years, as average pension funded status began to suffer from lower interest rates and two events of large stock market declines (the dot com bubble and the Great Financial Crisis). In response to concerns over PBGC funding, congress began raising PBGC premiums significantly starting in 2014, and the VRP now stands at over 5 times its 2013 level. Nevertheless, criticism of the PBGC has persisted. Romaniuk (2021) proposes restricting the equity portion of pension assets to 30%. She argues that the PBGC insurance remains unfairly priced, so that well-funded plans subsidize poorly funded ones.

While underpriced PBGC insurance can create incentives for risk shifting, the tax benefits enjoyed by pension plan sponsors could create a counteracting effect. Black (1980) and Tepper (1981) devise a max-min strategy where firms should maximize pension plan funding while minimizing the riskiness of plan assets. Their work lays the framework for the tax arbitrage hypothesis, which suggests that companies can create value by issuing debt, whose interest is tax deductible, and investing the proceeds in debt instruments inside the pension plan. Because pension contributions are tax deductible and pension investments may grow tax-free, companies could generate value by fully funding their pension plans with borrowed funds and investing the pension plan entirely in debt securities. Frank (2002) found some support for the tax arbitrage hypothesis, as firms with higher potential tax benefits allocate a larger percentage of their pension plan assets to bonds. More recently, borrowing-to-fund has received additional attention due to the increase in the VRP rate. Goldman Sachs Asset Management (2016) discusses the borrow-to-fund strategy in light of the VRP increase, and shows that underfunded pension sponsors can experience larger savings when the VRP is high. In one high-profile example, Verizon contributed $3.4 billion of borrowed funds to their pension, specifically citing rising VRP as the motive (Monga 2017).

Overall, pension sponsors have competing incentives created by their complex regulatory environment. The moral hazard/ risk-shifting hypothesis would indicate that firms poorly fund their pensions and invest in equities, while the tax arbitrage/ borrow-to-fund hypothesis suggests that companies should fully fund their pensions and invest plan assets in bonds. While the literature has extensively investigated risk shifting and tax consequences, the impact of VRP increases remains largely unstudied.

Our primary measure of the riskiness of a pension plan's assets is its allocation to equity versus debt. Larger allocations to debt within the pension plan are generally viewed as lower risk, as bond returns are less volatile than equity returns, and also provide a hedge against interest rate changes that impact the present value of pension liabilities. However, the riskiness of equities is somewhat mitigated by the correlation between equity returns and wage increases. Pension benefits grow more when wage increases are larger, making equity returns a hedge against rising wages (Sundaresan and Zapatero (1997) and Lucas and Zeldes (2009)). In today's environment, where most pensions are frozen, the equity/wage correlation is relatively unimportant, as hard-frozen plans will not face increased benefits if wages rise. Large equity allocations in the pension plan should be viewed as more risky than large debt allocations.

The empirical research on risk shifting is mixed, as incentives for risk shifting must be weighed against tax benefits as well as risk management incentives. Pension sponsors may be incentivized to manage their pension risk to avoid harmful mandatory contributions and costly financial distress. Rauh (2006) exploits sharply nonlinear mandatory contributions to show that firms invest less when their funding requirements are high. The risk of capital constraints from mandatory contributions, along with the risk of financial distress, create a risk management incentive where firms may choose to take on less risk in their pension to avoid the costs that come with being severely underfunded. Rauh (2009) empirically studies the competing risk shifting and risk management hypotheses, and finds that risk management tends to dominate risk shifting: firms with poorly funded pension plans invest a larger share of their pension assets in debt. Coronado and Liang (2006) find that firms closer to bankruptcy contribute less to their pensions, but do not choose more aggressive investment allocations.

Other studies have found evidence of risk shifting. Guan and Liu (2016) show that firms are more likely to shift risk when they are financially distressed with severely underfunded plans. An et al. (2013) find that risk management tends to dominate risk shifting, except with financially distressed firms, who take on more aggressive asset allocations. Chen et al. (2013) find that sponsors with high bankruptcy risk make lower voluntary contributions that decrease with bankruptcy risk, while sponsors with low bankruptcy risk make larger voluntary contributions that increase with their tax rate. Bartram (2018) finds that plan sponsors generally do not take additional pension risk if they face high business risk, but does find some evidence of risk shifting during financial crises.

Throughout these studies, risk shifting and risk management behavior is identified by pension contributions and pension asset allocation. We contribute to the literature by studying the impact of VRP increases on the risk shifting versus risk management debate.

3.3 Hypothesis Development

In this section we detail four hypotheses, H1-H4, which describe the ways in which we expect firms to react to the threat of VRP. Larger VRP rates increase the incentive for firms to fully fund their pension plans. The most obvious way for a firm to achieve full funding is by making larger contributions to the plan. Pension sponsors must make minimum required contributions in order to comply with the Employee Retirement Income Security Act of 1974 (ERISA) and the Pension Protection Act of 2006 (PPA.) VRP rate increases likely incentivized underfunded pension sponsors to make even larger contributions, so we expect

> **H1 – Larger contributions:** firms at risk of paying VRP will make larger contributions, especially in years where the VRP was high. This relationship should hold for both voluntary and total contributions.

We test H1 using Equation 3.1.

$$CONT = \alpha + \beta_1 * UFD + \beta_2 * UFD * UF\% + \gamma + \epsilon \tag{3.1}$$

Where CONT is contributions made before the PBGC filing deadline (in the 10th month of the fiscal year, usually October 15th), scaled by pension liabilities, γ is a vector of control variables, and ϵ is the error term. UFD is determined as of the beginning of the year, and is a dummy variable equal to one if the firm is expected to make variable rate premium payments during the year unless they make a contribution. Contributions made before the PBGC filing deadline would reduce any VRP owed. UF% is the size of the underfunded amount as of the beginning of the year (if it exists), scaled by pension liabilities. We expect β_1 and β_2 to be positive, as firms that pay larger VRP amounts are more incentivized to make large contributions. To examine reactions to the size of the VRP penalty, we interact UFD and UF% with the VRP rate during the year, as shown in equation 3.2

$$CONT = \alpha + \beta_1 * UFD + \beta_2 * UFD * UF\% + \beta_3 * UFD * VRP + \beta_4 * UFD * UF\% * VRP + \gamma + \epsilon \tag{3.2}$$

The incentive for underfunded firms to contribute and avoid penalties should be even stronger in years where the VRP rate is high, so we expect β_3 and β_4 to also be positive. Our setup differs from many previous studies which have focused on funded status% (pension assets divided by pension liabilities.) In contrast to previous work, we do not allow funded status to range from 0 to infinity, and instead focus on the penalty associated with being underfunded (a strictly positive amount.) We use similar econometric setups to explore hypothesis 2.

> **H2 – Borrow to fund:** Firms at risk of paying VRP will make larger contributions, and we expect these contributions will sometimes be financed by debt issuances. For firms with underfunded pension plans, pension contributions will be related to debt issuances. We expect for the relationship to be stronger in years where the VRP was higher.

H2 is motivated by the observation that in recent years, the VRP rate has been larger than the average cost of debt. A firm with an underfunded pension plan could potentially realize savings by issuing debt and placing the proceeds in the pension. An unfunded pension liability is essentially a debt to employees. By shifting the debt from employees to debtholders, the firm can realize a net benefit if the cost of debt to traditional debtholders is lower than the cost of an unfunded pension liability. The firm realizes several additional benefits, in both accounting and cash terms. Pension contributions and interest expense are both tax deductible, increasing incentives to borrow-to-fund. Expected return on pension assets positively impacts net income regardless of actual return, as it is subtracted during the pension expense calculation[2]. While the company has virtually no ability to recoup dedicated pension assets[3], return on pension asses does benefit the company in economic terms by reducing the need for future contributions.

Table 3.2 illustrates the effects of borrowing-to-fund to close a funding gap of \$100 in 2020, for a firm with a 4% cost of debt when the VRP was 4.5%. The illustration is similar in spirit to Goldman Sachs (2016.) The \$100 contribution is tax deductible. Using a 20% tax rate, the

[2]If actual return is less(greater) than expected return, an unrecognized loss(gain) is created on the balance sheet. The loss(gain) will only be recognized in future years if it is greater than the "corridor" of 10% of the larger of projected benefit obligation or market value of plan assets. Losses(gains) in excess of the corridor will be amortized over average remaining service (for open plans) or average remaining lifetime (for frozen plans.) These accounting rules result in very small earnings risk in the near-term if actual return differs from expected return.

[3]Excess assets could only be withdrawn from the pension in the event of a plan termination, where pension assets and liabilities are transferred to a separate entity such as an insurance company. In this case, excess assets reverted to the firm would be subject to a 50% excise tax as well as ordinary income taxes.

Table 3.2: Borrow-to-fund Illustration

Initial Pension Deficit	$ 100.00
Tax Rate	20%
Cost of Debt	4%
Net Debt Issued	**$ 80.00**
Expected Return on Plan Assets	7%
Increased Interest Expense (4% of $80)	$ (3.20)
Decreased Pension Expense (7% of $100)	$ 7.00
VRP Savings (4.5% of $100)	$ 4.50
Subtotal:	**$ 8.30**
Tax Provision (20% of decreased expense)	$ 1.66
Total Savings:	**$ 6.64**

firm will realize a $20 tax benefit, which could be used to repurchase debt, therefore financing a $100 pension contribution with an $80 increase in net debt. Using a 4% interest rate, the firm will only see an increase in interest expense of $3.2, while it will see a total reduction in its pension expense of $11.50 ($4.50 from the VRP reduction and $7.00 in expected return on plan assets.) After tax considerations, the net benefit per year is $6.64, or 6.64% of the unfunded liability. While borrowing-to-fund has always been profitable (as shown by Black (1980) and Tepper (1981)), higher VRP rates have increased the profitability of this strategy. Larger VRP rates give underfunded firms an incentive to borrow-to-fund, so we expect to see firms issuing more debt in years where they contribute more to their pensions. Equations (3.3) and (3.4) show our econometric models to test borrow-to-fund activity.

$$\frac{DI}{TA} = \alpha + \beta_1 * \frac{CONT}{TA} + \beta_2 * UFD * \frac{CONT}{TA} + \beta_3 * UFD + \gamma + \epsilon \tag{3.3}$$

Here we scale Debt Issuances (DI) and Contributions (CONT) by Total Assets (TA). In these tests we choose to scale by total assets instead of pension liabilities in order to avoid dividing Debt

Issuances by pension liabilities. This would create many outliers resulting from small denominators for large firms with small pensions. If a dollar of pension contributions was associated with a dollar of debt issuances in underfunded firms, then we would expect the sum of β_1 and β_2 to be equal to one. In equation 4, we add interactions with the Variable Rate Premium (VRP), similar to the contribution tests. This allows us to assess whether borrow-to-fund activity was more common in years where the VRP was high. We expect that the rise in VRP led to more borrow-to-fund activity for underfunded firms, so we expect β_5 in equation 3.4 to be positive.

$$\frac{DI}{TA} = \alpha + \beta_1 * \frac{CONT}{TA} + \beta_2 * UFD * \frac{CONT}{TA} + \beta_3 * UFD + \beta_4 * VRP * \frac{CONT}{TA} \\ + \beta_5 * UFD * VRP * \frac{CONT}{TA} + \gamma + \epsilon \tag{3.4}$$

While the borrow-to-fund hypothesis would only make economic sense if the relationship was positive, H3 tests a two-tailed hypothesis. Firms may react to the threat of VRP by changing their asset allocations.

H3 – Asset Allocation: Do firms with higher expected VRP payments increase or decrease the riskiness of their pension assets?

If pension assets generate large returns, then an unfunded liability may be reduced. In search of higher returns that could reduce future VRP payments, managers may choose more aggressive asset allocations when their expected VRP payments are large. Alternatively, managers could try to hedge the risk of paying even higher VRP by investing in bonds. If interest rates fall, pension liabilities increase along with bond prices, so a larger asset allocation to debt securities would hedge against the risk of paying future VRP. In response to VRP rate hikes, managers may choose more aggressive pension asset allocations (equity), or they may choose safer ones (bonds). We test the aggressiveness of pension asset allocation using equations 3.5 and 3.6.

