DEPARTMENT OF ACCOUNTING AND FINANCE

ESSAYS IN FINANCIAL ECONOMICS

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Panayiotis Papakyriakou

Περίληψη

Η παρούσα διατριβή αποτελείται από τρία κεφάλαια. Τα πρώτα δύο κεφάλαια είναι συνεχόμενα, στην Εμπειρική Εταιρική Χρηματοοικονομική, και συγκεκριμένα στα ταμεία προνοίας Καθορισμένων Παροχών (ΚΠ) από δημόσιες εταιρίες των Ηνωμένων Πολιτειών της Αμερικής. Το τρίτο κεφάλαιο είναι στην Εμπειρική Αποτίμηση Κεφαλαίων και εξετάζει την αντίδραση των χρηματαγορών διαφόρων χωρών του κόσμου όταν η πιστοληπτική ικανότητα αυτών των χωρών αλλάζει από τους τρεις μεγάλους οίκους αξιολόγησης, την Fitch, την Moody's και την Standard and Poor's. Στο πρώτο κεφάλαιο ορίζω μια καινούργια μονάδα μέτρησης του αναλογιστικού σφάλματος στις υποθέσεις χρηματοδότησης των ταμείων προνοίας ΚΠ και συγκρίνω τα συμπεράσματα μου με αυτά από προηγούμενες μελέτες που δεν χρησιμοποιούν την νέα μονάδα μέτρησης. Στο δεύτερο κεφάλαιο χρησιμοποιώ την μέθοδο διαφορά των διαφορών (difference-in-differences) ως τη κύρια μέθοδο ανάλυσης αποτελεσμάτων και εξετάζω κατά πόσο μεγάλες πτώσεις στο επίπεδο χρηματοδότησης των ταμείων προνοίας ΚΠ είναι συνυφασμένες με μεγαλύτερα αναλογιστικά σφάλματα την επόμενη χρονιά. Στο τρίτο κεφάλαιο εξετάζω αν η αλλαγή του κανονισμού (EU, 2013) για τους Διεθνείς Οίκους Αξιολόγησης (ΔΟΑ), που αλλάζει την απροσδιόριστη φύση των αλλαγών στην πιστοληπτική ικανότητα των χωρών σε προσδιορισμένη, επηρέασε την επίδραση στις χρηματαγορές που βρήκαν οι Μιχαηλίδης και άλλοι (2015) πριν από αλλαγές στην πιστοληπτική ικανότητα χωρών απο τους 3 μεγάλους ΔΟΑ.

Στο πρώτο κεφάλαιο ορίζω και χρησιμοποιώ μια καινούργια μονάδα μέτρησης για τα σφάλματα των αναλογιστών στις υποθέσεις χρηματοδότησης ταμείων προνοίας καθορισμένων παροχών, το Αναλογιστικό Σφάλμα (ΑΣ). Το αναλογιστικό σφάλμα ορίζεται ως η διαφορά μεταξί των Αναμενόμενων Αποδόσεων (ΑΑ) των συνταξιοδοτικών στοιχείων του ενεργητικού για δύο συνεχείς χρονιές (π.χ. $ΑΣ_{t+1} = ΑΑ_{t+1} – ΑΑ_{t}$). Χρησιμοποιώντας δεδομένα,

από το 2000 μέχρι το 2011, απο το Αμερικάνικο Τμήμα Εργασίας (US Department of Labour), από την Compustat και την Datastream βρίσκω ότι τα πιο ασθενή οικονομικά ταμεία προνοίας ΚΠ είναι συνυφασμένα με μεγαλύτερα ΑΣ την επόμενη χρονιά, κάτι που κάνει τις υποχρεώσεις που έχει το ταμείο να φαίνονται μικρότερες. Αυτό το αποτέλεσμα είναι παρόμοιο με αυτά άλλων μελετών, π.χ. Kisser, Kiff & Soto (2016), που βρίσκουν πως οι αναλογιστές κάνουν υποθέσεις μείωσης υποχρεώσεων όταν τα ταμεία προνοίας είναι ασθενέστερα οικονομικά.

Στο δεύτερο κεφάλαιο, χρησιμοποιώ το Αναλογιστικό Σφάλμα και την διεθνή οικονομική κρίση του 2008 ως εξωγενή παράγοντα αλλαγής της χρηματοοικονομικής κατάστασης των ταμείων προνοίας ΚΠ και βρίσκω ότι τα ασθενέστερα ταμεία προνοίας ΚΠ είναι συνυφασμένα με μεγαλύτερα ΑΣ την επόμενη χρονιά. Συγκεκριμένα, βρίσκω ότι ταμεία των οποίων η οικονομική κατάσταση επιδεινώνεται σημαντικά από την προηγούμενη χρονιά (*t-1*) στην φετινή χρονιά (*t*) είναι συνυφασμένα με μεγαλύτερα ΑΣ την επόμενη χρονία (*t+1*). Τα αποτελέσματα είναι στατιστικά σημαντικά μόνο μετά το έτος 2008. Για επαλήθευση των αποτελεσμάτων επαναλαμβάνω την ανάλυση, χωρίζοντας το δείγμα στον χρόνο 2006, αντί στον χρόνο 2008, για τον λόγο ότι το 2006 ψηφίστηκε ο νόμος προστασίας των ταμείων προνοίας στην Αμερική εισάγοντας πρόσθετους περιορισμούς και κανονισμούς για τα ταμεία προνοίας ΚΠ και μη, και βρίσκω παρόμοια αποτελέσματα. Τελειώνοντας τα αποτελέσματα δεν αλλάζουν αν λάβουμε υπόψη παραμέτρους όπως οι αμοιβές των αναλογιστών και η γενική χρηματοοικονομική κατάσταση των ταμείων.

Στο τρίτο κεφάλαιο, εξετάζω κατα πόσο ο Ευρωπαικός Κανονισμός 462/2013 του Ευρωπαικού Κοινοβουλίου και Συμβουλίου που άλλαξε την φύση των ανακοινώσεων της πιστοληπτικής ικανότητας χωρών από απροσδιόριστη σε προσδιορισμένη, επηρέασε τα ευρήματα από τον Μιχαηλίδη και άλλους (2015) που βρίσκουν πρόωρη επίδραση τέτοιων ανακοινώσεων στις χρηματαγορές. Συγκεκριμένα οι Μιχαηλίδης και άλλοι (2015) βρίσκουν αποτελέσματα που δυνητικά εξηγούνται από διαρροή πληροφοριών στις χρηματαγορές χωρών χαμηλής θεσμικής ποιότητας που υποβαθμίζεται η οικονομία τους. Στην παρούσα μελέτη, εξετάζω κατά πόσο η αλλαγή στον Ευρωπαικό κανονισμό επηρέασε την διαρροή πληροφοριών μετά τον Ιούνιο του 2013. Χρησιμοποιώ μια βάση δεδομένων ανάλυσης ειδήσεων για να δημιουργήσω μια μεταβλητή που μετρά τον αιφνιδιασμό των χρηματαγορών σε ανακοινώσεις σχετικά με την πιστοληπτική ικανότητα χωρών, μετρώντας την βαρύτητα ειδήσεων, και εξετάζω τις αντιδράσεις των χρηματαγορών όταν αιφνιδιάζονται θετικά ή αρνητικά. Αρχικά βρίσκω ότι οι αγορές αντιδρούν θετικά σε απρόβλεπτες αναβαθμίσεις της πιστοληπτικής ικανότητας των χωρών τους. Ακολούθως, όταν οι αγορές αιφνιδιάζονται θετικά, οι χρηματαγορές αντιδρούν θετικά την ημέρα της ανακοίνωσης αλλά και μετά. Εν τέλει, όταν οι αγορές αιφνιδιάζονται αρνητικά, δεν παρατηρείται στατιστικά σημαντική αντίδραση στις αγορές γύρω ή κατά την ημέρα της ανακοίνωσης κάτι που υποδηλέι πως οι χρηματαγορές δεν αντιλαμβάνονται τις ανακοινώσεις αρνητικού αιφνιδιασμού σαν συμβάντα γεγονότα.

Abstract

This dissertation consists of three Chapters. The first two chapters are sequential, on empirical corporate finance, and specifically on Defined Benefit (DB) pension plans from publicly traded firms in the US. The third chapter is on empirical asset pricing and examines the reaction of stock markets around the world to sovereign rating changes from the three big Credit Rating Agencies, namely Fitch, Moody's and Standard and Poor's. In the first Chapter I define a new measure for actuarial estimation errors in the funding assumptions of DB pension plans and compare findings to those from past literature when the new measure is put in use. In the second Chapter I employ a difference in differences research design as the main identification strategy to investigate whether big drops in the funding level of DB pension plans are associated to bigger actuarial estimation errors in the subsequent year. In the third Chapter I investigate whether a change of regulation (EU, 2013) for Credit Rating Agencies, henceforth CRAs, changing the unscheduled nature of sovereign debt rating announcements to scheduled, affected the pre-announcement effect that Michaelides et al. (2015) document prior to sovereign debt rating changes from the big 3 CRAs.

In Chapter 1, I develop and use a new measure for actuarial estimation errors in pension funding assumptions of defined-benefit pension plans, the Actuarial Estimation Error (AEE). The AEE is defined as the difference between the Expected Return (ER) of pension plan assets for two consecutive years (e.g. $AEE_t = ER_t - ER_{t-1}$). Using data, spanning 2000-2011, from the US Department of Labour, Compustat and DataStream I find that financially weaker DB pension plans are associated with bigger AEEs in the following year, an obligation reducing assumption. This result is consistent with findings from the literature, e.g. Kisser, Kiff, & Soto (2016), suggesting that actuaries make obligation reducing assumptions when DB pension plans are underfunded.

In Chapter 2, I use the proposed Actuarial Estimation Error and the 2008 global financial crisis as an exogenous shock on the financial strength of pension plans and find that more distressed pension plans are associated to bigger AEEs in the next period. In particular, I find that plans which experience big drops in their financial strength from the previous (time *t-1*) to the current year (time *t*) are associated to bigger AEEs in the following year (time *t+1*). Results are only important after the 2008 landmark. As robustness I redo the same analysis, splitting the sample on year 2006, instead of 2008, as in 2006 the Pension Protection Act was voted into law introducing additional restrictions and regulations for DB pension plans and their sponsors, and find similar results. Last, results are robust to a number of controls like actuarial compensation incentives and the overall financial strength level of the pension plan.

In Chapter 3, I investigate whether the EU regulation *No 462/2013 of the European Parliament and of the Council* by which sovereign rating announcements became scheduled events has affected the pre-announcement effect that Michaelides et al. (2015) document before sovereign rating announcements. The authors find evidence consistent with information leakage in the stock markets of downgraded, low institutional quality countries. In particular, I examine the impact of this change in regulation on the potential leakage of information after June 2013. I use a news analytics database to build a surprise measure as captured by news articles to examine market reactions with respect to positive and negative surprises. First I find that markets respond positively to unscheduled upgrades, regardless of surprise. The positive reaction is documented on the announcement day and after. Second, when positive surprises are considered, stock markets react positively at the time of the announcement and after. Finally, when negative surprises are considered, I do not find significant market reaction around the announcement a result suggesting that the stock market perceives the negative surprise announcements as non-events.

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Dedication

To my parents, Andreas and Maria

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Chapter 1: Pension Expected Asset Returns: Errors or Biases?