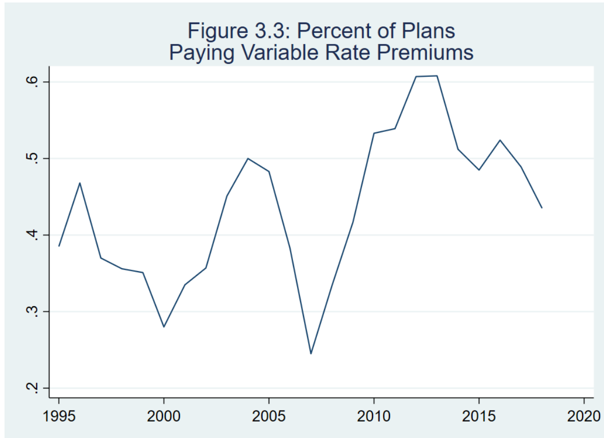
$$Equity\% = \alpha + \beta_1 * UFD + \beta_2 * UFD * UF\% + \gamma + \epsilon \tag{3.5}$$

$$Equity\% = \alpha + \beta_1 * UFD + \beta_2 * UFD * UF\% + \beta_3 * UFD * UF\% * VRP + \beta_4 * UFD * VRP + \gamma + \epsilon \tag{3.6}$$

The coefficients β_1 through β_4 are expected to be positive if firms take on aggressive equity allocations when threatened with VRP payments and negative if they take on safer allocations. Finally, firms may react to VRP by freezing their pension plan, motivating H4.

H4 – Pension Plan Freezes: Firms will be more likely to freeze their pension plans when their expected VRP payments are high.

When a pension plan is frozen, no further benefits may accrue, limiting the risk of larger future pension liabilities. While a firm may freeze its plan at any time, a firm with a frozen plan is still obligated to pay benefits to employees who have already accrued them. Over the past few decades, many pension plans have frozen benefit accruals as liabilities have ballooned due to low interest rates. According to Willis Towers Watson (2020), only 14% of Fortune 500 companies offered defined benefit plans in 2019, while 59% of those same employers offered them in 1998. The threat of higher VRP payments may play a role in a firm's decision to freeze their pension. Figure 3.3 shows the percentage of plans covered by the PBGC that paid VRP each year. There were large spikes in the percentage of plans paying VRP following the bear markets and interest rate declines of the dot-com bubble and the Global Financial Crisis. In the past decade, the percentage of plans paying VRP far exceeds its level during the 1990s. Despite continued low interest rates, the percentage has fallen over the past few years as funded status has improved, in part due to the lack of benefit accruals in frozen plans.



Did VRP increases influence plan freeze decisions? The cost of sponsoring an underfunded plan grew significantly when VRP rates rose, so underfunded plans may have been more likely to freeze when their expected VRP payment was high. We test H4 using a logit model, as in equations 3.7 and 3.8.

$$Freeze = \alpha + \beta_1 * UFD + \beta_2 * UFD * UF\% + \gamma + \epsilon \tag{3.7}$$

$$Freeze = \alpha+\beta_1*UFD+\beta_2*UFD*UF\%+\beta_3*UFD*UF\%*VRP+\beta_4*UFD*VRP+\gamma+\epsilon \tag{3.8}$$

Freeze is a dummy variable equal to one if the plan is frozen during the year. We expect that β_1 and β_2 will be positive if firms are more likely to freeze their plan when they pay VRP. β_3 and β_4 will be positive if that effect is stronger in years where the VRP rate is high. We identify frozen plans as those with a target normal cost of zero. Target normal cost is the present value of benefits expected to accrue during a plan year, so frozen pension plans have a target normal cost of zero. We identify freeze years as years in which the target normal cost is zero, but the previous year's target normal cost was positive. We remove plans from our sample starting in the year after they are frozen, or if they were already frozen at the beginning of our studied time period. This creates an appropriate sample for a logit model in which the binary outcome is the decision to freeze the plan. Plans that are already frozen cannot be frozen again, so they are removed from the sample.

3.4 Data Process

Data comes from four sources: The Form 5500 Schedule SBs, Compustat, CRSP, and the PBGC data tables. The PBGC data tables end in 2018, and the Schedule SBs begin in 2009, so we study the time period of 2009-2018. This time period gives us five years before variable rate premiums were increased and five years after they began increasing.

We cannot directly observe UFD or UF% using this data, as plan-level PBGC filings are not public, but we can compute a very close approximation. A detailed explanation of the calculation is provided in the appendix, which we summarize here.

All pension sponsors with PBGC coverage must file the Form 5500 Schedule SB, but not all Schedule SB filers are covered by the PBGC (e.g. small plans that have always had less than 25 participants.) The Schedule SB data contains the pension asset values that we need to calculate UFD and UF%, but the Schedule SB funding target differs from the liability calculated for PBGC VRP purposes. The PBGC liability is calculated using a different set of interest rates. A plan with assets 5% larger than liabilities on the Schedule SB may potentially still be underfunded on their unobservable PBGC filing. Because the PBGC data tables report the aggregate percentage of plans that pay VRP, we can sort the plans according to their schedule SB funded status and draw a cutoff after which firms are estimated to be so poorly funded that they must pay VRP.

For example, we may know that 60% of plans in a year paid VRP. We sort plans in that year by their Schedule SB funded status, and we apply the UFD dummy to firms below the 60th percentile. During this procedure we can also scale plan liabilities to arrive at our estimate of UF%. The process involves choosing between two samples that could be used in the scaling of liabilities and the calculation of UF%. We could use the entire Schedule SB population, or we could use only the sample of plans with verifiable PBGC coverage. The Form 5500 data contains a code to indicate that the plan has PBGC coverage, but based on summary statistics from the PBGC, we know that many covered plans are missing the applicable code on their form. One sample would likely overestimate the true PBGC funding target while the other would likely underestimate it. For robustness, we perform our calculations using both samples. In our main results, we calculate UFD and UF% using only the sample of Schedule SBs with verifiable PBGC coverage. In the robustness section, we recreate these tables after using all Schedule SBs to perform our intermediate calculations.

The Form 5500 Schedule SBs provide pension data, while Compustat informs us about firm financial characteristics. We use two separate vectors of control variables: one is designed to control for capital structure determinants (for the borrow-to-fund tests) while the other is chosen to control for pension decision determinants (for the contribution, asset allocation, and pension freeze tests.) Berg and Gider (2017) study leverage differences between banks and nonbanks, and utilize a long vector of control variables to show asset risk is one of the greatest determinants of capital structure. When testing the relationship between debt issuances and pension contributions, we include a vector of control variables in their study to control for the determinants of debt issuances. We also control for the firm's operating cash flows and beginning of year leverage, since debt issuances will be lower when cash flows and lagged leverage are higher. Following Berg and Gider as well as related capital structure studies, we lag the controls by one period.

In our asset allocation, pension contribution, and pension freeze tests, we use a vector of control variables from Guan and Tang (2018), which focuses on pension asset allocation. The definitions of variables and summary statistics are in tables 3.3 and 3.4.

The Summary Statistics reported in table 3.4 show that across our full sample time period, roughly half of firms are at risk of paying VRP. On average, the underfunded firms contribute more to their pensions and allocate a higher portion of their pension assets to equity. The underfunded firms are also smaller, have lower market-to-book ratios, use more leverage, have higher capital expenditures, and have higher stock returns. Underfunded firms may fail to fully fund their pension plan because they have a higher cost of capital, which is consistent with what we observe in the summary statistics.

Table 3.3: Definition of Variables

Variable	Definition
Panel A: Dependent Variables	
Contributions / Pension Liability	Total pension contributions made during the firm's fiscal year divided by total pension funding target. Data comes from the form 5500 Schedule SB
Debt Issuances to Assets	Total debt (compustat items dltt plus dlc) at the end of the year minus total debt at the beginning of year, divided by beginning of year assets.
Equity%	The percent of pension assets allocated to equities (compustat item pnate)
Debt%	The percent of pension assets allocated to debt (compustat item pnatd)
Panel B: Capital Structure Controls	
Asset Risk	The log of asset risk. Asset risk is the standard deviation of monthly stock returns over the past 12 months / book leverage. Book leverage is total liabilities over total assets
Market-to-Book	(Total assets plus market cap minus book value of equity) / Total Assets
Dividend Payer	Dummy variable equal to 1 if the firm pays dividends
Firm Size	The log of total firm assets
Depreciation/Assets	Depreciation divided by total assets
Tangibility (PPE/AT)	Property, Plant, and Equipment divided by total assets
SG&A/Assets	Selling, General, and Administrative divided by total assets
R&D	Research and Development divided by total assets
Advertising/Assets	Advertising expense divded by total assets
Tax Rate	Taxes divided by Pretax income
Loss Carryforwards	Tax loss carryforwards divided by total assets
Asset Growth	Total Assets divided by previous year total assets minus one
Merger Dummy	Dummy variable equal to 1 if sales from acquisitions in a year are greater than half of total sales
Capex	Capital Expenditures divided by total assets
Industry Growth	Total asset growth by 2 digit sic code and year
Previous Year Return	Stock return over the last 12 months
Industry Leverage	Median Book Leverage by SIC Code and Year
Debt-to-Assets	Total debt (not total liabilities) divided by total assets
Operating Cash Flows	Operating Cash Flows, before pension contributions, scaled by total assets
Panel C: Pension Decision Controls	
Pension Size	The log of total pension assets
Firm Size	The log of total firm assets
Pension Return	Actual return on pension assets divided by beginning of year pension assets
Duration	Service Cost divided by the sum of service cost and interest cost
Operating Cash Flows	Operating Cash Flows, before pension contributions, scaled by total assets
Operating Cash Flow Volatility	The standard deviation of operating cash flows over the last 5 years
Tax Rate	Taxes divided by Pretax income
Debt-to-Assets	Total debt (not total liabilities) divided by total assets
Active %	The percent of pension beneficiaries that are active employees
Service Cost	Pension service cost, scaled by total assets

Table 3.4: Summary Statistics

	Fully Funded			Underfunded			
	Mean	5th %	95th %	Mean	5th %	95th %	Difference in Means
Panel A: Dependent Variables							
Contributions / Pension Liability	0.029	0.000	0.135	0.048	0.000	0.150	-0.018***
Debt Issuances to Assets	0.018	-0.085	0.175	0.017	-0.085	0.175	0.001
Equity%	0.477	0.220	0.730	0.513	0.220	0.730	-0.036***
Debt%	0.431	0.160	0.690	0.392	0.160	0.690	0.039***
Panel B: Capital Structure Controls							
Asset Risk	-2.147	-3.066	-1.039	-1.968	-2.961	-0.857	-0.179***
Market-to-Book	1.637	0.932	3.257	1.465	0.865	2.584	0.172***
Dividend	0.870	0.000	1.000	0.718	0.000	1.000	0.153***
Assets (000s)	51,052	458.086	209,474	21,102	204.933	61,942	29949.95***
Depreciation	0.031	0.001	0.072	0.038	0.002	0.089	-0.007***
Tangibility	0.258	0.007	0.768	0.308	0.014	0.808	-0.05***
SG&A	0.128	0.000	0.383	0.146	0.000	0.419	-0.019***
R&D	0.015	0.000	0.075	0.012	0.000	0.042	0.003***
Advertising	0.010	0.000	0.047	0.008	0.000	0.048	0.002***
Tax Rate	0.270	0.049	0.537	0.261	-0.247	0.602	0.009
Loss Carryforward	0.047	0.000	0.222	0.087	0.000	0.435	-0.04***
Asset Growth	0.053	-0.112	0.263	0.053	-0.130	0.316	0
Merger	0.005	0.000	0.000	0.004	0.000	0.000	0.001
Capex	0.039	0.000	0.112	0.045	0.002	0.133	-0.006***
Industry Growth	0.033	-0.059	0.125	0.043	-0.059	0.130	-0.01***
Stock Return	0.125	-0.354	0.628	0.207	-0.366	0.875	-0.082***
Industry Leverage	0.609	0.399	0.899	0.574	0.399	0.896	0.035***
Debt-to-Assets	0.235	0.026	0.528	0.269	0.025	0.558	-0.034***
Operating Cash Flows	0.097	0.009	0.222	0.093	0.007	0.193	0.004
Panel C: Pension Decision Controls							
Pension Size (000s)	3,351	24.587	15,348	1,906	9.758	9,626	1445.111***
Assets (000s)	51,052	458.086	209,474	21,102	204.933	61,942	29949.95***
Pension Return	0.077	-0.055	0.195	0.094	-0.032	0.197	-0.017***
Duration	0.294	0.000	0.558	0.208	0.000	0.517	0.086***
Operating Cash Flows	0.097	0.009	0.222	0.093	0.007	0.193	0.004
Operating Cash Flow Volatility	0.001	0.000	0.005	0.002	0.000	0.006	0*
Tax Rate	0.270	-0.138	0.537	0.261	-0.247	0.602	0.009
Debt-to-Assets	0.235	0.026	0.528	0.269	0.025	0.558	-0.034***
Active %	0.411	0.115	0.727	0.322	0.037	0.713	0.088***
Service Cost	0.003	0.000	0.009	0.002	0.000	0.008	0.001***
Observations		2,014			1,919		

3.5 Empirical Results

We begin by testing H1 – Larger Contributions. Underfunded firms will almost certainly contribute more to their pension, in large part due to required minimum contributions. The more interesting empirical questions are whether voluntary contributions are larger for underfunded firms, and whether the relationship between funded status and contributions strengthens when the VRP is high.