Abstract

In this study I develop and use a new measure for actuarial estimation errors in pension funding assumptions, the Actuarial Estimation Error (AEE). The AEE is defined as the difference between the expected return (ER) of DB pension plan assets for two consecutive years (for instance $AEE_t = ER_t – ER_{t-1}$). The expectations about pension asset returns for a year are set in place at the beginning of the year by pension plan actuaries. Using defined benefit (DB) pension data, spanning 2000-2011, from publicly traded firms in the US I find that when corporate DB pension plans are financially distressed then AEEs are bigger the following year. The most likely explanation of this finding is that actuaries make obligation reducing assumptions to help sponsors of financially weak DB plans avoid the need of taking corrective measures (e.g. make bigger contributions towards their pension plans) to improve the financial condition of their plans. The results of this study support findings from existing literature claiming that there is association between the funding level of DB pension plans and pension funding assumptions. However I do not find support for previous literature findings claiming association between actuarial compensation incentives and pension funding assumptions.

1. Introduction

Since year 2008, when the global financial crisis arrived, a great number of firms in the US went out of business or became financially distressed. Moreover firms that happened to sponsor DB pension plans had one more burden to shoulder, which was to keep their pension plan adequately funded. Inadequately funded or underfunded pension plans have present value of liabilities exceeding the current value of assets set aside to pay them.

In this paper I study the assumptions that appointed actuaries make when corporate defined-benefit (DB) pension plans are underfunded. For this purpose I develop and use a new measure for actuarial estimation errors in pension funding assumptions, the Actuarial Estimation Error (AEE), defined as the difference between the expected return (ER) of DB pension plan assets for two consecutive years (e.g. $AEE_t = ER_t - ER_{t-1}$). By using the AEE, a sample of 4,459 firm-year observations spanning 12 years (2000-2011) from publicly traded US firms, panel and OLS regressions I find that underfunded DB pension plans are associated with bigger AEEs in the following year. A possible interpretation of this result is that actuaries make their assumptions in such a way to assist firms sponsoring financially weaker DB plans decrease the amount of fund contributions they need to make towards their plans. When DB pension plans are underfunded their sponsors are required by law to improve their plans' financial condition. One way to make this happen is by shifting firm funds towards the DB plans, a situation that is not ideal provided that it has a number of negative implications for the firm and the plan (Rauh J. D., 2006). Hence to reduce the amount of contributions that need to be made, sponsoring firms could signal their DB plan actuaries to inflate the assumed expected return of pension assets as this would imply a smaller annual pension cost. [1] Then less contributions would be required to cover the annual pension cost and at the same time

[1] Annual Pension Cost (Expense) ≈ Additional Benefits Accrued in Current Year + Interest on Accrued Benefits at the Beginning of Current Year – Expected Return on Plan Assets for Current Year.

improve the financial condition of the DB pension plan. In other words by adjusting their assumptions for expected pension asset returns upwards, which implies that AEEs of the following year would increase as well, actuaries manage to decrease, in theory, the funds that sponsoring firms need to pay in order to cover the annual pension expense and also reduce their plan's funding deficiency.

Since the United States governments usually offer their employees defined benefit pension plans it is important to describe the key findings of two relevant studies. Rauh & Novy-Marx (2009) state that as of December 2008 the Unites States governments set aside an amount of 1.94 trillion dollars to cover their pension liabilities. In a follow-up study the authors (Novy-Marx & Rauh, 2010), estimate the governments' pension liabilities at 3.20 trillion dollars (4.43 trillion dollars) if the state general obligation debt rate (zero-coupon treasury yield) is used for discounting. First it is clear that the trillion dollar gap separating the state pension liabilities and the assets set aside to pay them will need to be covered somehow, most probably at the taxpayers' (or the pensioners') expense. Second, pension assumptions matter. They matter because depending on, for example, the choice of the discount rate used to bring pension liabilities to present, the gap separating pension assets and liabilities can vary greatly, making plans appear adequately funded, when in fact they are not.

Similar to US State governments, private firms sponsoring DB pension plans face similar funding issues. Cocco (2014) provides an extensive literature review of studies on corporate pension plans. The author focuses mainly on DB plans sponsored by US firms and analyses a number of issues that pension literature is mostly concerned about. Among the issues discussed are government intervention, for example how do plan sponsors behave in the presence of Pension Benefit Guarantee Corporation (PBGC), an independent government agency who acts as insurance, protecting the benefits accumulated by DB plan participants. On this matter, studies investigating how the presence of such an insurance could potentially provoke the investment of pension assets to risky investments in order to maximize returns include Harrison & Sharpe (1983), Treynor (1977) and Sharpe (1976). In addition there are also studies that consider the insurance of PBGC as a put option, where sponsors can sell their underfunded DB pension plans, and attempt to estimate its value and the appropriate premiums that should come with it. Some notable examples of such studies are Marcus (1987), Hsieh, Chen & Ferris (1994), Boyce & Ippolito (2002) and Pennacchi & Lewis (1994). Pension literature is also interested in the strategies that underfunded DB pension plan sponsors follow with regards to investing pension assets. For example Bodie, Light, Morck & Taggard (1985) and Bodie, Light & Morck (1987) find that firms sponsoring such plans invest in riskier assets. There are also examples of studies, e.g. Friedman (1984) and Rauh (2009), finding that sponsors of underfunded DB pension plans invest in safer assets. Regarding pension funding assumptions, the two main variables that actuaries use to determine the funding status of a DB plan is the discount rate of pension liabilities and the expected return of pension plan assets. The use of the former is confined by strict rules[2] so relevant literature is instead focusing on the use of the latter and the factors predicting it. On this subject, Amir & Benartzi (1998) find that the expected return of pension assets is weakly associated to the proportion of pension assets that are invested in equity. Amir, Guan, & Oswald (2010) study the reaction of plan sponsors' to the adoption of the SFAS 158 that required firms sponsoring DB pension plans to include net pension surplus / deficit on their balance sheet and actuarial gains / losses in other comprehensive income. The authors find that firms response to the new pension disclosures was, on average, to shift pension assets from equity to debt securities.

[2] SFAS 87 requires corporate plan sponsors to use the 30 year US Treasury bond yield, a requirement that was subsequently relaxed in SFAS 158 in to using the investment grade corporate bond yield.

For protecting the best interests of plan participants, that is current and future retirees, the United States government voted ERISA (Employee Retirement Income Security Act) into federal law in 1974. This law upgraded the role of the actuary in pension plans as it required all benefit plans exceeding 100 participants to use the services of an enrolled actuary in estimating the plan liabilities and assets, and to submit on a yearly basis a report to the Department of Labor and the Internal Revenue Service. An Enrolled Actuary is any individual who has satisfied the standards and qualifications as set forth in the regulations of the Joint Board for the Enrollment of Actuaries and who has been licensed by the Joint Board of the Department of the Treasury and the Department of Labor to perform actuarial services required under ERISA. It is required, among others, by enrolled actuaries to assert that to the best of their knowledge the report, containing their assumptions, is complete and accurate and must also certify the amount of any contribution necessary to reduce the accumulated funding deficiency to zero. All of these requirements, combined with the fact that all reports and certifications are subject to public disclosure and examination, make the actuary's role much more visible, and raise his accountability (Hager & Chretien, 1982).

Since the enactment of ERISA, Pension Benefit Guaranty Corporation (PBGC) was created which is an independent agency of the United States government, acting as insurance, which guarantees, subject to a pension insurance premium paid by plan sponsors, pension benefits accumulated by plan participants. When an employer chooses to terminate a single employer pension plan there are two options, standard termination and distress termination. In standard termination the plan must have enough funds to pay all accrued benefits. In distress termination PBGC pays guaranteed benefits and then tries to recover funds from the plan sponsor.

The bottom-line is that sponsors of DB plans may find themselves in situations where their plan is underfunded. When this happens they are required by law to take corrective measures to improve the funding level of their plans. This often includes shifting firm funds towards their plans, a situation that is not ideal. In an attempt to avoid having to make such contributions, sponsors may ask their plan actuaries to inflate expected returns of pension assets in the next period. The reason for that is the fact that expected pension plan assets return is a component of annual pension cost and the higher it is the lower the cost[3]. So, in theory, if the assumed expected pension plans asset return is bigger, then the need of having to make bigger contributions is mitigated to some extent. In order to measure the magnitude by which actuaries inflate expected pension asset returns, I define the Actuarial Estimation Error, henceforth AEE, estimated at *t*, as the difference between the expected return on pension assets for time *t* and the expected return of pension assets for time *t-1*.[4]

The present paper draws from the Insurance and Economics literature in addition to the Pensions' literature. More specifically, the AEE is the equivalent of the Loss Reserve Error in Insurance and Economics literature. The Loss Reserve Error is defined[5] as the difference between the originally reported loss reserve, i.e. the estimate of future insurance claims not yet paid, and a future revised estimate or future insurance claims actually paid (e.g. 5 years after the initial estimate). On this topic Grace & Leverty (2012) find that financially weak insurers under-reserve, i.e. put less money to the side for covering future insurance claims, to a greater extent than healthier insurers and are therefore associated to larger loss reserve errors.

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[3] Annual Pension Expense (Cost) ≈ Additional Benefits Accrued in Current Year + Interest on Accrued Benefits by the Beginning of Current Year – Expected Return on Plan Assets for Current Year.
[4] The expected return of pension assets for a year is released at yearend (December 31st) however it is assumed at an earlier time, usually the beginning of the year.
[5] The definition of the Loss Reserve Error I discuss is taken from Kazenski et al. (1992). There is an alternative definition which is also widely accepted that was first introduced by Weiss (1985).

More recently, Kamiya & Milidonis (2016) study actuarial independence when estimating loss reserves for insurance companies. The authors find that when appointed actuaries also hold an officer position in the insurance company they face managerial incentives. Using the US sample of in-house appointed actuaries, spanning 2007-2014, they find evidence of less conservative reserving, i.e. making bigger loss reserve estimates, by officer actuaries relative to non-officer actuaries. This difference in reserving is associated with tax shielding incentives and earnings management. In their concluding remarks the authors state that results are consistent with managerial discretion dominating actuarial independence and that their findings are economically significant and should cause concern to regulators and professional institutions.

The essence in the two papers from the Insurance and Economics literature discussed above is that Insurance companies for reasons including tax shielding and financial distress put less funds to the side for covering future claims. This is something that could potentially be happening to corporate defined benefit pension plans as well. This would be the case if for example pension plan actuaries make their pension funding assumptions in such way to reduce the amount of required contributions that DB plan sponsors need to make towards their plans.

Anantharaman (2012), one of the papers from the recent pension literature, is studying what determines actuarial assumptions in corporate DB pension plans. The author explores the factors that predict the raw discount rate, used to discount pension liabilities, which actuaries assume. Using data that range from 1999 to 2007, she finds that economically important clients receive higher (obligation reducing) raw discount rate assumptions for their pension liabilities, a result that is particularly evident in highly leveraged firms and firms with longer duration plans. Moreover, she finds that, economically important clients are more likely to receive lower (obligation increasing) raw discount rates for their pension liabilities when they have the intention to freeze their defined benefit plan. In the present paper I take a different approach than the one adopted in Anantharaman (2012) by using the proposed AEE as dependent variable in my regression models. I do this as the raw discount rate employed by Anantharaman is not a flexible measure. It is fixed and stipulated to be equal to the 30-year US Treasury bond yield by the Statement of Financial and Accounting Standards (SFAS 87), later revised to be equal to the investment grade corporate bond yield (SFAS 158).[6][7]

Another study from the recent pension literature is authored by Kisser, Kiff & Soto (2016). The authors devise a measure defined as the difference between two distinct liability concepts. During the period 1999-2007 the Internal Revenue Service (IRS) of the United States government required plan sponsors to use different measures for accrued and current liabilities in the US. Current liabilities were imposed by legislation, and were therefore fixed. However in the case of accrued liabilities, the plan's actuary had more room to decide what to choose. Put differently, the actuary had the flexibility to choose a discount rate for accrued liabilities making them appear bigger or smaller, depending on the chosen rate. The authors take the difference of the two liability concepts as a measure of actuarial bias. In their results they find that reported liabilities for defined benefit pension plans of US private firms are understated by approximately 10%. In other words, they find that current liabilities (fixed) exceed accrued liabilities (flexible) by approximately 10%. Furthermore this difference is even greater in financially distressed pension plans. In their conclusions the authors state that most of the bias is attributed to higher assumed discount rates for accrued pension liabilities and lower life expectancy for retirees.