Table 3.5 reports the results for equations 3.1-3.2 using all contributions. In models 1 and 3 we use industry fixed effects while in models 2 and 4 we use firm fixed effects. Firm fixed effects will be more effective than industry fixed effects at controlling for unobserved firm characteristics that drive contribution decisions. We interact VRP with UFD and UF% separately, and then together, in models 5-7, which all include firm fixed effects. The coefficient on UFD X UF% is always positive and highly significant, while the coefficient on UFD is usually positive and significant. This suggests that underfunded firms contribute more to their pensions, and that larger funding gaps are associated with even higher contributions. In model 4, we estimate that for each dollar of underfunding, underfunded firms contribute 20.88 cents to their pension plans. In model 5, the interaction between VRP and UFD is positive and significant at the 1% level, suggesting that underfunded firms contribute even more in years where the VRP is high. In models 6 and 7, we see a positive statistically significant relationship between UF% and VRP: larger levels of underfunding are associated with larger contributions, especially when the VRP is high. The statistical significance on the interaction between UFD and VRP is lost in model 7, where we simultaneously interact the VRP with both UFD and UF%.

Table 3.6 reports the results of equations 3.1-3.2 again, but this time using only voluntary contributions. We calculate voluntary contributions as total contributions minus the required cash contribution. We calculate the required cash contribution as the difference between the required minimum contribution and the sum of the funding standard carryover balance and the prefunding balance. If this calculation results in a negative amount, we set it equal to zero. In other words,

Table 3.5: Determinants of Pension Contributions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
UFD	-0.0047*	0.0082***	0.0029	0.0087***	0.0004	0.0078***	0.0063
	(-1.67)	(3.11)	(1.24)	(3.38)	(0.11)	(2.93)	(1.45)
UFD X UF%	0.1990***	0.2001***	0.2103***	0.2088***	0.2098***	0.1473***	0.1541***
	(9.62)	(9.06)	(12.89)	(10.03)	(9.97)	(5.98)	(5.39)
UFD X VRP					0.0046***		0.0009
					(2.85)		(0.44)
UFD X UF% X VRP						0.0398***	0.0357**
						(3.18)	(2.21)
Plan Size			-0.0016	0.0026	0.0020	0.0022	0.0022
			(-1.40)	(0.73)	(0.51)	(0.57)	(0.57)
Firm Size			-0.0019	-0.0034	-0.0029	-0.0025	-0.0025
			(-1.56)	(-0.81)	(-0.70)	(-0.61)	(-0.61)
Pension Return			-0.0056	-0.0171	-0.0053	-0.0051	-0.0052
			(-0.34)	(-1.05)	(-0.31)	(-0.30)	(-0.31)
Duration			0.0864***	0.0630***	0.0608***	0.0602***	0.0601***
			(9.61)	(4.77)	(4.58)	(4.54)	(4.53)
Operating Cash Flow			0.1152***	0.1294***	0.1312***	0.1305***	0.1305***
			(6.11)	(4.99)	(5.13)	(5.13)	(5.13)
Operating Cash Flow Vol			0.2553	-1.0284**	-1.0398**	-1.0684**	-1.0688**
			(1.07)	(-2.29)	(-2.41)	(-2.43)	(-2.44)
Tax Rate			0.0007	0.0019**	0.0018*	0.0016*	0.0016*
			(0.68)	(1.99)	(1.92)	(1.81)	(1.83)
Debt-to-Assets			0.0081	-0.0179	-0.0181	-0.0171	-0.0173
			(1.10)	(-1.29)	(-1.29)	(-1.23)	(-1.24)
Active Percent			0.0342***	0.0571***	0.0587***	0.0590***	0.0592***
			(4.46)	(2.72)	(2.83)	(2.87)	(2.88)
Service Cost			-0.0897	0.7432	0.8770	0.8241	0.8388
			(-0.19)	(0.71)	(0.88)	(0.83)	(0.84)
Constant	0.0293***	0.0230***	0.0259*	-0.0436	-0.0363	-0.0446	-0.0447
	(16.19)	(16.79)	(1.66)	(-0.54)	(-0.43)	(-0.52)	(-0.52)
Time Fixed Effects	Year	Year	Year	Year	Year	Year	Year
Time Invariant FE	Industry	Firm	Industry	Firm	Firm	Firm	Firm
Observations	3,933	3,933	3,933	3,933	3,933	3,933	3,933
Adjusted R-squared	0.1406	0.3431	0.2785	0.3715	0.3764	0.3778	0.3776

Notes: The dependent variable is pension contributions made before the PBGC filing deadline, scaled by pension liabilities. UFD is a dummy variable equal to one if the pension is expected to pay PBGC premiums if they do not contribute during the year. UF% is the estimated dollar amount of PBGC funding shortage as of the beginning of the year, scaled by pension liabilities, and is equal to zero if UFD equals one. VRP is the level of the PBGC Variable-Rate Premium.

a pension plan's required cash contributions are reduced by their credit balances, since credit balances can be used to satisfy required minimum contributions. Credit balances are created when a firm contributes more than the required minimum. If the required minimum contribution is smaller than the pension's existing credit balances, then the required cash contribution is zero.

Table 3.6: Determinants of Voluntary Pension Contributions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
UFD	-0.0006	0.0108***	0.0063**	0.0114***	-0.0027	0.0099***	0.0056
	(-0.20)	(3.89)	(2.43)	(4.19)	(-0.61)	(3.54)	(1.23)
UFD X UF%	0.0297	0.0658***	0.0458**	0.0777***	0.0813***	-0.0168	0.0031
	(1.38)	(2.79)	(2.37)	(3.35)	(3.48)	(-0.64)	(0.10)
UFD X VRP					0.0079***		0.0026
					(4.64)		(1.18)
UFD X UF% X VRP						0.0620***	0.0501***
						(4.35)	(2.62)
Plan Size			0.0001	0.0093**	0.0089**	0.0093**	0.0093**
			(0.12)	(2.23)	(1.99)	(2.04)	(2.05)
Firm Size			-0.0026**	-0.0026	-0.0020	-0.0014	-0.0015
			(-2.08)	(-0.63)	(-0.49)	(-0.34)	(-0.36)
Pension Return			0.0038	-0.0020	0.0044	0.0047	0.0046
			(0.22)	(-0.12)	(0.25)	(0.27)	(0.26)
Duration			0.0721***	0.0493***	0.0457***	0.0450***	0.0447***
			(7.39)	(3.62)	(3.44)	(3.41)	(3.39)
Operating Cash Flow			0.1118***	0.1298***	0.1305***	0.1295***	0.1296***
			(5.78)	(4.64)	(4.75)	(4.75)	(4.75)
Operating Cash Flow Volatility			0.0044	-1.0252**	-1.0632**	-1.1026**	-1.1040**
			(0.02)	(-2.07)	(-2.27)	(-2.30)	(-2.33)
Tax Rate			0.0005	0.0017*	0.0017	0.0014	0.0015
			(0.41)	(1.66)	(1.63)	(1.47)	(1.52)
Debt-to-Assets			0.0035	-0.0128	-0.0137	-0.0119	-0.0124
			(0.46)	(-0.91)	(-0.96)	(-0.86)	(-0.89)
Active Percent			0.0304***	0.0504**	0.0533**	0.0537**	0.0540**
			(3.68)	(2.13)	(2.29)	(2.34)	(2.35)
Service Cost			0.0578	0.5822	0.8087	0.7119	0.7550
			(0.11)	(0.52)	(0.77)	(0.68)	(0.72)
Constant	0.0285***	0.0209***	0.0024	-0.1779*	-0.1777*	-0.1894*	-0.1895*
	(15.84)	(15.24)	(0.15)	(-1.96)	(-1.86)	(-1.95)	(-1.95)
Time Fixed Effects	Year	Year	Year	Year	Year	Year	Year
Time Invariant FE	Industry	Firm	Industry	Firm	Firm	Firm	Firm
Observations	3,933	3,933	3,933	3,933	3,933	3,933	3,933
Adjusted R-squared	0.0590	0.2560	0.1656	0.2796	0.2879	0.2904	0.2905

Notes: The dependent variable is voluntary pension contributions made before the PBGC filing deadline, scaled by pension liabilities. UFD is a dummy variable equal to one if the pension is expected to pay PBGC premiums if they do not contribute during the year. UF% is the estimated dollar amount of PBGC funding shortage as of the beginning of the year, scaled by pension liabilities, and is equal to zero if UFD equals one. VRP is the level of the PBGC Variable-Rate Premium.

The results in table 3.6 are largely consistent with those in table 3.5: model 4 shows that firms contribute more when they are underfunded, as the signs on UFD and UFD X UF% are both positive and significant. The significance varies in models 5-7 which include the interaction terms. The interactions UFD X VRP and UFD X UF% X VRP are both positive and highly significant in models 5 and 6, but when VRP is interacted with both UFD and UF% in the same equation (model 7), the significance is lost on UFD. Overall, this suggests that firms make larger voluntary contributions when they are at risk of paying VRP. In years where the VRP was high, this relationship was even stronger. Higher VRP rates were associated with more contributions by underfunded firms, consistent with their intended purpose of encouraging contributions.

H2 – Borrow to fund states that underfunded firms will likely issue debt and place the proceeds in the pension plan to avoid paying VRP. This effect will be larger in years where the VRP rate was high. Table 3.7 reports the results of equations 3.3 and 3.4. We only report the results using voluntary contributions as opposed to total contributions. In unreported results, we use total contributions instead, and the findings are qualitatively the same.

We regard models 4 and 5 as the most accurate in measuring borrow-to-fund activity, as they include both control variables and firm fixed effects. If we add the coefficients from UFD X Contributions and Contributions, we get the economic impact that a dollar of contributions has on debt issuances for underfunded firms. In model 4, an increase in a dollar of contributions is associated with an increase in \$0.252 of debt issuances for underfunded firms. In model 5, a dollar of contributions is associated with \$0.33 of debt issuances for underfunded firms. If the coefficients on UFD X Contributions and Contributions in models 4 and 5 are correct, then fully funded firms issue less debt when they contribute to their pension, but underfunded firms issue more debt when they contribute. While the economic magnitude of these estimates seems reasonable, the estimates are generally statistically insignificant.

The negative relationship between debt issuances and pension contributions for fully funded firms may be explained by firms with excess free cash flows having the ability to both contribute to the pension and repurchase debt. Operating Cash Flows are negatively related to debt issuances. While the sign on UFD X Contributions is positive (consistent with our expectation) across all specifications, the estimates are mostly statistically insignificant. In model 5, the estimates on VRP X Vol Contribution and UFD X VRP X Vol Contribution are weakly significant, and the opposite signs of what we would predict (positive and negative, respectively.) We would expect that when the VRP was high, underfunded firms would borrow-to-fund, and their voluntary contributions

Table 3.7: Borrow-to-fund Tests

	(1)	(2)	(3)	(4)	(5)
Vol Contribution	-0.2080	0.0203	-0.1161	-0.1321	-0.9275*
	(-0.39)	(0.03)	(-0.46)	(-0.40)	(-1.72)
UFD X Vol Contribution	0.1470	0.2080	0.4270	0.3841	1.2575**
	(0.26)	(0.29)	(1.42)	(1.04)	(2.04)
UFD	-0.0054	-0.0142***	-0.0033	-0.0073**	-0.0074***
	(-1.61)	(-2.87)	(-1.48)	(-2.57)	(-2.59)
VRP X Vol Contribution					0.4188*
					(1.75)
UFD X VRP X Vol Contribution					-0.4698*
					(-1.71)
Asset Risk			-0.0002	0.0005	0.0004
			(-0.06)	(0.15)	(0.11)
Market-to-Book			0.0161***	0.0147*	0.0142*
			(3.42)	(1.93)	(1.88)
div_dummy			-0.0027	0.0032	0.0034
			(-0.85)	(0.59)	(0.62)
log_at_lag			0.0030***	0.0098	0.0097
			(4.32)	(1.26)	(1.25)
depreciation			0.1826**	0.1768	0.1855
			(2.04)	(1.28)	(1.34)
tangibility			0.0142	0.1066***	0.1074***
			(1.36)	(3.46)	(3.44)
SGandA			0.0283**	-0.0084	-0.0070
			(2.26)	(-0.17)	(-0.14)
RandD			-0.1156*	0.0332	0.0239
			(-1.81)	(0.14)	(0.10)
Advertising			0.0938	0.3908	0.4006
			(1.28)	(1.11)	(1.14)
Tax Rate			-0.0004	0.0004	0.0004
			(-0.32)	(0.33)	(0.34)
Loss Carryforwards			-0.0178*	-0.0237	-0.0228
			(-1.93)	(-1.43)	(-1.39)
Asset Growth			0.4331***	0.4390***	0.4388***
			(22.13)	(22.35)	(22.39)
Merger Dummy			0.1316***	0.1181***	0.1182***
			(4.53)	(4.34)	(4.35)
Capex			0.0663	0.0206	0.0215
			(1.25)	(0.24)	(0.25)
Industry Growth			-0.0451**	-0.0467**	-0.0468**
			(-2.26)	(-2.33)	(-2.34)
Stock Return			-0.0079**	-0.0078**	-0.0079**
			(-2.50)	(-2.29)	(-2.32)
Industry Leverage			0.0182	0.0241	0.0232
			(0.64)	(0.72)	(0.69)
Firm Leverage			-0.0431***	-0.2473***	-0.2465***
			(-3.67)	(-8.88)	(-8.84)
Operating Cash Flows			-0.2908***	-0.3474***	-0.3451***
			(-6.12)	(-8.25)	(-8.16)
Constant	0.0208***	0.0243***	-0.0378*	-0.0655	-0.0647
	(9.02)	(9.36)	(-1.89)	(-0.92)	(-0.91)
Time Fixed Effects	Year	Year	Year	Year	Year
Time-Invariant FE	Industry	Firm	Industry	Firm	Firm
Observations	3,933	3,933	3,933	3,933	3,933
Adjusted R-squared	0.0387	0.0321	0.6556	0.6955	0.6957

Notes: The dependent variable is Debt Issuances. Debt Issuances is debt at the end of the year minus debt at the beginning of year, divided by beginning of year assets. Contribution is pension contributions divided by beginning of year assets. UFD is a dummy variable equal to one if the pension is expected to pay VRP if they do not contribute during the year. VRP is the level of the PBGC Variable-Rate Premium would be associated with larger debt increases. The negative estimate suggests the opposite, but is statistically weak.

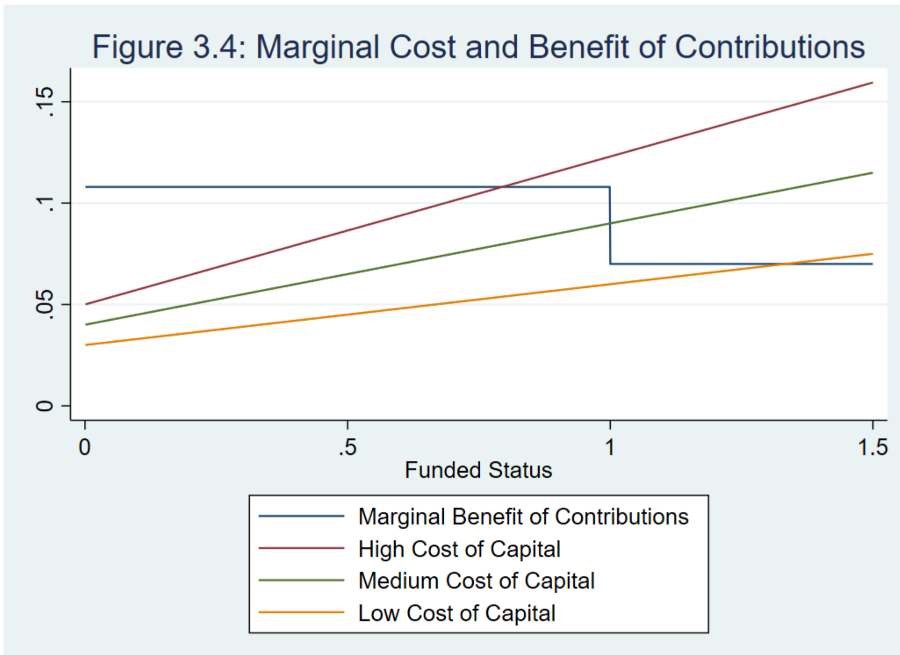
Overall, the statistical evidence that firms borrowed-to-fund in order to avoid rising VRP is weak. This is despite significant anecdotal evidence of firms using this strategy. Goldman Sachs (2016) cites several borrow-to-fund deals in company filings and press releases, but our econometric tools fail to pick up statistically significant evidence in the data. Our analysis does suffer from missing the post-2018 time period, when borrowing-to-fund was most profitable (interest rates after 2018 were historically low while the VRP was historically high).

This motivates the question: why don't more firms borrow-to-fund? The answer could lie in variations in the cost of capital. The summary statistics show that underfunded firms are smaller, have more debt, lower market-to-book ratios, higher capex, and higher stock returns. All these characteristics are consistent with a higher cost of capital. Underfunded firms may have less access to cheap debt, making a borrow-to-fund strategy less profitable.

Why don't firms fully fund their pensions? The tax arbitrage hypothesis of Black (1980) and Tepper (1981) would suggest that firms should fully fund their pensions even before we consider the effects of the VRP. However, the tax arbitrage theory assumes a constant cost of debt, while we find evidence that underfunded firms have a higher cost of capital. We would expect that a rational manager would contribute to their pension so long as the marginal benefit of contributing to the pension is larger than the marginal cost. The borrow-to-fund hypothesis is motivated in part by the fact that in recent years, the variable rate premium is larger than the cost of corporate debt. An underfunded company with a low cost of debt could issue debt, place the proceeds in the pension plan, and realize immediate cash savings. The company would also benefit from the expected return on pension plan assets. Expected return on plan assets positively impacts the company's net income regardless of what actual return materializes. Over time, the return on plan assets will also reduce the need for future contributions so long as returns are positive.

Consider a company with an underfunded pension plan in the year 2018, when the variable rate premium was 3.8%. Assume the company has an expected return on pension assets of 7%.

Any contributions to the pension plan will result in a marginal benefit of 10.8% (pre-tax). In this example, the firm should contribute to the pension so long as its cost of capital is less than 10.8%. If the firm contributes enough to reach 100% funded status, the marginal benefit of contributing will fall to 7%. Figure 3.4 illustrates the marginal cost and benefit of contributing to the pension for firms with a high, medium, and low cost of capital.



We assume that the marginal cost of capital is increasing. This assumption is reasonable for several reasons. A firm that finances a small pension contribution with retained earnings will have no adverse selection costs. However, if the same firm made a larger contribution that required external capital, the cost of capital would include flotation costs and adverse selection costs. Larger contributions may also compete for capital with other projects available to the firm. The firm would prioritize the most profitable projects first, and only contribute to the pension if it had already financed more profitable opportunities. A small pension contribution may only require forgoing a project that is minimally profitable, while larger contributions would have a higher opportunity cost as they competed for capital with more profitable ventures.

In the figure, a firm with a high cost of capital would only be willing to partially fund their pension, while a firm with a low cost of capital would be willing to overfund their pension. The firm with the medium cost of capital would have an opportunity cost of between 10.8% and 7%, and would therefore be willing to fund their pension up to exactly 100% funded status. This theoretically could motivate firms with a low cost of capital to excessively overfund their pension. However, firms have limited ability to revert assets back out of the pension plan, making excessive overfunding undesirable. Excess assets could only be withdrawn from the pension in the event of a plan termination, where pension assets and liabilities are transferred to a separate entity such as an insurance company. In this case, excess assets reverted to the firm would be subject to a 50% excise tax as well as ordinary income taxes.

When it comes to borrowing-to-fund and the VRP, we show that a higher VRP rate increases the motivation to fund the pension plan using either internal or external funds. A higher VRP increases the marginal benefit of contributing to the pension plan, but firms with a high cost of capital will still forgo pension contributions. The empirical evidence that VRP increases led to a widespread increase in borrow-to-fund activity is weak.

We now shift our analysis to focus on pension asset allocation. Firms at risk of paying VRP may choose to shift their pension asset allocation towards equity in hopes of improving their funded status. If equities return higher amounts than bonds, then investments in equities will improve funded status over time and reduce the VRP for underfunded plans. The additional expected return offered by equities comes with additional risk, as equity returns lack the interest rate hedging benefits of bonds. While a manager could argue for increasing the pension asset allocation towards equity in an effort to reduce future VRP payments, it could also be argued that the risk of additional VRP motivates an increased allocation towards bonds. More risky asset allocations increase the risk of unfunded pension deficits when asset returns are poor or liabilities swell in the face of interest rate decreases (such was the fate of pension funds during the dot-com bubble burst and the GFC). A pension with 100% of its assets allocated towards duration matched bonds will face very little interest rate risk, as a decrease in interest rates would increase the value of the bond portfolio at the same rate as it increased the value of pension liabilities. Higher VRP rates increase the potential benefits as well as the downside risk of holding equities, as changes in the underfunded status of the pension plan become more relevant.

Our tests of the relationship between VRP and asset allocation are two-tailed: managers may choose to increase their asset allocations towards equity in hopes of reducing their underfunded amount, or they may choose to increase their asset allocations towards debt in order to hedge against larger future VRP payments.

Table 3.8 reports the results of our asset allocation tests, where the dependent variable equity% ranges from zero to one. Model 4 reports the results of equation 5 with firm and year fixed effects. Model 4 estimates that firms with underfunded pensions allocate 2.34 percentage points more towards equity. For underfunded firms, each additional percentage point of underfunded status is associated with a 0.1551 percentage point increase in equity allocation (UF% and equity% are both bounded between zero and one). In model 4, both terms are significant at the 1% level. This adds evidence towards the risk shifting hypothesis over the risk management hypothesis, as more poorly funded plans allocate a higher portion of their assets towards equity. Once we begin including interaction terms, the significance levels of these estimates vary, but the signs remain positive in each model. In models 5 and 7, the interaction term between UFD and VRP is positive and significant at the 5% level, indicating that the positive relationship between equity% and underfunded status was stronger in years where the VRP was higher. A higher VRP is associated with greater risk taking by underfunded plans. However, the interaction term UFD X UF% X VRP is insignificantly different from zero. The results suggest that firms at risk of paying VRP allocate a higher portion of their pension assets towards equity, and that this relationship was stronger in years where the VRP was higher.

One limitation of the results presented in table 3.8 is that equity% does not perfectly capture risk-taking within the pension plan. Some equity securities are riskier than others, and not all pension investments are confined to equity and debt securities. Pension asset allocation within the Compustat database can also be categorized as “real estate” or “other.” While equity is clearly riskier than debt, an equity allocation that results from a reduction in real estate or other may not

Table 3.8: Pension Asset Allocation to Equity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
UFD	0.0257**	0.0235***	0.0306**	0.0234***	0.0031	0.0221***	0.0023
	(2.05)	(3.50)	(2.53)	(3.50)	(0.29)	(3.31)	(0.20)
UFD X UF%	0.1300	0.1274**	0.0694	0.1551***	0.1660***	0.0831	0.1728*
	(1.32)	(2.18)	(0.71)	(2.67)	(2.88)	(1.02)	(1.81)
UFD X VRP					0.0113**		0.0117**
					(2.42)		(2.14)
UFD X UF% X VRP						0.0494	-0.0043
						(1.37)	(-0.10)
Plan Size			-0.0052	0.0210**	0.0220**	0.0218**	0.0220**
			(-0.88)	(2.35)	(2.40)	(2.39)	(2.39)
Firm Size			-0.0177***	0.0286**	0.0292**	0.0294**	0.0291**
			(-2.71)	(2.01)	(2.05)	(2.08)	(2.05)
Pension Return			0.4030***	0.0603*	0.0596	0.0602*	0.0596
			(5.41)	(1.65)	(1.64)	(1.66)	(1.64)
Duration			0.0194	0.0347	0.0305	0.0318	0.0306
			(0.41)	(0.79)	(0.69)	(0.72)	(0.69)
Operating Cash Flow			-0.0745	-0.1202*	-0.1218*	-0.1219*	-0.1217*
			(-0.96)	(-1.74)	(-1.77)	(-1.76)	(-1.76)
Operating Cash Flow Vol			-2.1066	0.9199	0.8279	0.8374	0.8314
			(-1.15)	(0.47)	(0.42)	(0.43)	(0.42)
Tax Rate			0.0044	-0.0012	-0.0013	-0.0015	-0.0013
			(0.92)	(-0.35)	(-0.36)	(-0.41)	(-0.36)
Debt-to-Assets			-0.0243	-0.0121	-0.0142	-0.0119	-0.0143
			(-0.61)	(-0.32)	(-0.37)	(-0.31)	(-0.38)
Active Percent			0.1124***	-0.0056	-0.0017	-0.0031	-0.0017
			(2.80)	(-0.11)	(-0.03)	(-0.06)	(-0.03)
Service Cost			4.9944**	4.7318	4.9869*	4.7964	4.9915*
			(2.03)	(1.62)	(1.70)	(1.64)	(1.70)
Constant	0.4750***	0.4762***	0.6518***	-0.1918	-0.2161	-0.2146	-0.2151
	(53.68)	(120.02)	(7.72)	(-0.91)	(-1.02)	(-1.01)	(-1.01)
Time Fixed Effects	Year	Year	Year	Year	Year	Year	Year
Time-Invariant FE	Industry	Firm	Industry	Firm	Firm	Firm	Firm
Observations	3,933	3,933	3,933	3,933	3,933	3,933	3,933
Adjusted R-squared	0.1959	0.7064	0.2663	0.7102	0.7111	0.7105	0.7110

Notes: The dependent variable is the equity% allocation of pension assets. UFD is a dummy variable equal to one if the pension is expected to pay PBGC premiums if they do not contribute during the year. UF% is the estimated dollar amount of PBGC funding shortage as of the beginning of the year, scaled by pension liabilities, and is equal to zero UFD equals one. VRP is the level of the PBGC Variable-Rate Premium.

necessarily indicate higher risk taking within the pension. We can further identify the riskiness of a pension plan's assets by analyzing the allocation to debt. Debt and equity allocations combined make up an average of 91% of the asset allocation in our sample. Table 3.8 shows a positive relationship between underfunded status and equity allocation. If this relationship results from higher risk taking (in search of higher returns) then we would expect to see a negative relationship between underfunded status and debt allocation. We therefore model equations 3.5 and 3.6 again, but replace the dependent variable equity% with debt%. The results are presented in table 3.9.