The contribution of the present study is on two levels. First, I introduce a novel measure for actuarial errors, the Actuarial Estimation Error (AEE) defined, similarly to the Loss Reserve

[6] SFAS 87 was released in December 1985 while SFAS 158 in September 2006.
[7] The restrictions apply to the discount rate of corporate DB pension plan liabilities only.

Error from the Insurance and Economics literature, as the difference of expected pension plan asset returns of the current and previous time period. Second I use a more recent data period, spanning from 2000 to 2011, making the findings of this study newer and broader. By using the AEE I am able to take the existing literature to the next level by testing whether the more recent crisis data strengthened, weakened or left unaltered previous findings.

The remaining of this paper is structured as follows. In Section 2 I introduce and define Actuarial Estimation Error, in Section 3 I describe the Data and Section 4 the Methodology. In Section 5 I present Results and in Section 6 I conclude.

2. Actuarial Estimation Error

The dependent variable used in this paper's regression equations is the Actuarial Estimation Error. The Actuarial Estimation Error is defined as the difference between the expected return of DB pension plan assets for two consecutive years. For instance the Actuarial Estimation Error of year t+1 is estimated from the following formula:

$$Actuarial\ Estimation\ Error_{t+1} = Expected\ Return\ of\ Plan\ Assets_{t+1} - Expected\ Return\ of\ Plan\ Assets_{t}. \tag{1}$$

The formula for expected pension plan assets return at time t+1 is given by:

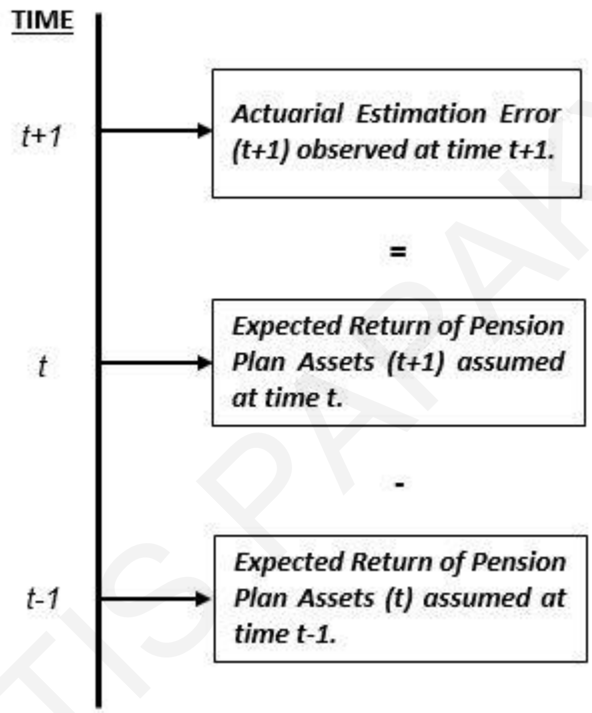
$$Expected\ Return\ of\ Plan\ Assets_{t+1} = \frac{Expected\ Change\ in\ Value\ of\ Plan\ Assets_{t+1}}{Actual\ Value\ of\ Plan\ Assets_{t}} \times 100. \tag{2}$$

And for time t by:

$$Expected\ Return\ of\ Plan\ Assets_{t} = \frac{Expected\ Change\ in\ Value\ of\ Plan\ Assets_{t}}{Actual\ Value\ of\ Plan\ Assets_{t-1}} \times 100. \tag{3}$$

It should be noted that the Expected Change in Value of Plan Assets for time t+1 (t) is assumed at time t (t-1) by the plan's actuary. It represents the expected change (increase or decrease) in the value of pension assets for the specific year (t+1 or t) without taking into account paid-in contributions or paid-out benefits. A figure providing a graphical representation of the definition of Actuarial Estimation Error is provided below.

Figure 1: Definition of Actuarial Estimation Error (t+1)



3. Data

The data I use are the form 5500 filings, and specifically, the form 5500 research files[8], spanning 2000-2011, from the United States Department of Labor, henceforth US DOL. Public and private firms sponsoring plans with more than 100 participants have to fill the form 5500 once per year while smaller plan sponsors, with less than 100 participants, can fill a more simplified form for example the form 5000-SF (Shortened Form) less frequently (once

[8] A refined version of the form 5500 data specifically prepared for researchers.

per 3 years). I also use additional Schedule B and Schedule H data from US DOL for years 2000 – 2011 as they contain useful actuarial and financial information not found in the initial form 5500 filings. I also use Compustat (2000-2012) data from the Wharton Research Data Services (WRDS) to complement the data from the US DOL. Compustat is used to obtain additional financial and actuarial pension data from publicly traded firms in North America which are then merged with the US DOL data to form the final panel of data used for the descriptive statistics and the regressions. Last I use annual data from DataStream and specifically four US indices for Equity, Debt, Real Estate and Commodities for years 2000-2011. Specifically those indices are the S&P 500 index, Barclays Capital Aggregate Bond index, MSCI Real Estate index and Bloomberg Commodity Total Return index. The annual returns of these indices are combined with pension asset allocations taken from Compustat to produce a weighted average return that approximates the annual return of pension assets. Merging the samples from US DOL, Compustat and DataStream, deleting the duplicates, entries that don't have a match with Compustat as well as the entries from non-defined benefit pension plans results in the final dataset (panel), of 4,459 firm-year observations from 536 unique firms.

3.1. Funding Level of Pension Plans

The main independent variable of the regression models is Funding % Liabilities. It measures the percentage of DB pension plan projected benefit obligations covered by pension assets. I include this variable in the analysis as competing studies in the literature include it in their analysis too, e.g. (Kisser, Kiff, & Soto, 2015) & (Anantharaman, 2012). Moreover it has been found that public DB pension plans are very underfunded (Novy-Marx & Rauh, 2009), (Novy-Marx & Rauh, 2010), a result that could potentially imply that the funding level of DB pension plans is tied to the Actuarial Estimation Error. Underfunding is a situation that plan sponsors do not wish to find themselves in as it may lead to large mandatory contributions that can persist several years into the future (Cocco, 2014). To avoid having to make the contributions plan sponsors might, among other things, exercise pressure on their actuaries to make obligation reducing assumptions, i.e. assume higher expected return for pension assets. Such assumptions would affect the AEE by definition.

3.2. Control Variables

I am using four groups of control variables based on actuary, plan, firm and audit characteristics.

The first group, actuary characteristics, consists of two variables that control for the size of the actuarial firm and the economic bonding of the actuary with the plan sponsor. The first variable is Big Actuarial Firm which is an indicator variable set to 1 if, for a specific year, the actuarial firm from which the plan sponsor is buying services, is one of the top 5% actuarial firms with respect to the number of clients (DB plan sponsors); set to 0 otherwise. Bigger and more independent actuarial firms have an incentive to protect their reputation and avoid litigation costs and are therefore less likely to succumb to pressure from their clients in issuing obligation reducing actuarial assumptions (Reynolds & Francis, 2001), (YU, 2007). Furthermore I argue that big actuarial firms have a large number of clients and can afford to lose the bad (non-paying or financially distressed) clients who have greater probability of sponsoring underfunded pension plans.

The second variable of actuary characteristics is FEE and is the proportion of professional fees that an actuary receives by a specific plan sponsor, divided by the sum of all professional fees the actuary earns for the whole year. I expect that, similar to Anantharaman (2012), the bigger the FEE, the bigger the economic bonding of the actuary to the plan sponsor, a situation that gives the plan sponsor more persuasive power over the actuary. In other words the actuary can more easily succumb to pressure for issuing favoring assumptions (i.e. inflated expected return / raw discount rate) for the firm's pension plan when the FEE is bigger.

In the second group, plan characteristics, I control for those plan characteristics that potentially affect the expected return of plan assets and therefore the AEE. First I control for the frozen plans, where FROZEN is an indicator set to 1 if the plan is frozen, 0 otherwise. There are several reasons for freezing a plan, for example to reduce volatility in funding obligations due to fluctuating equities markets, plan asset values and interest rates (Golumbic & Levine, 2014). Moreover, Anantharaman (2012) is suggesting that in some cases firms sponsoring frozen plans (or with intention to freeze their plans) have incentives to keep their plans frozen in order to prevent more beneficiaries joining the plan and current beneficiaries accumulating more benefits, which would happen if the plan got out of the frozen status. In such cases interested firms would signal the plan actuary to assume smaller expected return for pension assets, in order to show bigger annual pension expense, affecting in this manner AEE downwards.

I control for the percentage of the plan participants who are currently active workers (Active % Employees), since young firms seem to have a preference on stocks rather than bonds for their pension plan assets (Lucas & Zeldes, 2006). This essentially means that the proportion of beneficiaries, who are currently active workers, is associated to more volatile AEE.

I control for sole plans, where Soleplan is an indicator variable set to 1 if the plan is the sole plan of a sponsor, 0 otherwise, as one might expect a sponsor to be able to manage (fund) better one plan only and, also, I control for the size of the plan (Plansize) which might affect actuarial estimation errors in many different ways. For example, actuaries might find it harder to issue inflated expected returns due to bigger plans receiving increased audit but at the same time one could also argue that firms with big plans have more persuasive power over their plan's actuary, in getting favoring assumptions.

Finally I control for the Return of Plan Assets (ROA Plan) by constructing an index that approximates pension plan assets annual return, taking into account plans' pension asset allocation and average annual returns from appropriate industry indices. Put differently this is a weighted average index of annual returns from different industries that estimates pension plans actual assets return. It controls for the pension asset allocation that actuaries need to take into account before assuming the expected return of pension assets in the following period, hence it could be affecting AEE.

In the third group of control variables, firm characteristics, I control for the characteristics of sponsoring firms that could be tied to AEE. First I control for the size of the firm (Firmsize) as big firms ought to be more careful and accurate in their estimates, leading to less volatile AEEs. Moreover, since the fees that big firms pay for professional advice are usually higher it would be reasonable to expect more accurate estimations of the expected return of pension assets, hence affecting AEE by making it less volatile. I also control for leverage as highly leveraged firms have significantly bigger risk of defaulting, especially if the interest paid on firm debt is bigger that the firm's return on assets. Such firms are regarded as distressed, as they are working with loss, meaning that they face fund scarcity. As such when fund contributions are required in their DB pension plans, highly leveraged firms are more likely to inflate the expected return of plan assets, resulting in a bigger AEE, as this would reduce the amount of contributions required to be made in the DB pension plans. I control for the firm's return on assets (ROA Firm) since firms with high (low) returns on assets have bigger (smaller) cash availability to pay pension contributions and are therefore less (more) likely to inflate expected return on pension assets, a component of AEE. Last I control for the firm's credit risk by including an indicator variable, LowZscore, which is equal to 1 if the firm's Z score is below 1.81 and 0 otherwise, following Altman (1968). The Altman Z score, first introduced by Altman in 1968, stipulates that firms with small Z-Score, specifically firms with Z score smaller than 1.81, are in the distress zone and have high risk to default in short period of time. I include this variable in the model equations as it is indicative of how healthy a firm is and consequently it is an indication of how well the pension plan, the firm is sponsoring, is performing.

The fourth, and last, group of control variables, actuarial characteristics, consists of one variable, Big 4 Auditor. It is an indicator variable which is equal to 1 if the firm and plan's auditor is one of the big 4 auditors (PWC, Deloitte, KPMG, Ernst & Young) and 0 otherwise. It has been found in the literature that bigger audit offices provide higher quality of audit due to the fact that they are less dependent from their clients and are less likely succumb to their pressure to overlook (actuarial) earnings manipulation (YU, 2007), hence leading to more accurate estimation of pension plan assets and less volatile AEE.

4. Methodology

This paper belongs in the literature of corporate DB pension plans and specifically in an area of research that studies the factors affecting actuarial pension valuation assumptions. Many papers in this field, e.g. Anantharaman (2012) and Kisser, Kiff & Soto (2016), study the factors that determine the discount rate used to find the present value of pension liabilities. I differ by studying the factors that determine the Actuarial Estimation Error, and by using my very own panel of data, which is more recent and broader than what most of the studies use, spanning 2000-2011. The purpose of this paper is to test whether literature's findings hold when using the AEE as the dependent variable. The AEE is an improved measure compared to the raw discount rate and expected return of pension assets that competing studies use: it benchmarks, the assumed by the actuaries, expected pension assets return of the current period to expected pension assets return of the previous period, essentially measuring the actuarial error. It is also similar, to some extent, to the loss reserve error used in the Insurance and Economics Literature discussed in the Introduction.

Both Anantharaman (2012) and Kisser, Kiff & Soto (2016) run their regressions taking dependent and independent variables at the same time horizon (contemporaneous regressions). This, potentially creates risk of measuring correlations, meaning that independent and dependent variables could be related without the relationship being necessarily causal. To tackle this issue I take dependent and independent variables at different time horizons and, more specifically, I regress the AEE (the dependent variable) of the following period against independent variables of the current time period.

I employ two regression equations to test an equal number of relationships. First I test whether the current period funding level (Funding % Liabilities) of pension plans predicts AEE of the following period. Then I test whether the proportion of yearly actuarial income from a single plan sponsor conditional on the level of funding of pension plans (i.e. the interaction of the two variables) predicts AEE of the following period. For each of the model equations I use, I conduct both panel and OLS regressions taking the dependent variable at time *t+1* and the independent variables at time *t*. More specifically for each regression equation I run four regressions, three panel regressions with fixed effects at different levels: firm, actuary-firm, actuary office[9] and a pooled OLS regression. In every model I control for firm, plan, audit and actuarial characteristics. As base case I take the sample spanning 2000-2007, as prior literature does, but for robustness I also take the full sample spanning 2000-2011. Results are presented in Tables 4 - 7.

Equation 4 below produces results in Tables 4 & 5, with Table 4 containing results of the small sample (2000-2007) and Table 5 results from the full sample (2000-2011). The model

[9] Determined by the physical address of the office where the actuary is working.

examines whether the funding level of a pension plan, as measured by Funding % Liabilities, and AEE of the next period are associated. In other words I examine whether funding level of pension plans at time t, affects pension funding assumptions that actuaries make for time *t+1*. The model is structured in this way as the assumptions made by actuaries for time *t+1*, i.e. the fiscal year end, are usually made at the beginning of the fiscal year, which is some time after the previous fiscal year end, i.e. time *t*.

$$\begin{aligned} AEE_{t+1} = a_0 + a_1 * Funding\ \%\ Liabilities_t \\ + \beta * Plan\ Characteristics_t + \gamma * Firm\ Characteristics_t \\ +\delta * Auditor\ Characteristics_t + \varepsilon * Actuary\ Characteristics_t + \eta_t + FE + \varepsilon_{t+1}. \end{aligned} \tag{4}$$

Equation 5 that comes next produces results in Tables 6 & 7, with Table 6 containing results of the small sample (2000-2007) and Table 7 results from the full sample (2000-2011). The purpose of the model described by Equation 5 is to examine whether the proportion of yearly actuarial income coming from a single plan sponsor, as measured by FEE, and AEE of the next period are associated. The equation also includes an interaction term (FEE * Funding % Liabilities) which measures the additional effect of FEE on AEE of the following period conditional on the funding level of pension plans. If the coefficient of the interaction term comes up as statistically significant it will provide evidence that the FEE becomes more (or less) important, in predicting AEE of the next period, as the funding level of pension plans fluctuates.

$$\begin{aligned} AEE_{t+1} = a_0 + a_1 * Funding\ \%\ Liabilities_t + a_1 * FEE_t \\ + a_3 * FEE_t * Funding\ \%\ Liabilities_t + \beta * Plan\ Characteristics_t \\ +\gamma * Firm\ Characteristics_t + \delta * Auditor\ Characteristics_t \\ + \varepsilon * Actuary\ Characteristics_t + \eta_t + FE + \varepsilon_{t+1}. \end{aligned} \tag{5}$$

In both equations, element a_0 represents the intercept, *Funding % Liabilities*$_t$ measures the proportion of pension liabilities covered by the pension assets at time t. FEE_t is the proportion the yearly actuarial income coming from a single plan sponsor. *Plan Characteristics, Firm Characteristics, Auditor Characteristics* and *Actuary Characteristics* are vectors of control variables. Parameter η_t represents the year indicators while FE are fixed effects taken at different levels (only for panel regressions). The error terms ε_{t+1} are assumed to be heteroskedastic and serially correlated. Last, AEE_{t+1} is the Actuarial Estimation Error at time *t+1* and is defined as the difference between the expected at time *t+1* and the expected at time *t*, pension plan assets' return.

5. Results

In this section I discuss descriptive statistics (Tables 2 & 3) and how the results of the regression models (Tables 4 - 7) compare to expectations. Tables 4 - 7 consist of four columns, with the first three containing panel regression results with fixed effects taken at firm, actuary-firm and actuary office levels. The fourth column contains results from a pooled OLS regression. All variable definitions are provided in Table 1.

5.1. Descriptive Statistics

In this study I use data from the form 5500 filings, spanning 2000-2011, from the US DOL. I use additional actuarial (Schedule B) and financial (Schedule H) data also from US DOL for the same time period to complement the form 5500 data. US DOL data is then merged with data from Compustat, years 2000-2012, as Compustat contains useful financial and actuarial and other info, needed for the regression models. Last I use DataStream data, in particular four US indices, one for Equity, one for Debt, one Real Estate and one Commodities, for years 2000-2011, to construct a yearly weighted average return which serves as an estimate of the actual return of DB pension plan assets. In total after merging US DOL with Compustat & DataStream data, I delete those entries for which Compustat does not have a match and end up with 3,505 firm-year observations from 515 unique firms for years 2000-2007 (Table 2) and 4,459 firm-year observations from 536 unique firms for years 2000-2011 (Table 3).

5.2. Empirical Results: Does the funding level of DB pension plans affect AEE?

First I examine whether the funding level of pension plans, given by Funding % Liabilities, while also controlling for a number of firm, plan, and audit characteristics, affects AEE of the following year. I attempt to give an answer to the empirical question by running panel and OLS regressions using the model described by Equation 4 (Results in Tables 4 & 5[10]).

Comparing results from the small sample (2000-2007) to those of the full sample (2000-2011) it becomes evident that while results remain in the same direction, they become stronger once the full sample is used. Overall the funding level of pension plans and AEE of the following period are associated with a negative relationship that is also statistically significant in 3 out of the four regressions for both the small sample (Table 4) and the full sample (Table 5). This essentially means that when the funding level of a pension plan is higher actuaries adjust their estimates of pension asset returns downwards the following year. And the opposite. When the funding level of pension plans is smaller, then actuaries adjust their estimates upwards. A possible explanation is that when a plan is less funded, actuaries issue bigger expected returns for pension assets to reduce pension expenses. Annual pension expenses consist primarily from the service cost that is the amount employers must set aside in a period to match the retirement benefits accrued by plan participants in a year, the interest cost, i.e. the interest earned on the benefits accrued by the end of the previous period, minus the expected return on pension assets for the current year. So when the expected return on pension assets for a specific year is higher, the contributions that need to be made into the plan by the employer the same year are lower, indicating that actuaries

[10] For every Equation the first Table corresponds to results from the small sample (2000-2007) and the second Table to results from the full sample (2000-2011). This is true for the entire Results section.

make obligation reducing assumptions when a plan is less funded. This finding is in-line with the findings of prior literature that actuaries tend to make obligation reducing assumptions when DB pension plans are financially distressed.

5.3. Empirical Results: Does the fee plan sponsors pay to actuaries of DB pension plans affect AEE?

In this section I extent the analysis of the previous section (§5.2), by examining whether the proportion of yearly fees an actuary receives from a single plan sponsor, given by FEE, affects AEE of the next year. Moreover, I examine, by including in the regression equation the interaction term FEE_t * Funding *% Liabilities*$_t$, whether the FEE conditional on the overall funding level of the pension plan affects AEE of the next year. In order to test this setting I employ a new model given by Equation 5. As with Equation 4 discussed earlier, I conduct regressions using the small sample (2000-2007) and also the full sample (2000-2011) storing the results in Tables 6 and 7 respectively. For each of the samples I conduct four regressions, three panel regressions with fixed effects taken at the firm, actuary firm and actuary office levels and a pooled OLS regression.

Results suggest that the FEE does not affect AEE of the following year: The FEE and the interaction of the FEE with Funding % Liabilities are not found statistically significant in the regressions meaning that the effect of FEE on AEE of the next year is not statistically significant neither by itself nor conditional on the funding level of the pension plan. This result is not in-line with the findings of prior literature (Anantharaman, 2012) claiming there is statistically significant positive association between actuarial compensation incentives and pension funding assumptions. In other words, based on this finding, actuaries do not factor the fees received by plan sponsors when making pension valuation assumptions even when conditioning on the overall funding level of pension plans. I attribute the different result to a number of differences between the present study and Anantharaman (2012) including, this study not using contemporaneous regressions, using more recent and broader samples of data and using a new measure for actuarial estimation errors in pension funding assumptions as the dependent variable.

Overall, evidence from the models suggests that the funding level of pension plans does indeed affect pension funding assumptions, in some occasions, as literature suggests, while the fees paid to actuaries do not. More specifically, I find negative association between the funding level of pension plans and AEE of the next year, indicating that actuaries adjust their estimates for pension asset returns in the next year upwards, when the funding level of pension plans in the current year is lower. Moreover the FEE, that is the proportion of all fees an actuary receives in a year from a single plan sponsor, does not affect AEE of the following year suggesting that actuarial assumptions are not influenced by compensation incentives.

6. Conclusions

In the present study I develop a new measure for actuarial estimation errors in pension funding assumptions of corporate defined benefit (DB) pension plans, the Actuarial Estimation Error (AEE). The AEE is defined as the difference between the expected return (ER) of DB pension plan assets for two years in a row (for instance $AEE_t = ER_t – ER_{t-1}$). The expected return of pension assets for a year is assumed by the plan's actuary, usually at the beginning of the year. I conduct several panel and OLS regressions, on a sample of 4,459 firm-year observations spanning 12 years (2000-2011) from publicly traded US firms, and find that lower funding levels in DB pension plans in the current year *(t)* are associated with bigger AEEs in the next year *(t+1)*, an obligation reducing assumption. Results are in-line with findings from the literature, for example Kisser, Kiff & Soto (2016) who find that when the funding level of DB pension plans is low then actuaries make more optimistic pension funding assumptions. An interesting question for future research would be whether it is the overall funding level or changes (shifts) in the funding level of DB pension plans, for example from the previous to the current period, that it is affecting AEEs of the next year. Last, the results of this study do not lend support for the findings of Anantharaman (2012) who finds that the fees paid to DB pension plan actuarial professionals are affecting the pension valuation assumptions that they consequently make.