Table 3.9: Pension Asset Allocation to Debt

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
UFD	-0.0280**	-0.0311***	-0.0366***	-0.0312***	-0.0143	-0.0293***	-0.0237**
	(-2.43)	(-4.39)	(-3.27)	(-4.48)	(-1.29)	(-4.22)	(-2.00)
UFD X UF%	-0.0771	-0.1493**	-0.0945	-0.1894***	-0.1985***	-0.0832	-0.1088
	(-0.92)	(-2.47)	(-1.16)	(-3.14)	(-3.30)	(-1.08)	(-1.29)
UFD X VRP					-0.0094*		-0.0034
					(-1.87)		(-0.59)
UFD X UF% X VRP						-0.0728**	-0.0575
						(-2.20)	(-1.53)
Plan Size			-0.0021	-0.0260**	-0.0268**	-0.0272**	-0.0272**
			(-0.37)	(-2.43)	(-2.46)	(-2.48)	(-2.48)
Firm Size			0.0126**	-0.0231	-0.0236	-0.0243	-0.0242
			(1.99)	(-1.50)	(-1.54)	(-1.59)	(-1.59)
Pension Return			-0.1611**	0.0015	0.0021	0.0017	0.0019
			(-2.28)	(0.04)	(0.05)	(0.04)	(0.05)
Duration			-0.1133**	-0.0537	-0.0502	-0.0494	-0.0490
			(-2.34)	(-1.03)	(-0.96)	(-0.95)	(-0.94)
Operating Cash Flow			0.0930	0.1489**	0.1502**	0.1514**	0.1513**
			(1.17)	(2.01)	(2.03)	(2.04)	(2.04)
Operating Cash Flow Vol			4.6857**	-0.3829	-0.3062	-0.2612	-0.2595
			(2.34)	(-0.19)	(-0.15)	(-0.13)	(-0.13)
Tax Rate			0.0061	0.0087**	0.0088**	0.0091**	0.0090**
			(1.09)	(1.98)	(1.99)	(2.03)	(2.02)
Debt-to-Assets			0.0165	-0.0200	-0.0183	-0.0203	-0.0197
			(0.41)	(-0.47)	(-0.43)	(-0.48)	(-0.47)
Active Percent			-0.0442	-0.0292	-0.0325	-0.0328	-0.0332
			(-1.02)	(-0.52)	(-0.58)	(-0.59)	(-0.60)
Service Cost			-4.8752*	-6.2342*	-6.4468**	-6.3295**	-6.3853**
			(-1.92)	(-1.94)	(-2.00)	(-1.97)	(-1.97)
Constant	0.4300***	0.4356***	0.4172***	1.1722***	1.1925***	1.2059***	1.2060***
	(49.05)	(101.36)	(5.21)	(4.79)	(4.83)	(4.87)	(4.87)
Time Fixed Effects	Year	Year	Year	Year	Year	Year	Year
Time-Invariant FE	Industry	Firm	Industry	Firm	Firm	Firm	Firm
Observations	3,933	3,933	3,933	3,933	3,933	3,933	3,933
Adjusted R-squared	0.1335	0.6310	0.1753	0.6382	0.6388	0.6390	0.6390

Table 9: The dependent variable is the debt% allocation of pension assets. UFD is a dummy variable equal to one if the pension is expected to pay PBGC premiums if they do not contribute during the year. UF% is the estimated dollar amount of PBGC funding shortage as of the beginning of the year, scaled by pension liabilities, and is equal to zero UFD equals one. VRP is the level of the PBGC Variable-Rate Premium.

The results from table 3.9 are consistent with the results from table 8. Model 4 finds that firms at risk of paying VRP allocate 3.12 percentage points less of their pension assets towards debt, and that for each additional percentage point of underfunded status, they allocate 0.1894 less percentage points towards debt. Again, riskier asset allocations are associated with poorly funded pension plans. In model 5, the interaction between UFD and VRP is negative and significant at the 10% level, suggesting that the negative relationship between debt% and UFD was stronger in years when the VRP was high. In model 6, the interaction between UF% and VRP is negative and statistically significant at the 5% level. Much of the statistical significance is lost in model 7, but the signs remain consistent. The loss of statistical significance in the fully specified model likely results from overfitting. In addition to the loss of significance on the individual interaction dummies, the significance of UFD and UFD X UF% are both greatly reduced in model 7 relative to model 4, although model 4 is not necessarily inferior to 7.

Overall, our asset allocation tests provide additional evidence against the risk management hypothesis. When corporate pension plans are underfunded, managers do not hedge against further deterioration of funded status by increasing allocation towards debt. Instead, they increase their asset allocation towards equity, likely in hopes of improving funded status through higher pension asset returns. Our results extend previous work by focusing specifically on the cost of underfunding. Other studies have allowed funded status to extend to all possible values between zero and infinity. A linear estimate using a traditional funded status calculation would include the impact of excessively overfunded plans, who face no benefit in terms of VRP reduction. The asset allocation effects we observe are stronger in years where the VRP was higher, suggesting that managers were motivated to take additional risk in the pension in hopes of avoiding paying higher premiums payments.

We now focus our investigation on whether firms are more likely to freeze their pension plans when their expected VRP payment is high. The plan freeze tests require the use of a logistic (logit) model, where the dependent outcome is a binary variable equal to one if the plan is frozen. The setup for the plan freeze tests required us to treat our data slightly differently, since firms can have and freeze multiple plans.

Table 3.10 presents summary statistics for our plan freeze sample. Initially, this plan-level sample would be slightly larger than our previous firm-level sample in which firms with multiple plans have their plans consolidated. The increase in the number of plan-level observations is offset almost exactly by the removal of already frozen plans, leading to a final sample of 3,893 plan-years with 123 plan freezes. The most common year for a plan to be frozen was 2013, just before the VRP began to rise. 60 plan freezes occurred out of a total of 1,741 underfunded plan years (3.21%) while 63 freezes occurred out of a total of 2,152 fully funded plans (2.88%). The underfunded plans were only slightly more likely to be frozen during our sample.

Table 3.10: Pension Plan Freeze Frequency by Year

	Active Plans	Total Freezes	% Frozen	Underfunded Plans	Freezes (UFD=1)	% Frozen	Fully Funded Plans	Freezes (UFD=0)	% Frozen
2010	436	11	2.52%	253	8	3.16%	183	3	1.64%
2011	477	15	3.14%	212	11	5.19%	265	4	1.51%
2012	472	15	3.18%	256	8	3.13%	216	7	3.24%
2013	462	23	4.98%	250	14	5.60%	212	9	4.25%
2014	452	9	1.99%	176	2	1.14%	276	7	2.54%
2015	428	11	2.57%	122	2	1.64%	306	9	2.94%
2016	410	14	3.41%	201	9	4.48%	209	5	2.39%
2017	389	9	2.31%	187	4	2.14%	202	5	2.48%
2018	367	16	4.36%	84	2	2.38%	283	14	4.95%
Total:	3893	123	3.16%	1741	60	3.21%	2152	63	2.88%
Pre 2014:	1847	64	3.46%	971	41	4.27%	876	23	2.66%
Post 2013:	2046	59	2.97%	770	19	2.50%	1276	40	3.03%

Notes: Plans are only included if they are open, or if they are frozen during the year. Plans are excluded if they were already frozen in the previous year

Table 3.11 presents the results of a logit model where the dependent variable is a dummy equal to one if the plan is frozen during the year. If the threat of VRP payments (and increases in the VRP rate) motivated firms to freeze their pensions, then we would expect for the coefficients on UFD and UFD X UF% to be positive. We also expect the interaction between VRP and UFD to be positive, along with the interaction between VRP and UFD X UF%. The results in table 11 provide no evidence consistent with our hypothesis. In model 3, the signs on UFD and UFD X UF% are insignificant and have different signs. Focusing on the interaction terms, model 4 shows no relationship between UFD X VRP and plan freezes. While UFD X UF% X VRP is negative and statistically significant in model 5, it contradicts the statistically significant sign on UFD X VRP in model 6. We do not include firm fixed effects, since a firm can only freeze its pension once. The inclusion of industry fixed effects would create a multicollinearity problem, as many industries have only a few firms with pensions. If every firm within an industry froze, or did not freeze, during our sample, then the industry fixed effects would require excluding that industry altogether. In unreported results, this would reduce our sample size by over 10% and yield qualitatively identical results. The results are largely inconclusive, and we conclude that higher VRP rates were not a determining factor in the decision of whether or not to freeze a pension plan.

Table 3.11: Logit Results: Likelihood of a Plan Freeze

	(1)	(2)	(3)	(4)	(5)	(6)
UFD	0.2069	0.2104	0.1074	0.1552	0.1956	-0.6950
	(0.83)	(0.83)	(0.41)	(0.38)	(0.75)	(-1.40)
UFD X UF%	-0.5516	-0.8506	-1.5229	-1.5272	2.8801	6.9380**
	(-0.34)	(-0.52)	(-0.89)	(-0.89)	(1.21)	(2.29)
UFD X VRP				-0.0253		0.4792**
				(-0.15)		(2.18)
UFD X UF% X VRP					-3.0013**	-5.5633***
					(-2.25)	(-2.98)
Plan Size			-0.0059	-0.0053	0.0076	0.0089
			(-0.06)	(-0.05)	(0.08)	(0.09)
Firm Size			-0.0808	-0.0809	-0.0861	-0.0900
			(-0.84)	(-0.84)	(-0.89)	(-0.93)
Pension Return			0.4763	0.4772	0.4237	0.3977
			(0.23)	(0.23)	(0.20)	(0.19)
Duration			-1.7527**	-1.7588**	-1.8252**	-1.7670**
			(-2.09)	(-2.10)	(-2.19)	(-2.11)
Operating Cash Flow			-3.3994**	-3.4082**	-3.5195**	-3.4374**
			(-2.05)	(-2.06)	(-2.11)	(-2.07)
Operating Cash Flow Vol			21.8186	22.0004	24.9520	24.0625
			(0.79)	(0.79)	(0.90)	(0.86)
Tax Rate			-0.2022	-0.2034	-0.2107	-0.1961
			(-1.16)	(-1.16)	(-1.22)	(-1.13)
Leverage			-1.1351*	-1.1361*	-1.2532*	-1.3416*
			(-1.66)	(-1.66)	(-1.82)	(-1.93)
Active %			-1.1535**	-1.1514**	-1.1052**	-1.1070**
			(-2.21)	(-2.20)	(-2.12)	(-2.13)
Service Cost			-1.5418	-1.4205	-0.6258	-2.7672
			(-0.05)	(-0.05)	(-0.02)	(-0.09)
Constant	-3.4908***	-3.6963***	-1.2854	-1.4798	-1.8073	-1.6022
	(-27.51)	(-11.90)	(-0.93)	(-1.05)	(-1.28)	(-1.13)
Fixed Effects	No	Year	Year	Year	Year	Year
Observations	3,893	3,893	3,893	3,893	3,893	3,893
Psuedo R2	0.001	0.010	0.043	0.043	0.049	0.053

Notes: This table reports the results of a logit model where the outcome variable is a plan freeze. Observations after the plan has been frozen are excluded, and all variables are lagged by one period

3.6 Robustness Checks

When we calculated the cutoff, after which firms are estimated to pay zero VRP, we only included plans if they had verifiable PBGC coverage. This methodology uses a subsample of the actual number of firms with PBGC coverage, since we cannot identify 100% of the covered firms. Alternatively, we could have calculated cutoff using the entire population of Form 5500 schedule SBs. This methodology would include all schedule SBs, even if they lacked the identifier which would flag them as PBGC-covered. The full schedule SB sample would include all PBGC-covered plans, but would also include many that don't have coverage. The PBGC data tables report the number of covered plans per year, so we know that many Schedule SB's only lack the PBGC identifier because of data errors (recall that all PBGC-covered plans file Schedule SB. The only reason we can't find the full number of firms from the PBGC data tables is because some Schedule SB's fail to include "1G" in their list of plan characteristic codes, even though they are actually covered by the PBGC.) As a robustness check, we recreate tables 3.5-3.9 and 3.11, but recalculate UFD and UF% using the entire schedule SB population.