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Appendix

Table 1: Variable Definitions

Variable	Definition & Source
Actuary	
Actuarial Estimation Error	The difference between the expected return (ER) of DB pension plan assets for two consecutive years (for example $AEE_t = ER_t – ER_{t-1}$ or $AEE_{t+1} = ER_{t+1} – ER_t$).
Expected Return of Pension Assets	The Expected Return of Pension Assets return is estimated by dividing the Expected Change in Pension Assets Value (Compustat item -1*PPRPA) by the Total Pension Assets at the end of the previous period (Compustat Item PPLAO) and then multiplying the result with 100.
Big Actuarial Firm	Indicator variable set to 1 if, in the current year, the actuarial firm belongs to the top 5% actuarial firms with respect to the number of clients, set to 0 otherwise. Number of clients is found from the number of entries corresponding to the same Actuarial Firm in Form 5500, Schedule B.
FEE (t)	Professional fees received by actuary from each plan sponsor client in the current year / Sum of all fees received by that actuary from all plan sponsor clients in the current year. Professional fees is given by Form 5500, Schedule H, Part II, Item 2i (1).
Plan	
Funding % Liabilities	Measures the funding level of DB pension plans. Estimated from the ratio of pension plan assets (Compustat item PPLAO) divided by the projected benefit obligations of the same plan (Compustat item PBPRO).
FROZEN	Indicator variable set to 1 if a plan is frozen in the current year. Given by Form 5500 Part II, Item 8a.
Active % Employees	The proportion of active employees (Form 5500, Part II, Item 7a) amongst all plan beneficiaries (Form 5500, Part II, Item 7f).
Sole Plan	Set to 1 if the plan is the only plan of a sponsor. Given by Form 5500 Part I, Item A (2).
Plan Size	Natural logarithm of [1+total plan assets (Compustat item PPRPA)].
ROA Plan	Approximates the Real Return of DB Pension Plan Assets. Weighted average return estimated by multiplying annual returns for the S&P 500 (DataStream item S&PCOMP), Barclays Capital Aggregate Bond (DataStream item LGAGGBD), MSCI Real Estate (DataStream item M2USR2$) and S&P Commodities (DataStream item GSCITOT) to the proportion of DB plan assets in invested in Equity (Compustat item PNATE), Debt (Compustat item PNATD), Real Estate (Compustat item PNATR) and Other Investments (Compustat item PNATO) respectively and then adding the results together.
Firm	
Firm Size	Natural logarithm of [1+Total Firm Assets (Compustat item AT)].
Leverage	Long-term debt (Compustat item DLTT) + Debt in current liabilities (Compustat item DLC) / Total Firm Assets (Compustat item AT).
ROA Firm (t)	Income before extraordinary items (Compustat item IB) + Periodic Pension Cost (PPC) / Total Firm Assets (Compustat item AT).

LowZscore (t)	Indicator variable set to 1 if the Altman Z Score for the particular plan sponsor (firm) is below the 1.81 threshold; set to 0 otherwise. Altman Z Score is estimated by 1.2 * [Current Firm Assets (Compustat item ACT) – Current Firm Liabilities (Compustat item LCT)] / Total Firms Assets (Compustat item AT) + 1.4 * Retained Earnings (Compustat item RE) / Total Firm Assets (Compustat item AT) + 3.3 * Operating Income After Depreciation (Compustat item OIADP) / Total Firm Assets (Compustat item AT) + 0.6 * [Firm Stock Price (Compustat item PRCC_F) * Number of Shares Outstanding (Compustat item CSHO)] / [Debt in Current Liabilities (Compustat item DLC) + Long Term Debt (Compustat item DLTT)] + 0.99 * Total Sales (Compustat item SALE) / Total Firm Assets (Compustat item AT).
Auditor	
Big 4 Auditor	Indicator variable set to 1 if the benefit plan is audited by one of the big 4 audit firms. Audit firm is Form 5500, Schedule H, Item 3c.

Table 2: Descriptive Statistics (2000-2007)

This table presents the descriptive statistics of all the variables (dependent and independent) used in every model of this paper, spanning 2000 - 2011. Each variable falls under one of the four categories based on Actuary, Plan, Firm, and Audit characteristics. The Actuarial Estimation Error (AEE) is defined as the difference between the expected return (ER) of DB pension plan assets for two years in a row (for example $AEE_t = ER_t - ER_{t-1}$). Big Actuarial Firm is an indicator variable set to 1 if, for a specific year, the actuarial firm belongs to the top 5% actuarial firms with respect to the number of clients, set to 0 otherwise. FEE is the ratio of professional fees that an actuary receives from a plan sponsor divided by the sum of all the fees the actuary receives in that year. Funding % Liabilities is the percentage of pension liabilities funded by the pension assets. Frozen is an indicator variable set to 1 if for a specific year a plan is frozen, set to 0 otherwise. Active % Employees is the proportion of active employees amongst all plan beneficiaries. Plan Size and Firm Size are computed by the natural logarithm of unity plus the worth, in millions, of plan and firm assets respectively. Sole Plan is an indicator variable set to 1 if a plan is the only plan of a sponsor, set to 0 otherwise. ROA Plan is an estimate of pension assets actual return. Leverage is the ratio of long and short-term firm debt divided by the worth of firm assets in millions. ROA Firm is given by the ratio of the firm income before extraordinary items and pension expense divided by the worth of firm assets in millions. LowZscore is an indicator variable set to 1 if the Z score of the firm (plan sponsor) is below the 1.81 threshold, set to 0 otherwise. Big 4 Auditor is an indicator variable set to 1 if the benefit plan is audited by one of the big 4 audit firms, set to 0 otherwise. All variables are winsorized at 1% & 99% levels.

Variable	Obs.	Mean	Std Dev.	p25	p50	p75
Actuary						
Actuarial Estimation Error	2735	-0.13064	2.823712	-0.61	-0.06	0.354
Big Actuarial Firm	3111	0.63163	0.4824401	0	1	1
FEE	2508	0.23901	0.3711042	0	0	0.388
Plan						
Funding % Liabilities	3161	0.8612	0.2378603	0.714	0.83	0.963
Frozen	3168	0.06439	0.2454921	0	0	0
Active % Employees	3115	0.51374	0.2266589	0.371	0.53	0.676
Plan Size	3167	4.91395	2.0045993	3.407	4.76	6.359
ROA PLAN	1662	0.06576	0.1014565	0.032	0.07	0.113
Sole Plan	3168	0.04577	0.2090193	0	0	0
Firm						
Firm Size	3156	7.58219	1.9596466	6.259	7.58	8.872
Leverage	3152	0.27825	0.2152583	0.131	0.24	0.375
ROA FIRM	3156	0.03367	0.0863219	0.01	0.03	0.068
LowZscore	2242	0.19893	0.399284	0	0	0
Auditor						
Big 4 Auditor	3152	0.62595	0.4839529	0	1	1

Table 3: Descriptive Statistics (2000-2011)

This table presents the descriptive statistics of all the variables (dependent and independent) used in every model of this paper, spanning 2000 - 2007. Each variable falls under one of the four categories based on Actuary, Plan, Firm, and Audit characteristics. The Actuarial Estimation Error (AEE) is defined as the difference between the expected return (ER) of DB pension plan assets for two years in a row (for example $AEE_t = ER_t - ER_{t-1}$). Big Actuarial Firm is an indicator variable set to 1 if, for a specific year, the actuarial firm belongs to the top 5% actuarial firms with respect to the number of clients, set to 0 otherwise. FEE is the ratio of professional fees that an actuary receives from a plan sponsor divided by the sum of all the fees the actuary receives in that year. Funding % Liabilities is the percentage of pension liabilities funded by the pension assets. Frozen is an indicator variable set to 1 if for a specific year a plan is frozen, set to 0 otherwise. Active % Employees is the proportion of active employees amongst all plan beneficiaries. Plan Size and Firm Size are computed by the natural logarithm of unity plus the worth, in millions, of plan and firm assets respectively. Sole Plan is an indicator variable set to 1 if a plan is the only plan of a sponsor, set to 0 otherwise. ROA Plan is an estimate of pension assets actual return. Leverage is the ratio of long and short-term firm debt divided by the worth of firm assets in millions. ROA Firm is given by the ratio of the firm income before extraordinary items and pension expense divided by the worth of firm assets in millions. LowZscore is an indicator variable set to 1 if the Z score of the firm (plan sponsor) is below the 1.81 threshold, set to 0 otherwise. Big 4 Auditor is an indicator variable set to 1 if the benefit plan is audited by one of the big 4 audit firms, set to 0 otherwise. All variables are winsorized at 1% & 99% levels.

Variable	Obs.	Mean	Std Dev.	p25	p50	p75
Actuary						
Actuarial Estimation Error	4018	-0.1179	2.468284	-0.6	-0.1	0.31
Big Actuarial Firm	4369	0.64	0.48	0	1	1
FEE	3065	0.30	0.40	0	0.02	0.66
Plan						
Funding % Liabilities	4446	0.83	0.23	0.68	0.80	0.93
Frozen	4459	0.11	0.32	0	0	0
Active % Employees	4354	0.49	0.23	0.33	0.50	0.66
Plan Size	4457	5.01	2.00	3.53	4.92	6.45
ROA PLAN	2839	0.0529	0.126636	0.03	0.08	0.12
Sole Plan	4459	0.04	0.20	0	0	0
Firm						
Firm Size	4444	7.72	1.95	6.41	7.73	8.98
Leverage	4436	0.2661	0.205575	0.12	0.23	0.36
ROA FIRM	4443	0.0324	0.086399	0.01	0.03	0.07
LowZscore	3158	0.19	0.39	0	0	0
Auditor						
Big 4 Auditor	4430	0.56	0.50	0	1	1

Table 4: Panel and OLS regressions (Years 2000-2007)

In this table I present results of panel and OLS regressions to find what determines Actuarial Estimation Errors while also controlling for firm, plan, audit and actuary characteristics. The Actuarial Estimation Error (t+1) is defined as the expected return of pension assets for the following year (time *t+1*) minus the expected return of pension assets for the current year (time *t*). The remaining variables are described in Table 1. Fixed-effects, year indicators and robust clustered standard errors are used. For brevity considerations the coefficients of year indicators are not shown. All variables are winsorized at 1% & 99% levels. I denote statistical significance at the 1% (***), 5% (**) level and 10% (*) level.

	(1) Actuarial Estimation Error (t+1)	(2) Actuarial Estimation Error (t+1)	(3) Actuarial Estimation Error (t+1)	(4) Actuarial Estimation Error (t+1)
Funding % Liabilities (t)	0.177	-0.579**	-0.665**	-0.547**
	(0.899)	(0.265)	(0.301)	(0.278)
Frozen (t)	-0.893***	-0.153	-0.168	-0.185
	(0.342)	(0.173)	(0.214)	(0.165)
Active % Employees (t)	0.115	-0.130	-0.110	-0.0870
	(0.586)	(0.132)	(0.221)	(0.261)
Sole Plan (t)	-0.885**	-0.178	-0.251	-0.163
	(0.365)	(0.260)	(0.288)	(0.272)
Plan Size (t)	-2.945***	-0.0630	-0.0817	-0.0311
	(0.779)	(0.0383)	(0.0575)	(0.0445)
ROA PLAN (t)	1.114	-2.692	-3.549	-2.392
	(1.996)	(2.108)	(2.303)	(2.190)
Firm Size (t)	0.443	0.0239	0.0167	-0.0126
	(0.368)	(0.0263)	(0.0487)	(0.0402)
Leverage (t)	-0.871	-0.152	-0.0106	-0.129
	(1.094)	(0.160)	(0.229)	(0.195)
ROA FIRM (t)	-1.713	-0.907	-1.029	-0.952
	(1.395)	(0.916)	(0.924)	(0.742)
Big Actuarial Firm (t)	0.191	0.260***	0.236*	0.0496
	(0.159)	(0.0887)	(0.139)	(0.0898)
Big 4 Auditor (t)	0.131	0.0863	0.197*	0.0755
	(0.169)	(0.0709)	(0.102)	(0.0924)
Constant	10.91***	0.319	0.729	0.710*
	(3.032)	(0.319)	(0.475)	(0.395)
N	1531	1531	1531	1531
R^2	0.146	0.034	0.036	0.036
Year Dummies	Yes	Yes	Yes	Yes
Fixed Effects	Firm Level	Actuary-Firm Level	Office Level	No

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Panel and OLS regressions (Years 2000-2011)

In this table I present results of panel and OLS regressions to find what determines Actuarial Estimation Errors while also controlling for firm, plan, audit and actuary characteristics. The Actuarial Estimation Error (t+1) is defined as the expected return of pension assets for the following year (time *t+1*) minus the expected return of pension assets for the current year (time *t*). The remaining variables are described in Table 1. Fixed-effects, year indicators and robust clustered standard errors are used. For brevity considerations the coefficients of year indicators are not shown. All variables are winsorized at 1% & 99% levels. I denote statistical significance at the 1% (***), 5% (**) level and 10% (*) level.

	(1) Actuarial Estimation Error (t+1)	(2) Actuarial Estimation Error (t+1)	(3) Actuarial Estimation Error (t+1)	(4) Actuarial Estimation Error (t+1)
Funding % Liabilities (t)	-0.424	-0.945***	-1.148***	-0.796***
	(0.425)	(0.214)	(0.200)	(0.200)
Frozen (t)	-0.435**	-0.0669	-0.0572	-0.0937
	(0.172)	(0.0783)	(0.109)	(0.0921)
Active % Employees (t)	0.131	0.0111	0.0540	0.0548
	(0.374)	(0.100)	(0.162)	(0.180)
Sole Plan (t)	-0.632*	0.0624	0.179	-0.00589
	(0.334)	(0.153)	(0.236)	(0.177)
Plan Size (t)	-1.579***	-0.00833	-0.0140	0.00777
	(0.286)	(0.0319)	(0.0373)	(0.0322)
ROA PLAN (t)	-0.277	-1.038	-0.980	-0.839
	(0.906)	(0.900)	(0.904)	(0.988)
Firm Size (t)	0.185	-0.00161	-0.00594	-0.0263
	(0.140)	(0.0222)	(0.0305)	(0.0289)
Leverage (t)	-0.271	-0.244	-0.181	-0.206
	(0.576)	(0.161)	(0.181)	(0.154)
ROA FIRM (t)	-0.440	-0.473	-0.503	-0.533
	(0.648)	(0.622)	(0.558)	(0.464)
Big Actuarial Firm (t)	0.172	0.367***	0.350**	0.0822
	(0.123)	(0.101)	(0.141)	(0.0644)
Big 4 Auditor (t)	0.139	0.0616	0.135*	0.0637
	(0.115)	(0.0583)	(0.0731)	(0.0651)
Constant	6.711***	0.426	0.932**	0.765**
	(1.243)	(0.273)	(0.389)	(0.330)
N	2608	2608	2608	2608
R^2	0.164	0.106	0.107	0.105
Year Dummies	Yes	Yes	Yes	Yes
Fixed Effects	Firm Level	Actuary-Firm Level	Office Level	No

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Panel and OLS regressions (Years 2000-2007)

In this table I present results of panel and OLS regressions to find what determines Actuarial Estimation Errors while also controlling for firm, plan, audit and actuary characteristics. The Actuarial Estimation Error (t+1) is defined as the expected return of pension assets for the following year (time *t+1*) minus the expected return of pension assets for the current year (time *t*). The remaining variables are described in Table 1. Fixed-effects, year indicators and robust clustered standard errors are used. For brevity considerations the coefficients of year indicators are not shown. All variables are winsorized at 1% & 99% levels. I denote statistical significance at the 1% (***), 5% (**) level and 10% (*) level.

	(1) Actuarial Estimation Error (t+1)	(2) Actuarial Estimation Error (t+1)	(3) Actuarial Estimation Error (t+1)	(4) Actuarial Estimation Error (t+1)
FEE (t)	-0.0969	-0.0461	0.0548	0.213
	(0.978)	(0.975)	(0.995)	(0.755)
Funding % Liabilities (t)	-0.219	-0.472	-0.585	-0.380
	(0.975)	(0.331)	(0.425)	(0.342)
FEE(t) * Funding % Liabilities (t)	-0.138	-0.0178	-0.136	-0.283
	(1.147)	(1.160)	(1.207)	(0.871)
Frozen (t)	-0.645	-0.0379	-0.000204	-0.0585
	(0.409)	(0.163)	(0.254)	(0.163)
Active % Employees (t)	-0.328	0.0207	0.0652	0.192
	(0.790)	(0.203)	(0.280)	(0.275)
Sole Plan (t)	-0.589*	0.104	0.0756	0.165
	(0.318)	(0.111)	(0.154)	(0.267)
Plan Size (t)	-2.546***	-0.0542	-0.0499	-0.00563
	(0.793)	(0.0413)	(0.0710)	(0.0458)
ROA PLAN (t)	-0.419	-3.222	-4.007*	-3.684*
	(2.184)	(2.064)	(2.277)	(2.125)
Firm Size (t)	0.779*	0.00336	-0.00965	-0.0460
	(0.456)	(0.0295)	(0.0648)	(0.0424)
Leverage (t)	-1.805	-0.0563	0.0196	-0.0637
	(1.194)	(0.211)	(0.264)	(0.215)
ROA FIRM (t)	-1.701	-0.786	-0.882	-0.903
	(1.341)	(0.852)	(0.906)	(0.715)
Big Actuarial Firm (t)	0.276	0.335***	0.316*	0.0351
	(0.179)	(0.0801)	(0.175)	(0.0950)
Big 4 Auditor (t)	0.148	0.0765	0.185*	0.130
	(0.189)	(0.0792)	(0.111)	(0.101)
Constant	6.886*	0.222	0.541	0.407
	(4.110)	(0.480)	(0.606)	(0.426)
N	1265	1265	1265	1265
R^2	0.143	0.039	0.041	0.041
Year Dummies	Yes	Yes	Yes	Yes
Fixed Effects	Firm Level	Actuary-Firm Level	Office Level	No

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Panel and OLS regressions (Years 2000-2011)

In this table I present results of panel and OLS regressions to find what determines Actuarial Estimation Errors while also controlling for firm, plan, audit and actuary characteristics. The Actuarial Estimation Error (t+1) is defined as the expected return of pension assets for the following year (time *t+1*) minus the expected return of pension assets for the current year (time *t*). The remaining variables are described in Table 1. Fixed-effects, year indicators and robust clustered standard errors are used. For brevity considerations the coefficients of year indicators are not shown. All variables are winsorized at 1% & 99% levels. I denote statistical significance at the 1% (***), 5% (**) level and 10% (*) level.

	(1) Actuarial Estimation Error (t+1)	(2) Actuarial Estimation Error (t+1)	(3) Actuarial Estimation Error (t+1)	(4) Actuarial Estimation Error (t+1)
FEE (t)	-0.152	0.0675	0.127	0.166
	(0.680)	(0.597)	(0.581)	(0.528)
Funding % Liabilities (t)	-0.269	-0.551^{**}	-0.692^{**}	-0.465
	(0.593)	(0.245)	(0.333)	(0.300)
FEE(t) * Funding % Liabilities (t)	0.00232	-0.189	-0.228	-0.280
	(0.822)	(0.727)	(0.738)	(0.619)
Frozen (t)	-0.450^{*}	-0.0410	-0.0102	-0.0573
	(0.266)	(0.105)	(0.152)	(0.115)
Active % Employees (t)	-0.606	0.0255	0.0432	0.181
	(0.554)	(0.119)	(0.220)	(0.218)
Sole Plan (t)	-0.333	0.0758	-0.0223	0.171
	(0.329)	(0.0709)	(0.135)	(0.177)
Plan Size (t)	-1.563^{***}	-0.0421	-0.0304	-0.00340
	(0.397)	(0.0349)	(0.0509)	(0.0374)
ROA PLAN (t)	0.494	-1.042	-1.170	-1.209
	(1.213)	(1.203)	(1.434)	(1.230)
Firm Size (t)	0.519^{**}	0.0134	-0.00969	-0.0255
	(0.208)	(0.0249)	(0.0457)	(0.0344)
Leverage (t)	-0.961	-0.0869	-0.0557	-0.0820
	(0.728)	(0.175)	(0.212)	(0.182)
ROA FIRM (t)	-0.606	-0.482	-0.650	-0.612
	(0.806)	(0.764)	(0.666)	(0.557)
Big Actuarial Firm (t)	0.193	0.278^{**}	0.294^{*}	0.0440
	(0.153)	(0.115)	(0.174)	(0.0782)
Big 4 Auditor (t)	0.231	0.111	0.249^{**}	0.147^{*}
	(0.151)	(0.0782)	(0.0961)	(0.0822)
Constant	4.365^{**}	0.266	0.661	0.406
	(1.833)	(0.374)	(0.498)	(0.384)
N	1748	1748	1748	1748
R^2	0.158	0.103	0.105	0.099
Year Dummies	Yes	Yes	Yes	Yes
Fixed Effects	Firm Level	Actuary-Firm Level	Office Level	No

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Chapter 2: Do changes in corporate pensions' financial strength affect the underlying actuarial valuation assumptions?

Abstract

In this paper I employ a new measure for actuarial estimation errors in the funding assumptions of Defined Benefit (DB) pension plans. The Actuarial Estimation Error (AEE), developed and used for the first time in Papakyriakou (2016), is defined as the difference between the Expected Return (ER) of pension plan assets for two consecutive years (e.g. $AEE_t = ER_t – ER_{t-1}$). The expectations about pension asset returns for a year are set in place at the beginning of the year by pension plan actuaries. Using defined benefit (DB) pension data, spanning 2000-2011, from publicly traded firms in the US and the 2008 global financial crisis as an exogenous shock that causes pension funds to transition across different categories of financial strength I find that when the funding level of defined benefit (DB) pension plans falls significantly, enough for the plan to drop to a lower funding category, then Actuarial Estimation Errors of the following year become significantly bigger, an obligation reducing assumption. Findings only hold for the later years of the sample, i.e. after 2008 when the global financial crisis arrived. Results are robust to actuarial compensation incentives and the overall financial strength level of pension plans.