Our contribution robustness tests, reported in tables 3.12 and 3.13, are consistent with our original tests. We concluded that firms contribute more to their pensions when they pay higher VRP, and when the VRP rate is high. The statistical significance behind this conclusion is somewhat stronger in models 4-7. In model 7, table 3.12 (using all contributions) the interaction term UFD X VRP is significant instead of UFD X UF% X VRP. In model 7, table 3.13 (using voluntary contributions) the interaction terms on UFD X VRP and UFD X UF% X VRP are both significant. Including the interaction terms continues to dampen the statistical significance of our original variables of interest (UFD and UFD X UF%.)

In table 3.14, we recreate our borrow-to-fund tests, and find no statistically significant relationships between VRP payments, contributions, and borrowing activity. Similar to our previous tests, we do not find VRP to be a significant motivating factor in borrowing-to-fund.

Table 3.12: Robustness Check for Table 3.5

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
UFD	-0.0046	0.0097***	0.0023	0.0098***	-0.0045	0.0075***	-0.0009
	(-1.62)	(3.57)	(0.96)	(3.74)	(-1.00)	(2.74)	(-0.20)
UFD X UF%	0.1720***	0.1767***	0.1925***	0.1859***	0.1945***	0.1312***	0.1638***
	(9.71)	(9.31)	(13.58)	(10.19)	(10.45)	(5.84)	(6.27)
UFD X VRP					0.0073***		0.0049**
					(4.23)		(2.36)
UFD X UF% X VRP						0.0410***	0.0211
						(3.45)	(1.42)
Plan Size			-0.0016	0.0022	0.0021	0.0021	0.0022
			(-1.33)	(0.59)	(0.54)	(0.53)	(0.57)
Firm Size			-0.0019	-0.0043	-0.0036	-0.0032	-0.0033
			(-1.60)	(-1.03)	(-0.89)	(-0.79)	(-0.83)
Pension Return			-0.0108	-0.0224	-0.0082	-0.0091	-0.0085
			(-0.66)	(-1.37)	(-0.49)	(-0.54)	(-0.50)
Duration			0.0888***	0.0650***	0.0619***	0.0618***	0.0614***
			(9.78)	(4.96)	(4.71)	(4.71)	(4.66)
Operating Cash Flow			0.1155***	0.1271***	0.1292***	0.1283***	0.1287***
			(6.07)	(4.91)	(5.07)	(5.05)	(5.06)
Operating Cash Flow Vol			0.2809	-1.0231**	-1.0472**	-1.0668**	-1.0664**
			(1.15)	(-2.25)	(-2.41)	(-2.40)	(-2.45)
Tax Rate			0.0007	0.0019**	0.0018*	0.0016*	0.0017*
			(0.66)	(1.98)	(1.90)	(1.80)	(1.86)
Debt-to-Assets			0.0075	-0.0182	-0.0185	-0.0175	-0.0182
			(1.02)	(-1.28)	(-1.30)	(-1.24)	(-1.28)
Active Percent			0.0347***	0.0561***	0.0591***	0.0583***	0.0592***
			(4.53)	(2.64)	(2.82)	(2.81)	(2.85)
Service Cost			-0.1761	0.5480	0.8247	0.6781	0.7954
			(-0.38)	(0.53)	(0.83)	(0.69)	(0.80)
Constant	0.0278***	0.0193***	0.0222	-0.0293	-0.0356	-0.0376	-0.0405
	(13.26)	(11.78)	(1.40)	(-0.36)	(-0.42)	(-0.44)	(-0.47)
Time Fixed Effects	Year	Year	Year	Year	Year	Year	Year
Time Invariant FE	Industry	Firm	Industry	Firm	Firm	Firm	Firm
Observations	3,933	3,933	3,933	3,933	3,933	3,933	3,933
Adjusted R-squared	0.1371	0.3438	0.2786	0.3721	0.3793	0.3787	0.3797

Notes: The dependent variable is pension contributions, scaled by pension liabilities. UFD is a dummy variable equal to one if the pension is expected to pay PBGC premiums if they do not contribute during the year. UF% is the estimated dollar amount of PBGC funding shortage as of the beginning of the year, scaled by pension liabilities, and is equal to zero if UFD equals one. In this table, we calculate UFD and UF% using an estimate based on all form 5500's rather than just ones that we confirm have PBGC coverage. VRP is the level of the PBGC Variable-Rate Premium.

Table 3.13: Robustness Check for Table 3.6

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
UFD	0.0019	0.0134***	0.0079***	0.0136***	-0.0042	0.0108***	0.0017
	(0.65)	(4.70)	(3.08)	(4.90)	(-0.89)	(3.70)	(0.34)
UFD X UF%	0.0180	0.0593***	0.0421**	0.0711***	0.0808***	-0.0048	0.0303
	(0.99)	(2.96)	(2.55)	(3.56)	(3.98)	(-0.20)	(1.07)
UFD X VRP					0.0092***		0.0053**
					(5.12)		(2.36)
UFD X UF% X VRP						0.0560***	0.0346**
						(4.17)	(2.00)
Plan Size			0.0003	0.0092**	0.0093**	0.0093**	0.0095**
			(0.25)	(2.19)	(2.06)	(2.06)	(2.09)
Firm Size			-0.0027**	-0.0034	-0.0026	-0.0020	-0.0021
			(-2.15)	(-0.80)	(-0.64)	(-0.49)	(-0.53)
Pension Return			0.0015	-0.0060	0.0025	0.0014	0.0020
			(0.09)	(-0.36)	(0.14)	(0.08)	(0.11)
Duration			0.0740***	0.0505***	0.0465***	0.0461***	0.0456***
			(7.52)	(3.72)	(3.51)	(3.50)	(3.46)
Operating Cash Flow			0.1111***	0.1269***	0.1283***	0.1271***	0.1275***
			(5.71)	(4.55)	(4.68)	(4.67)	(4.68)
Operating Cash Flow Vol			0.0157	-1.0224**	-1.0585**	-1.0905**	-1.0900**
			(0.06)	(-2.06)	(-2.26)	(-2.27)	(-2.32)
Tax Rate			0.0005	0.0017*	0.0017	0.0014	0.0015
			(0.38)	(1.65)	(1.61)	(1.48)	(1.54)
Debt-to-Assets			0.0030	-0.0133	-0.0139	-0.0126	-0.0133
			(0.39)	(-0.95)	(-0.97)	(-0.90)	(-0.94)
Active Percent			0.0310***	0.0503**	0.0543**	0.0535**	0.0546**
			(3.76)	(2.12)	(2.33)	(2.32)	(2.37)
Service Cost			-0.0219	0.4465	0.8047	0.6303	0.7567
			(-0.04)	(0.41)	(0.77)	(0.61)	(0.73)
Constant	0.0274***	0.0177***	-0.0021	-0.1724*	-0.1828*	-0.1877*	-0.1908*
	(13.17)	(10.80)	(-0.13)	(-1.88)	(-1.90)	(-1.94)	(-1.96)
Time Fixed Effects	Year	Year	Year	Year	Year	Year	Year
Time Invariant FE	Industry	Firm	Industry	Firm	Firm	Firm	Firm
Observations	3,933	3,933	3,933	3,933	3,933	3,933	3,933
Adjusted R-squared	0.0591	0.2590	0.1678	0.2824	0.2920	0.2922	0.2934

Notes: The dependent variable is voluntary pension contributions made before the PBGC filing deadline, scaled by pension liabilities. UFD is a dummy variable equal to one if the pension is expected to pay PBGC premiums if they do not contribute during the year. UF% is the estimated dollar amount of PBGC funding shortage as of the beginning of the year, scaled by pension liabilities, and is equal to zero if UFD equals one. VRP is the level of the PBGC Variable-Rate Premium.

Table 3.14: Robustness Check for Table 3.7

	(1)	(2)	(3)	(4)	(5)
Vol Contribution	-0.4228	-0.1077	-0.0183	0.1031	-0.0766
	(-1.09)	(-0.22)	(-0.07)	(0.36)	(-0.14)
UFD X Vol Contribution	0.3737	0.2629	0.2454	0.0376	0.0478
	(0.83)	(0.48)	(0.87)	(0.12)	(0.08)
UFD	-0.0022	-0.0066	-0.0006	-0.0041	-0.0042
	(-0.66)	(-1.39)	(-0.27)	(-1.40)	(-1.41)
VRP X Vol Contribution					0.0789
					(0.40)
UFD X VRP X Vol Contribution					0.0340
					(0.16)
Asset Risk			-0.0002	0.0005	0.0005
			(-0.06)	(0.16)	(0.14)
Market-to-Book			0.0163***	0.0148*	0.0146*
			(3.46)	(1.94)	(1.91)
Dividend Payer			-0.0024	0.0034	0.0034
			(-0.77)	(0.62)	(0.61)
Firm Size			0.0031***	0.0101	0.0101
			(4.50)	(1.31)	(1.31)
Depreciation			0.1816**	0.1828	0.1898
			(2.04)	(1.32)	(1.37)
Tangibility			0.0140	0.1060***	0.1065***
			(1.33)	(3.44)	(3.45)
SG&A			0.0281**	-0.0082	-0.0084
			(2.27)	(-0.17)	(-0.17)
R&D			-0.1130*	0.0266	0.0235
			(-1.75)	(0.11)	(0.10)
Advertising			0.0904	0.3824	0.3766
			(1.24)	(1.10)	(1.07)
Tax Rate			-0.0004	0.0004	0.0004
			(-0.32)	(0.34)	(0.33)
Loss Carryforwards			-0.0181*	-0.0240	-0.0236
			(-1.96)	(-1.44)	(-1.42)
Asset Growth			0.4327***	0.4390***	0.4391***
			(22.11)	(22.34)	(22.37)
Merger Dummy			0.1323***	0.1190***	0.1189***
			(4.54)	(4.34)	(4.35)
Capex			0.0655	0.0214	0.0208
			(1.23)	(0.25)	(0.24)
Industry Growth			-0.0449**	-0.0466**	-0.0468**
			(-2.25)	(-2.33)	(-2.34)
Stock Return			-0.0079**	-0.0077**	-0.0077**
			(-2.50)	(-2.28)	(-2.28)
Industry Leverage			0.0189	0.0232	0.0229
			(0.66)	(0.69)	(0.68)
Firm Leverage			-0.0436***	-0.2483***	-0.2483***
			(-3.71)	(-8.86)	(-8.86)
Operating Cash Flows			-0.2907***	-0.3471***	-0.3467***
			(-6.09)	(-8.20)	(-8.18)
Constant	0.0195***	0.0213***	-0.0408**	-0.0688	-0.0689
	(8.34)	(7.76)	(-2.01)	(-0.97)	(-0.97)
Time Fixed Effects	Year	Year	Year	Year	Year
Time-Invariant FE	Industry	Firm	Industry	Firm	Firm
Observations	3,933	3,933	3,933	3,933	3,933
Adjusted R-squared	0.0383	0.0300	0.6554	0.6951	0.6949

Notes: The dependent variable is Debt Issuances. Debt Issuances is debt at the end of the year minus debt at the beginning of year, divided by beginning of year assets. Contribution is pension contributions divided by beginning of year assets. UFD is a dummy variable equal to one if the pension is expected to pay VRP if they do not contribute during the year. VRP is the level of the PBGC Variable-Rate Premium

We recreate our asset allocation tests in tables 3.15 and 3.16, and the results are similar to our previous findings. Model 4 shows significantly higher allocations to equity and lower allocations to debt in underfunded firms. In models 5, 6, and 7, we again see the rise in VRP was associated with higher allocations to equity and lower allocations to debt in underfunded firms. The statistical significance is somewhat weaker relative to tables 8 and 9, though.

Table 3.15: Robustness Check for Table 3.8

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
UFD	0.0144	0.0196***	0.0188	0.0193***	-0.0018	0.0170**	-0.0010
	(1.17)	(2.79)	(1.57)	(2.76)	(-0.17)	(2.49)	(-0.08)
UFD X UF%	0.1742**	0.1430***	0.1241	0.1650***	0.1802***	0.1039	0.1736**
	(2.13)	(2.79)	(1.52)	(3.22)	(3.51)	(1.47)	(2.05)
UFD X VRP					0.0110**		0.0105*
					(2.38)		(1.85)
UFD X UF% X VRP						0.0469	0.0045
						(1.44)	(0.11)
Plan Size			-0.0050	0.0207**	0.0220**	0.0217**	0.0220**
			(-0.85)	(2.33)	(2.42)	(2.39)	(2.41)
Firm Size			-0.0178***	0.0276*	0.0283**	0.0286**	0.0283**
			(-2.72)	(1.95)	(1.99)	(2.02)	(2.00)
Pension Return			0.3990***	0.0547	0.0559	0.0546	0.0558
			(5.29)	(1.48)	(1.53)	(1.49)	(1.53)
Duration			0.0212	0.0376	0.0334	0.0344	0.0333
			(0.44)	(0.85)	(0.76)	(0.78)	(0.75)
Operating Cash Flow			-0.0787	-0.1252*	-0.1253*	-0.1263*	-0.1254*
			(-1.02)	(-1.83)	(-1.83)	(-1.84)	(-1.83)
Operating Cash Flow Vol			-2.1425	0.9394	0.8667	0.8617	0.8626
			(-1.17)	(0.48)	(0.44)	(0.44)	(0.44)
Tax Rate			0.0042	-0.0013	-0.0013	-0.0015	-0.0013
			(0.89)	(-0.36)	(-0.38)	(-0.42)	(-0.38)
Debt-to-Assets			-0.0247	-0.0132	-0.0143	-0.0129	-0.0143
			(-0.61)	(-0.34)	(-0.38)	(-0.34)	(-0.38)
Active Percent			0.1120***	-0.0070	-0.0023	-0.0043	-0.0023
			(2.79)	(-0.13)	(-0.04)	(-0.08)	(-0.04)
Service Cost			4.8348*	4.4941	4.8635*	4.6070	4.8572*
			(1.95)	(1.54)	(1.65)	(1.57)	(1.65)
Constant	0.4733***	0.4727***	0.6490***	-0.1798	-0.2105	-0.2054	-0.2115
	(47.98)	(95.70)	(7.59)	(-0.86)	(-0.99)	(-0.97)	(-1.00)
Time Fixed Effects	Year	Year	Year	Year	Year	Year	Year
Time-Invariant FE	Industry	Firm	Industry	Firm	Firm	Firm	Firm
Observations	3,933	3,933	3,933	3,933	3,933	3,933	3,933
Adjusted R-squared	0.1955	0.7063	0.2654	0.7100	0.7108	0.7104	0.7107

Notes: The dependent variable is the equity% allocation of pension assets. UFD is a dummy variable equal to one if the pension is expected to pay PBGC premiums if they do not contribute during the year. UF% is the estimated dollar amount of PBGC funding shortage as of the beginning of the year, scaled by pension liabilities, and is equal to zero UFD equals one. In this table, we calculate UFD and UF% using an estimate based on all form 5500's rather than just ones that we confirm have PBGC coverage. VRP is the level of the PBGC Variable-Rate Premium.

In table 3.17, the robustness check on our logistic model again shows no relationship between VRP payments and the decision to freeze a pension plan. The only statistically significant signs

Table 3.16: Robustness Check for Table 3.9

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
UFD	-0.0157	-0.0263***	-0.0239**	-0.0265***	-0.0115	-0.0235***	-0.0214*
	(-1.32)	(-3.41)	(-2.02)	(-3.54)	(-1.04)	(-3.18)	(-1.84)
UFD X UF%	-0.1262*	-0.1821***	-0.1492**	-0.2154***	-0.2262***	-0.1324*	-0.1402*
	(-1.74)	(-3.33)	(-2.10)	(-3.94)	(-4.12)	(-1.92)	(-1.83)
UFD X VRP					-0.0079		-0.0012
					(-1.54)		(-0.20)
UFD X UF% X VRP						-0.0637**	-0.0590*
						(-2.08)	(-1.68)
Plan Size			-0.0023	-0.0261**	-0.0270**	-0.0273**	-0.0274**
			(-0.40)	(-2.45)	(-2.49)	(-2.51)	(-2.50)
Firm Size			0.0128**	-0.0219	-0.0224	-0.0232	-0.0232
			(2.01)	(-1.43)	(-1.46)	(-1.52)	(-1.52)
Pension Return			-0.1561**	0.0106	0.0098	0.0108	0.0106
			(-2.19)	(0.27)	(0.25)	(0.27)	(0.27)
Duration			-0.1154**	-0.0576	-0.0547	-0.0533	-0.0532
			(-2.37)	(-1.11)	(-1.05)	(-1.03)	(-1.02)
Operating Cash Flow			0.0984	0.1549**	0.1550**	0.1564**	0.1563**
			(1.24)	(2.12)	(2.12)	(2.13)	(2.13)
Operating Cash Flow Vol			4.7261**	-0.4203	-0.3685	-0.3147	-0.3148
			(2.37)	(-0.21)	(-0.19)	(-0.16)	(-0.16)
Tax Rate			0.0063	0.0088**	0.0088**	0.0091**	0.0091**
			(1.13)	(2.02)	(2.02)	(2.06)	(2.06)
Debt-to-Assets			0.0170	-0.0187	-0.0179	-0.0191	-0.0190
			(0.41)	(-0.44)	(-0.42)	(-0.45)	(-0.45)
Active Percent			-0.0436	-0.0282	-0.0316	-0.0318	-0.0321
			(-1.01)	(-0.51)	(-0.57)	(-0.57)	(-0.58)
Service Cost			-4.6772*	-5.9270*	-6.1901*	-6.0803*	-6.1083*
			(-1.84)	(-1.85)	(-1.92)	(-1.89)	(-1.89)
Constant	0.4306***	0.4410***	0.4195***	1.1681***	1.1899***	1.2028***	1.2035***
	(44.11)	(82.80)	(5.16)	(4.80)	(4.85)	(4.89)	(4.89)
Time Fixed Effects	Year	Year	Year	Year	Year	Year	Year
Time-Invariant FE	Industry	Firm	Industry	Firm	Firm	Firm	Firm
Observations	3,933	3,933	3,933	3,933	3,933	3,933	3,933
Adjusted R-squared	0.1322	0.6314	0.1737	0.6386	0.6389	0.6393	0.6392

Notes: The dependent variable is the debt% allocation of pension assets. UFD is a dummy variable equal to one if the pension is expected to pay PBGC premiums if they do not contribute during the year. UF% is the estimated dollar amount of PBGC funding shortage as of the beginning of the year, scaled by pension liabilities, and is equal to zero UFD equals one. In this table, we calculate UFD and UF% using an estimate based on all form 5500's rather than just ones that we confirm have PBGC coverage. VRP is the level of the PBGC Variable-Rate Premium.

contradict each other, as with the negative sign on UFD followed by the positive sign on UFD X UF in model 6.

Table 3.17: Robustness Check for Table 3.11

	(2)	(3)	(4)	(5)	(6)	(7)
UFD	-0.0763	-0.0753	-0.2047	-0.3858	-0.1025	-1.2144**
	(-0.30)	(-0.30)	(-0.78)	(-0.93)	(-0.39)	(-2.41)
UFD X UF%	0.5710	0.2943	-0.3529	-0.3097	2.4939	6.7077***
	(0.42)	(0.21)	(-0.25)	(-0.21)	(1.24)	(2.59)
UFD X VRP				0.0923		0.5926***
				(0.56)		(2.68)
UFD X UF% X VRP					-2.0667*	-4.7564***
					(-1.83)	(-2.99)
Plan Size			-0.0064	-0.0082	0.0030	0.0056
			(-0.07)	(-0.08)	(0.03)	(0.06)
Firm Size			-0.0830	-0.0824	-0.0868	-0.0881
			(-0.86)	(-0.86)	(-0.90)	(-0.91)
Pension Return			0.5256	0.5311	0.4397	0.3906
			(0.26)	(0.26)	(0.21)	(0.19)
Duration			-1.8918**	-1.8766**	-1.9393**	-1.9057**
			(-2.26)	(-2.24)	(-2.32)	(-2.28)
Operating Cash Flow			-3.3017**	-3.2765**	-3.4292**	-3.4311**
			(-2.01)	(-1.99)	(-2.08)	(-2.08)
Operating Cash Flow Vol			20.1517	19.7820	22.6738	23.4571
			(0.72)	(0.71)	(0.82)	(0.84)
Tax Rate			-0.2044	-0.2018	-0.2123	-0.2064
			(-1.17)	(-1.15)	(-1.22)	(-1.18)
Leverage			-1.0932	-1.0873	-1.1804*	-1.2628*
			(-1.60)	(-1.59)	(-1.72)	(-1.82)
Active %			-1.1623**	-1.1702**	-1.1224**	-1.1195**
			(-2.24)	(-2.25)	(-2.16)	(-2.16)
Service Cost			1.2242	1.0598	1.8513	1.3074
			(0.04)	(0.03)	(0.06)	(0.04)
Constant	-3.4204***	-3.6329***	-1.1515	-1.2135	-1.6150	-1.3414
	(-24.96)	(-11.48)	(-0.83)	(-0.86)	(-1.14)	(-0.94)
Time Fixed Effects	No	Year	Year	Year	Year	Year
Observations	3,893	3,893	3,893	3,893	3,893	3,893
Psuedo R2	0.0002	0.0096	0.0436	0.0439	0.0471	0.0535

Notes: This table reports the results of a logit model where the outcome variable is a plan freeze. Observations after the plan has been frozen are excluded, and all variables are lagged by one period

Overall, our robustness checks confirmed that firms contribute more (in both voluntary and total terms) to their pensions when they are at risk of paying VRP. The increases in the VRP rate appear to have strengthened this effect. Further, firms choose more aggressive pension asset allocations when they pay larger VRP. Again, larger VRP rates are associated with more risk-taking by poorly funded firms. We do not find any evidence that VRP rates influence borrow-to-fund or pension freeze decisions.

3.7 Conclusion

A more economically fair pension insurance premium has been proposed as a way of reducing risk-shifting incentives. The new PBGC premium calculation fails to perfectly price pension insurance, as it does not consider pension asset allocation or firm risk. However, it greatly improves over previous premium formulas by increasing the cost of sponsoring an underfunded pension plan. We find that in response to the threat of variable rate premium payments, corporations make greater mandatory and voluntary contributions to their pension plans. Additionally, firms at risk of paying more VRP take on more aggressive pension asset allocations, as measured by their exposure to debt and equity securities. In terms of overall pension safety, corporate reactions to VRP increases have mixed effects: larger contributions make pension plans safer while larger asset allocations to equity make them more risky. Management appears motivated to decrease total VRP payments, as both reactions will close the funding gap over the long term so long as equities outperform bonds. We find little evidence that VRP rate hikes led to increased borrow-to-fund activity, or to an increase in the frequency of pension plan freezes. Our econometric tests yield directional estimates consistent with borrowing-to-fund, but the estimates themselves are statistically insignificant. Given the lack of widespread evidence of borrow-to-fund activity, we consider variations in the cost of capital: only firms with high costs of capital would be willing to underfund their pension. This theory is consistent with the data, as underfunded firms exhibit several characteristics indicating a high cost of capital.

Overall, the evidence suggests that VRP rate hikes were associated with larger contributions and more aggressive asset allocations in underfunded plans. These findings are of particular importance to lawmakers, but further research may be merited, particularly because of the lack of perfect data and the necessity for estimating firm-level VRP payments.

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Appendices

Appendix A

Details of the Variable Rate Premium Estimation

In order to assess firm reactions to variable rate premiums, we must identify which firms are underfunded on a PBGC basis. According to the PBGC, most private-sector defined benefit plans are covered by the PBGC. A plan may be exempt from coverage if 1) It has not covered more than 25 active participants at any time since ERISA was enacted (September 2, 1974), and 2) It is established and maintained by a "professional service employer." An organization is considered a "professional service employer" if its principal business is the performance of professional services and it is owned or controlled by one or more "professional individuals." The Compustat sample that we study generally covers larger firms, and only 0.3% of the firm-years in our sample have fewer than 25 employees, so we assume all Compustat-Schedule SB linked plans have PBGC coverage.

US pension sponsors are required to file form 5500. However, the PBGC pension liability is measured differently from the Schedule SB Funding Target on the form 5500, and the PBGC does not report firm- or plan-level information on funded status. They do report the aggregate percentage of firms that are paying VRP on a year-by-year basis up until 2018. Because plans that are covered by the PBGC must file the form 5500, we can sort the sample by their form 5500 funding status and create a cutoff after which we estimate firms pay no VRP. The extent to which a plan is more poorly funded than the cutoff gives us an idea of how underfunded it is on a PBGC basis. Our identification of underfunded firms on a PBGC basis is described most easily through an example.

Consider the 2014 plan year for a plan with a 1/1/2014 valuation date. The PBGC filing, along with the PBGC premium, will be due by 10/15/2014. The form 5500 for the 2013 plan year will be due on 7/31/2014, or 10/15/2014 if the firm requests an extension. According to form 5558, which is used to file extensions, extensions are automatically approved. The PBGC unfunded vested benefit, used to calculate the VRP, is calculated as the PBGC premium funding target minus plan assets, which is almost always equal to the market value of assets as of 1/1/2014[1]. When calculating the 1/1/2014 market value of assets, the firm may include the present value of contributions made after the beginning of the year but before the 2013 form 5500 is filed, so the firm has up until 10/15/2014 to make contributions to its pension plan that would reduce any VRP. We can observe the market value of assets directly from the form 5500, but the PBGC premium funding target differs from the form 5500 funding target in two ways: 1) the PBGC calculation uses a different set of interest rates and 2) the funding target includes all liabilities, whereas the PBGC liability includes only vested benefits. We wish to calculate the PBGC unfunded vested benefit as the PBGC premium funding target (which we do not observe) minus the market value of assets (which we do observe). To estimate the premium funding target, we start by calculating funded statusSB% as the market value of assets divided by the funding target[2].