1. Introduction

In this paper, I extent the work of Papakyriakou (2016) who studies the behavior of appointed actuaries when corporate defined-benefit (DB) pension plans are underfunded. Papakyriakou (2016) is the first study that, to the best of my knowledge, introduced the concept of Actuarial Estimation Error (AEE), defined as the difference between the Expected Return (ER) of pension plan assets for two consecutive years (e.g. $AEE_t = ER_t – ER_{t-1}$). By using defined benefit (DB) pension data, spanning 2000-2011, from publicly traded firms in the US, panel regressions and difference-in-differences, I find that when pension plans drop to a lower category of financial strength, by becoming endangered or critical, then AEEs of the next year are bigger. Results are robust to a number of controls including actuarial compensation incentives and the overall financial strength level of the pension plan. Findings suggest that appointed actuaries make obligation reducing assumptions when DB pension plans are financially distressed. When DB pension plans are underfunded their sponsors are obliged by law to improve their plans' financial condition. This situation implies that firms need to make fund contributions towards their plans. One way to reduce the amount of contributions needed is to inflate the expected return of pension assets, part of actuarial pension assumptions, since doing so decreases the annual pension expense for the period[11]. The anticipated effect is that less funds will be needed to cover the annual pension expense and at the same time improve the funding level of the pension plan. Put differently by inflating expected pension plan asset returns, and hence AEEs of the next period actuaries decrease the amount of contributions that sponsors need to make in order to cover accrued benefits and at the same time improve the plan's financial condition. The results were only found to

[11] Annual Pension Expense (Cost) ≈ Additional Benefits Accrued in Current Year + Interest on Accrued Benefits at the Beginning of Current Year – Expected Return on Plan Assets for Current Year.

be significant in the later years of the sample, i.e. after 2008 when the financial crisis arrived to global markets.

Cocco (2014) discusses a number of papers studying pension asset allocation of underfunded pension plans. Some of those papers find that sponsors of such plans engage in risk shifting, by investing more in equity, in an attempt to improve their plans' financial condition (Bodie, Light, Morck, & Taggard, 1985), (Bodie, Light, & Morck, 1987) while some others engage in risk management by investing greater proportion of their plan assets in bonds (Friedman, 1984), (Rauh J. , 2009). In particular, Rauh (2009) is examining the risk shifting against the risk management incentives of financially constrained corporations. He finds that firms allocate pension funds to safer assets (debt and cash) when the plan is less funded and when they (the sponsoring firms) have a lower credit rating, a result that gives support to the risk management hypothesis.

Besides the literature studying how sponsors invest pension assets when the plan is underfunded, there is also literature studying the implications of sponsoring an underfunded DB pension plan. For example, Rauh (2006) finds that pension plan sponsors decrease capital expenditures, which could be profitable investments, in response to a reduction in internal resources caused by required pension contributions towards DB pension plans. Moreover, Franzoni (2009) finds that the market reacts significantly more strongly to a drop in cash, resulting from transferring funds to the pension plan account, in financially constrained firms. In contrast, the impact of a given drop in cash is far less significant in empire-building (expanding) firms. In addition, Franzoni & Marin (2006) find that the market is significantly overvaluing firms with severely underfunded pension plans and that the firms with the most underfunded pension plans earn lower raw returns compared to firms with healthier pension plans.

Given the findings of the papers discussed in the previous two paragraphs, it is natural to assume that DB pension plan sponsors are not particularly keen to maintain underfunded plans. It is safe to say that they (the sponsors) have incentives to manipulate pension funding assumptions to make their plans appear financially healthier and at the same time reduce the amount of fund contributions they have to make towards their plans. One way to achieve that is by discounting pension liabilities with an inflated rate to make their present value appear to be smaller today. However, the discount rate used to estimate the present value of pension liabilities is a highly regulated parameter so this is not option.[12][13] A different strategy that sponsors can potentially follow is to inflate the expected return on pension assets, also part of actuarial pension assumptions, in order to minimize the annual pension cost of their plans. That would imply that the amount of fund contributions needed to meet (or exceed) the pension cost of the period would be smaller.

Anantharaman (2012) attempts to answer the empirical question what are the factors that predict the raw discount rate actuaries assume. She finds that economically important clients receive higher (obligation reducing) raw discount rate assumptions for their pension liabilities, a finding that is particularly evident in highly leveraged firms and firms with longer duration plans. Moreover, she finds that, economically important clients are more likely to receive lower (obligation increasing) raw discount rates for their pension liabilities when they, the clients, have the intention to freeze their defined benefit plan. The last finding is also backed by Comprix and Muller (2011). Kisser, Kiff & Soto (2016), employ two different liability concepts, one regulated and one unregulated, and find that reported liabilities for defined

[12] SFAS 87 requires corporate DB plan sponsors to use the 30 year US Treasury bond yield, a requirement that was subsequently relaxed in SFAS 158 in to using the investment grade corporate bond yield.
[13] The restrictions apply to the discount rate of corporate DB pension plan liabilities only. For example public (state) DB pension plans follow a different set of accounting rules.

benefit pension plans are understated by approximately 10% in the US. The authors state that most of the bias is attributed to higher assumed discount rates for pension liabilities, a result that is more pronounced in plans that are financially distressed. Continuing with pension funding assumptions, Amir & Benartzi (1998) find that the assumed expected rates of return on plan assets tend to be only weakly correlated with the proportion of the assets that is invested in equities, a result that could be a cause for concern. On the one hand, it strengthens the findings of other studies on pension funding assumptions which suggest that actuaries base their assumptions on factors other than the obvious, for example their economic bonding with the plan sponsor and the overall financial strength level of the DB pension plan. On the other hand it suggests that actuaries do not always have the best interest of DB plan beneficiaries in mind when coming up with their pension funding assumptions, indirectly implying that the integrity of actuarial professionalism might be compromised.

The issues that arise by government intervention, and in particular the behaviour of DB plan sponsors in the presence of Pension Benefit Guarantee Corporation (PBGC) is an interesting topic in Pension Literature. PBGC is an independent government agency who acts as insurance, protecting the benefits accumulated by DB plan beneficiaries. Findings include that the presence of such an insurance provokes the investment of pension assets to risky assets to maximize returns (Harrison & Sharpe, 1983), (Treynor, 1977), (Sharpe, 1976). Some studies regard the insurance of PBGC as a put option, since sponsors of DB plans need to pay a premium to participate, essentially buying the right to sell their underfunded DB pension plans to PBGC if needed, and attempt to estimate its value and the appropriate premiums that should come with it (Marcus, 1987), (Hsieh, Chen, & Ferris, 1994), (Boyce & Ippolito, 2002), (Pennacchi & Lewis, 1994).

The contribution of the present study is on two levels. First, it uses a new measure of actuarial performance, the Actuarial Estimation Error (AEE), first introduced in Papakyriakou (2016). By using the AEE, defined as the difference between the expected return (ER) of DB pension plan assets for two consecutive years (for example, $AEE_{t+1} = ER_{t+1} - ER_t$), it is possible to explore the factors causing actuarial pension valuation assumptions to change from the current to the next year. What competing studies do, by using the raw discount rate and expected return of pension assets as dependent variables, is explore the factors causing actuarial pension valuation assumptions to change in the current year only, which is far less interesting. Furthermore the AEE has a number of notable advantages including not being as restricted as the raw discount rate for pension liabilities (restriction applies to corporate DB pension plans only) while also taking into account the assumed expected return of pension assets of both the current and next year, essentially measuring the error in actuarial estimates. Moreover the fact that the AEE as a measure, has similarities to the Loss Reserve Error from the Insurance and Economics Literature, further validates the argument that AEE is an appropriate measure. The first attempt to measure the Loss Reserve Error was made by Weiss (1985) who proposed taking the difference between the originally reported loss reserves and claims paid over the next five years. A later revised measure was proposed by Kazenski et al. (1992) who defined Loss Reserve Error as the difference between the originally reported loss reserve and a revised estimate five years later. Both the original and the later revised measure have been used in Insurance and Economics literature studies since they were first proposed, however, the revised measure is the one that is closer to AEE.

The second major contribution of the present study is it uses a broad and recent panel of data from both the pre and post crisis era, spanning 2000 - 2011. I exploit this by conducting a difference-in-differences regression analysis to investigate whether the overall drop in the funding level of DB pension plans, which was generated exogenously by the 2008 global financial crisis, caused any additional effect on AEEs. The present study is the first in recent pension literature that, to the best of my knowledge, employs a difference-in-differences identification strategy to draw conclusions about the assumptions made by actuarial professionals, making the findings more robust, compared to simply using traditional OLS and panel regressions. Furthermore this study made possible to observe and explore not just the factors affecting actuarial behavior but also the factors affecting changes in it, hence the findings are far more appealing to all the interested parties (i.e. government, sponsors of DB plans, DB plan beneficiaries, tax payers, etc.)

The remaining of this paper is structured as follows. In Section 2 I provide the Institutional background and in Section 3 I develop the hypothesis. In Section 4 I describe the sample, in Section 5 the methodology, in Section 6 I present the results and in Section 7 I conclude.

2. Institutional Background

Every pension plan sponsoring firm needs to appoint an actuary with the responsibility to make the actuarial assumptions which, among other things, determine the pension plan's funding status. The management has the final word in deciding these assumptions, because upon decision the assumptions are binding for the firm. However the complexity of this task is such that usually the management of the plan sponsoring firm relies upon the recommendations of the actuary to decide (Gunz, McCutcheon, & Reynolds, 2009).

The actuarial profession is mostly self-regulated, and comparably very similar to the accounting, profession prior to Sarbanes-Oxley Act of 2002; for example Gunz, McCutcheon, & Reynolds (2009) say "*The issues surrounding the professional independence of actuaries are not, in principle, unlike those that faced the audit profession before the regulatory changes* *early this century*" to point out that plan sponsors often exercise pressure on the actuaries they hire to make obligation reducing assumptions, with higher discount rates for the liabilities and / or bigger expected returns for the assets of the plan, actions that are against the best interest of the plan beneficiaries. In support of this comes a study about the actuarial profession in the United States quoting the following: "*as long as a client can threaten to find another actuary to provide actuarial services, the implied leverage might well have an effect on the actuary's work product*" (CRUSAP TASK FORCE, 2006). On the other hand, professional standards, the threat of litigation, and reputational considerations could provide the incentives for actuaries to resist client pressure.

The Employee Retirement Income Security Act 1974 (ERISA) is a US federal law, enacted on September 2nd 1974, that protects the assets of millions of plan beneficiaries in the United States in the sense that funds placed in retirement plans during their working lives are guaranteed to be safe. Prompted by the default in recent years of several large defined benefit pension plans and the increasing deficit of Pension Benefit Guaranty Corporation (PBGC), the Bush Administration in January 2005 advanced a proposal for pension funding reform, which was designed to increase the minimum funding requirements for pension plans and strengthen the pension insurance system. As a result, on August 17, 2006, the Pension Protection Act (PPA) was signed by President George W. Bush in to a law. The PPA of 2006 is the most comprehensive reform of the nation's pension laws since the enactment of the ERISA. It establishes new funding requirements for defined benefit pensions and includes reforms that affect cash balance pension plans, defined contribution plans, and deferred compensation plans for executives and highly compensated employees. One of its features is the classification of pension plans in categories of financial strength (safe, endangered, seriously endangered & critical) based on the level of funding of pension liabilities and a projected horizon for funding deficiency or insolvency[14].

3. Hypothesis Development

Concern can be raised about the deteriorating funding status of DB pension plans nowadays (Kilroy, 2015). Given this fact it is then natural to ask: How do plan sponsors respond to this new reality? Do they take more risk, in an attempt to improve the funding status of their pension plans, or do they invest in safer assets? Literature suggests that either of these directions is possible (Bodie, Light, Morck, & Taggard, 1985), (Bodie, Light, & Morck, 1987) (Friedman, 1984), (Rauh J. , 2009). Furthermore how do actuaries respond in forming their pension funding assumptions? It has been shown in recent literature that actuaries tend to issue obligation-reducing assumptions, usually by assuming bigger discount rates for pension liabilities (Anantharaman, 2012), (Kisser, Kiff, & Soto, 2016), (Novy-Marx & Rauh, 2009) or higher expected returns for pension plan assets (Bergstresser, Desai, & Rauh, 2006). I take the expected return of pension assets and provide a brief description of the accounting rules for pensions to clarify why an inflated assumed expected return of pension assets is an obligation reducing assumption. The annual pension expense as reported in a firm's income statement has three major components. The first is the service cost which is the value of the additional pension benefits that employees accrued during the year. The second is the interest cost defined as the difference in the present value of the pension benefits at the beginning of the year and the present value of the same benefits at the end of the year. The final component, which is subtracted from the previous two, is the assumed expected return earned on the pension assets. The equation follows.