Our measure of funded statusSB% differs slightly from the form 5500 Schedule SB Funding Target Attainment Percentage (FTAP) and Adjusted Funding Target Attainment Percentage (AFTAP), and serves as a better proxy for the PBGC funded status. FTAP is inferior to funded statusSB% as it subtracts credit balances from the market value of assets before dividing by the funding target. Firms create credit balances when they contribute more than the required minimum contribution, and can use credit balances to reduce required minimum contributions in future years. AFTAP uses the smoothed actuarial value of assets, whereas the PBGC unfunded vested benefit is calculated using market value of assets.

[1]There is an exception for small plans, but we are studying larger plans in the Compustat database. All of our plans have beginning of year valuation dates, which is required for large plans. This suggests we don't have many issues with small plans in our sample.

[2]We do not use Vested Funding Target as it is unavailable prior to 2014. For years when it is available, the Vested Funding Target is highly correlated with funding target (p=0.9998.)

Our calculation of funded statusSB% improves on both metrics and allows us to assess generally how well funded a plan is on a PBGC basis. Differences between the liability calculation for PBGC and Schedule SB purposes mean that a funded statusSB% of above 100% does not necessarily imply that a firm pays zero VRP. Table A.1 shows the median interest rates used to calculate the Form 5500 Funding Target versus the interest rates use to calculate the PBGC Premium Funding Target.

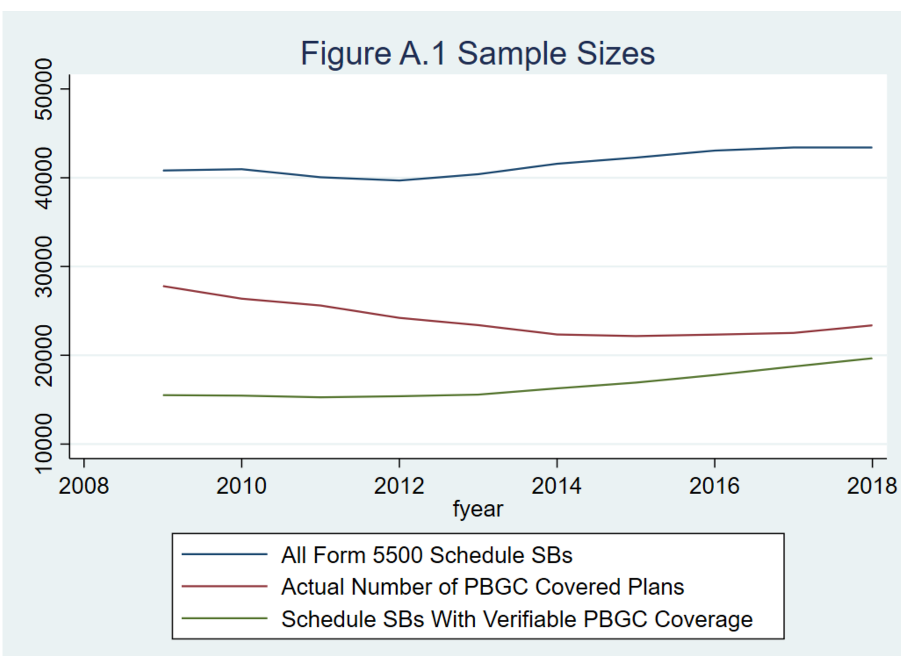
Table A.1: Pension Segment Rates

	Funding Segment Rates for Form 5500			PBGC Segment Rates		
Year	1st Segment Rate	2nd Segment Rate	3rd Segment Rate	1st Segment Rate	2nd Segment Rate	3rd Segment Rate
2009	5.31%	6.50%	6.69%	6.72%	7.12%	6.36%
2010	4.60%	6.65%	6.76%	2.35%	5.65%	6.45%
2011	2.94%	5.82%	6.45%	1.98%	5.23%	6.52%
2012	5.54%	6.85%	7.52%	2.07%	4.45%	5.24%
2013	4.94%	6.15%	6.76%	1.00%	3.57%	4.77%
2014	4.99%	6.32%	6.99%	1.25%	4.57%	5.60%
2015	4.72%	6.11%	6.81%	1.48%	3.77%	4.79%
2016	4.43%	5.91%	6.65%	1.82%	4.12%	5.01%
2017	4.16%	5.72%	6.48%	2.04%	4.03%	4.82%
2018	3.92%	5.52%	6.29%	2.33%	3.55%	4.11%

The PBGC segment rates are generally higher than the form 5500 funding segment rates in 2009, but decline much more rapidly over time. By 2018, the Funding Segment rates are about two percentage points higher than the PBGC Segment Rates. Map-21 increased the funding segment rates starting in 2012 by allowing for firms to use the average of segment rates over the previous 25 years. The same law also raised the VRP for the first time. The higher interest rate spread in later years implies that, relative to the form 5500, it will be harder to be fully funded on a PBGC basis in later years.

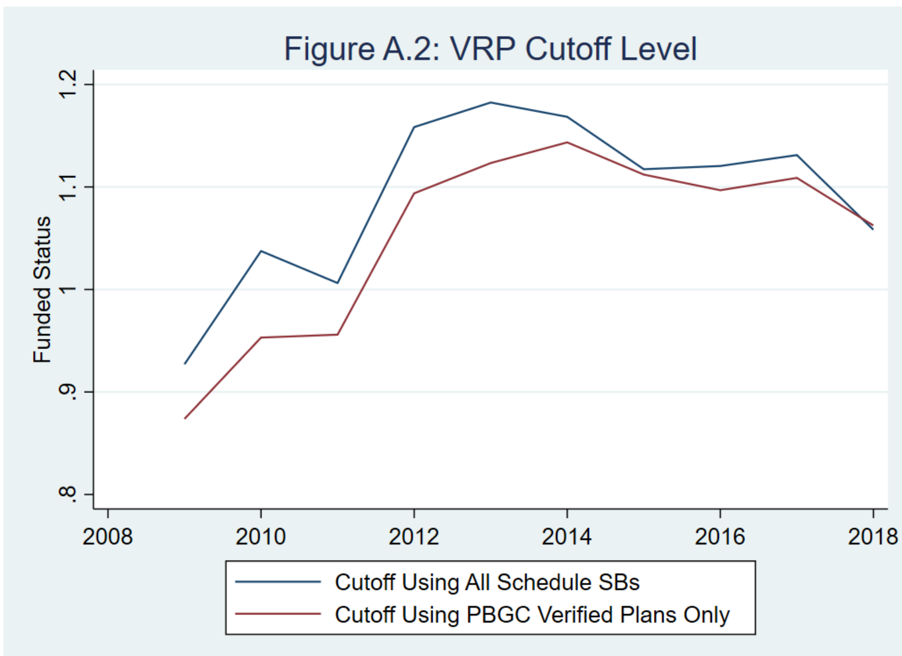
While it does not provide firm-level data, the PBGC data tables do report the aggregate percentage of plans that pay variable rate premiums in a given year. In 2014, 51.2% of PBGC-insured plans paid VRP and thus were underfunded on a PBGC basis. To assess which plans are underfunded, we sort each year's cross section by funded statusSB% and calculate the nth percentile of the distribution. In 2014, the 51.2nd percentile of funded statusSB% was 114.3%, so we create cutoff=1.143 and flag firms with funded status% below cutoff as being underfunded. A firm with a funded statusSB% of 110% is likely still paying PBGC premiums, since the PBGC premium funding target is higher than the Schedule SB Funding Target (as a result of lower PBGC interest rates).

When calculating cutoff, we only include plans that we can verify are covered by the PBGC. Not all pension plans that file form 5500 schedule SB are covered by the PBGC. A small plan can be exempt from PBGC coverage if it has always covered less than 25 employees (since ERISA passage in 1974) and the plan is established and maintained by a "professional service employee". As a result, the total population of form 5500 Schedule SB's is larger than the population of plans with PBGC coverage. We calculate our preferred cutoff using plans that we can verify are covered by the PBGC, and recalculate cutoff using all schedule SB filings as a robustness check. To flag covered firms, we rely on two sources. The PBGC website has a list of currently covered plans by EIN and plan number . Additionally, prior to 2013, the form 5500 List of Plan Characteristics Codes included code "1G" to indicate that a firm was covered by the PBGC. If the EIN and plan number match to the list of PBGC plans, or if the plan's form 5500 has ever listed code "1G", we treat the plan as being covered by the PBGC. Figure A.1 shows the actual number of plans covered by the PBGC (reported in the PBGC data tables), the total number of plans in the form 5500 dataset, and the number of Form 5500s that we can verify are covered by the PBGC.



The full sample of form 5500's would include many firms that aren't covered by the PBGC, while the sample of 5500's with verifiable PBGC coverage includes only a subset of the actual plans covered by the PBGC.

Using either sample, we can calculate an estimate of the cutoff, after which firms pay no VRP. Figure A.2 shows the cutoff over time, calculated once using the entire Schedule SB dataset and once using only those plans with verifiable PBGC coverage.



Cutoff rises significantly in 2012 upon the passage of MAP-21, which makes it easier to be fully funded on the Schedule SB. The 2014 cutoff of 1.143 also implies that PBGC liabilities were 114.3% as large as form 5500 liabilities during 2014. We estimate the PBGC liability as the schedule SB funding target times the cutoff.

Our research questions deal with how firms avoid paying PBGC premiums. While the premium funding target is fixed at the beginning of the year, PBGC assets may be increased if the firm contributes to the plan after the beginning of the plan year and before the form 5500 is filed (due by 10/15/2014, the same date as the PBGC filing). It is likely that firms are aware of their PBGC funding shortfall (through communications with their actuary) at some point between 1/1/2014 and 10/15/2014, and make contributions in order to avoid paying the VRP. Since our study focuses on whether firms borrow-to-fund and avoid premiums, we calculate the preliminary beginning of year assets and funded status by taking the market value of assets and subtracting the present value of all contributions that are made after 1/1/2014 and allocated towards the 2013 plan year. We discount the contributions using the effective interest rate, consistent with the form 5500 instructions. Using this procedure we create market value of assets pre, or MVA Pre.

We then create an underfunded dummy equal to one if MVA Pre is less than the estimated premium funding target. The underfunded dummy is equal to one if the firm is expected to pay VRP if they don't make additional contributions to the pension. We expect that firms will make contributions during the year to avoid the penalty associated with being underfunded. We calculate the final funded status metrics that we use in our analysis as

$$\$UF = max(PBGC\ Liability - MVA\ Pre, 0) \tag{A.1}$$

$$UFD = 1\ if\ \$UF > 0, and\ 0\ otherwise \tag{A.2}$$

$$UF\% = \frac{\$UF}{PBGC\ Liability} \tag{A.3}$$

These metrics allow us to assess how large a pension's VRP would be if they did not take action during the year to reduce them. UFD =1 indicates that if a firm does not contribute by October 15th, they will pay VRP. $UF and UF% give us an idea of the size of the VRP. These metrics have several advantages over those used in the existing literature. Studies often allow for funded status% to exceed 100%. While there is nothing inherently wrong with that approach, our study focuses specifically on the VRP penalty of being underfunded. We therefore only need a measure of the underfunded level: overfunding a pension plan beyond 100% does not reduce the cost of variable rate premiums. Further, we wish to identify actions taken to reduce VRP. A firm that makes extra contributions during the year using borrowed money may avoid the VRP entirely, but would not ultimately show up as underfunded on their final filing. They would only show up as underfunded at the beginning of the year according to MVA Pre. This motivates the use of our adjusted MVA Pre, which assesses the funded status of a firm before actions are taken to avoid the VRP.

We merge the Schedule SB data with the Compustat and CRSP data, which gives us access to firm characteristics as well as pension asset allocation. The asset allocation data available from the form 5500 includes vague categories such as "mutual funds," which often does not differentiate between stocks and bonds. The Compustat data, on the other hand, breaks down pension asset allocation into debt, equity, real estate, and other. Using the Compustat data, we can measure asset allocation at the end of the year and assess how it relates to underfunded status as of the beginning of the year. In some cases, the fiscal year end date in Compustat does not match the fiscal year end on the form 5500. To minimize issues associated with year-end timing, we limit our sample to firms whose pension plan year-end is within 31 days of the Compustat fiscal year end. The final sample consists of 3,933 firm-years. The sample is slightly smaller on a firm-per-year basis than comparable samples in previous studies, partly because of the fiscal year-end matching requirement, and partly because of the decline over time in the number of pension plans.