[14] For more details a summarized read is provided by Purcell (Purcell, 2006).

$$Annual\ Pension\ Expense\ (Cost) \approx \text{Service Cost} + \text{Interest Cost} - \text{Expected Return on Pension Assets} \tag{1}$$

It should be noted that I have only included the major components of the Annual Pension Expense, also known as Net Periodic Pension Cost, in Equation 1 therefore the approximate equality sign has been set in place. This is done to make Equation 1 valid under both the IFRS (International) and GAAP (US) accounting standards. There are additional (far) less significant components that constitute the Annual Pension Expense but as these change, depending on the accounting standards followed, they are omitted from Equation 1 for the sake of clarity and simplicity. Continuing from the previous paragraph, the higher the assumed expected rate of return the lower the reported pension expenses. Note that it is the expected rate of return, and not the realized rate of return, that is used to determine the pension expense. Thus, by assuming a higher expected rate of return on plan assets, actuaries are able to decrease the annual pension expense, and also the amount of fund contributions sponsoring firms have to make towards the plan, increasing, in this way, accounting profits as well.

The empirical question I pursue to answer is how do actuaries form their assumptions when the financial condition of DB pension plans becomes weaker. Previous literature finds that they (the actuaries) issue obligation reducing (i.e. optimistic) assumptions when DB plans become underfunded, in order to decrease the amount of fund contributions the employers need to make towards their DB pension plans. In this study I differ by employing a new measure for actuarial estimation errors in pension funding assumptions, the AEE, that was developed in Papakyriakou (2016) and is defined as the difference between the expected return (ER) of pension assets for two consecutive years (for instance $AEE_{t+1} = ER_{t+1} - ER_t$).

Furthermore I use more recent and broader data that include the post crisis years as well, spanning 2000-2011.

Papakyriakou (2016) finds that larger actuarial estimation errors, or equivalently obligation reducing pension assumptions, are associated with a lower level of funding in DB pension plans. The author explains this finding in the following manner. When the funding level of DB pension plans is low, below specific thresholds[15], it needs to improve by law. For this to happen, sponsors of DB pension plans need to make fund contributions towards their plan. The alternative would be to reduce the pension expense, by inflating the expected return of pension assets for the next period, and hence make actuarial estimation errors bigger. This would result in the sponsors having to contribute less funds towards their plans and at the same time increase the accounting profits of their firms.

Moving on, I argue that big and sudden drops in the funding level of DB pension plans, which result in the plan taking the endangered or critical status, also affect actuarial pension assumptions. Put differently, when the financial strength level of DB pension plans deteriorates vastly in short periods of time, i.e. in a year, actuaries make more aggressive assumptions, inflating the expected return of pension assets and also the AEE of the next year. The hypothesis follows.

Hypothesis: When Defined Benefit pension plans fall to a lower category of financial strength level, by taking the endangered or critical status, actuarial estimation errors become bigger in the year following the drop.

[15] For more information about the thresholds refer to Papakyriakou (2016) or Pension Protection Act of 2006.

Sponsors of DB plans that fall in the endangered or critical status need to improve the funding level of their plan within a specific time horizon, usually 10 years. This involves taking corrective measures which, among others, include fund contributions from the sponsor side towards the plan, significantly above the minimum required level. What potentially follows, and is also the idea behind this paper's hypothesis, is that sponsors signal their plans' actuaries to make more aggressive assumptions, i.e. issue even higher expected returns for pension plan assets for the following year, in an attempt to reduce the annual pension expense and at the same time mitigate the need having to make bigger contributions towards their plans.

4. Sample

The data I use come mainly from the form 5500 annual reports, and specifically, the form 5500 research files, years 2000-2011, from the United States Department of Labor (US DOL), the primary source of information about the operations, funding and investments of welfare benefit plans from public and private firms in the United States. Every plan sponsor of more than 100 participants is obliged to fill the form 5500 once per annum, specifically in the plan year end, while smaller plans, which comprise of less than 100 participants, can fill a more simplified form for example the form 5000-SF (Shortened Form) on a less frequent basis (once per 3 years). Additional Schedule B and Schedule H data are used for years 2000 – 2011 to accompany the form 5500 data as they contain useful actuarial and financial information respectively, about the pension plans that populate the form 5500 research files.

I also use Compustat (2000-2012) data obtained from the Wharton Research Data Services (WRDS) to complement the data from the United States Department of Labor. Specifically Compustat is used to obtain additional financial and actuarial pension data from publicly traded firms in North America. Finally I use DataStream to download indices for Equity, Debt, Real Estate and Commodities in the US, for years 2000-2011. In particular, these indices are the S&P 500, Barclays Capital Aggregate Bond, MSCI Real Estate and Bloomberg Commodity Total Return. I use these four indices in combination with pension asset allocations from Compustat to come up with a weighted average return that approximates the actual yearly return of DB pension assets.

The final dataset (panel) is a result of merging the data from US DOL, Compustat and DataStream, deleting the duplicates, and deleting entries that don't have a Compustat match as well as the entries from non-defined benefit pension plans. The panel consists of 4,459 firm-year observations from 536 publicly traded firms in the US and is used to produce descriptive statistics and regression results. It needs to be noted that for the regressions, the number of observations eventually used is usually less and varies, depending on the variables included in the model. That is because missing variable entries do not count towards regression results.

4.1. Actuarial Estimation Error

The dependent variable I use is the Actuarial Estimation Error, developed by Papakyriakou (2016). The Actuarial Estimation Error at time *t+1* is defined as the difference between the expected at time *t+1* and the expected at time *t*, pension plan assets' return. It is given by the following formula:

$$Actuarial\ Estimation\ Error_{t+1} = Expected\ Return\ of\ Plan\ Assets_{t+1} - Expected\ Return\ of\ Plan\ Assets_{t}. \tag{2}$$

The expected pension plan assets return at time t+1 is defined as:

$$Expected\ Return\ of\ Plan\ Assets_{t+1} = \frac{Expected\ Change\ in\ Value\ of\ Plan\ Assets_{t+1}}{Actual\ Value\ of\ Plan\ Assets_{t}} \times 100. \qquad (3)$$

And at time t as:

$$Expected\ Return\ of\ Plan\ Assets_{t} = \frac{Expected\ Change\ in\ Value\ of\ Plan\ Assets_{t}}{Actual\ Value\ of\ Plan\ Assets_{t-1}} \times 100. \qquad (4)$$

The expected return of plan assets for a year is usually announced on December 31 or the fiscal year end, however it is assumed by the actuary at an earlier time, usually at the beginning of the fiscal year, and it is an estimate of how the plan assets are expected to perform during fiscal year.

The main advantage of AEE over the raw discount rate, that competing studies use, is that it consists of two components, making it a normalized measure. It compares current actuarial expectations to those of the previous year. Since in the regressions I am controlling for all the factors that could affect actuarial assumptions, this measure is essentially measuring the actuarial error. Moreover, the AEE has similarities with the loss reserve error[16], used in the Insurance and Economics Literature, which is a widely known and accepted measure.

Alternatively, instead of the AEE, I could use the raw discount rate, also part of pension funding assumptions, as my dependent variable. However, the raw discount rate that some competing studies use is a highly regulated so actuaries cannot choose it freely. More specifically, Cocco (2014) states that SFAS 87, which was released in December 1985, required firms to use the yield on the US 30-year Treasury bond as the raw discount rate for

[16] Defined as the difference between an originally reported reserve estimate and a later revised one (Kazenski et al., 1992), (Kamiya & Milidonis, 2016) etc.

pension liabilities. This value was subsequently relaxed with SFAS 158, released in September 2006, and set equal to the yield of investment grade corporate bonds.[17] As a result, in this study, I choose to use AEE instead of the raw discount rate for pension liabilities as my dependent variable.

4.2. Main Regressors

The main independent variable of the regression models is Funding % Liabilities. It represents the proportion of a DB pension plan projected benefit obligations covered by the pension assets. I include this variable in the regression models as it is used as main and control variable in relevant studies, e.g. (Kisser, Kiff, & Soto, 2016), (Anantharaman, 2012), (Papakyriakou, 2016) but more importantly because past studies found that public (state) DB pension plans are very underfunded (Novy-Marx & Rauh, 2009), (Novy-Marx & Rauh, 2010). Underfunding is a situation that could also affect corporate DB plan sponsors and could lead to significant cash contributions from the firm towards the plan (Cocco, 2014). To mitigate the need of having to make big fund contributions sponsors may signal the plan actuaries to make obligation reducing assumptions, e.g. inflate expected return for pension assets, essentially affecting AEE.

Using a simplified traffic light system that determines pension plan health I define three indicator variables. The first, Green, is equal to 1 when the Funding % Liabilities is above 0.8. In other words this variable is equal to 1 when the funding level of a DB pension plan is above 80% and considered safe. Similarly Orange is equal to 1 when the Funding % Liabilities variable is between 0.65 and 0.8, a category that is considered endangered and last Red

[17] It should be noted that the restrictions apply to the discount rate of corporate DB pension plans only (that follow the accounting rules of FASB). Public (state) DB pension plans, following the GASB set of accounting rules, are not confined by such restrictions.

when the Funding % Liabilities is below 0.65, where the plan is considered to have the critical status. The traffic light system I use in this paper is a simplification of the one stipulated in Pension Protection Act (PPA) law of 2006. In PPA there were originally four categories for the financial strength level of a pension plan: healthy, endangered, seriously endangered and critical. [18]

4.3. Transition Variables

Using the indicator variables described in the previous section (§4.2), I define four additional indicators, the transition variables. The first three are Green2Red, Green2Orange & Orange2Red and are defined in a similar way. Taking as example the indicator variable Green2Red, it is set to 1 if at time t-1 the corresponding plan is in the Green (Safe) funding category and by time t it falls in Red (Critical) funding category. Otherwise it is set to 0. The fourth variable, named Transitions, is the sum of the first three and it captures the proportion of all plans that drop to a lower category of funding level from time t-1 to time t.

4.4. Control Variables

I am using four groups of control variables based on actuary, plan, firm and audit characteristics.

In the first group, actuary characteristics, I use two variables to control for the size of the actuarial firm and the economic bonding of the actuary with the plan sponsor. The first variable is Big Actuarial Firm and is set to 1 if, for a specific year, the actuarial firm is one of the top 5% actuarial firms with respect to the number of clients, set to 0 otherwise. Bigger and more independent actuarial firms have an incentive to protect their reputation and avoid litigation costs and therefore are less likely to succumb to (client) pressure in issuing

[18] For more information about the (original) traffic light system defined in Pension Protection Act 2006, refer to Purcell (2006).

obligation reducing actuarial assumptions (Reynolds & Francis, 2001), (YU, 2007). Furthermore I argue that big actuarial firms have a large number of clients and can afford to lose the bad (non-paying or financially distressed) clients which have greater probability of sponsoring underfunded pension plans and who would therefore have bigger incentives to be persistent in getting more favorable, obligation reducing, actuarial assumptions for their pension plans.

The second variable is FEE[19], defined as the proportion of professional fees that an actuary receives by a specific plan sponsor, divided by the sum of all professional fees the actuary earns for the whole year. By definition, the bigger the FEE, the bigger the economic bonding of the actuary to the plan sponsor, a situation that gives the plan sponsor more persuasive power over the actuary. This implies that the actuary may succumb to pressure to issue favoring assumptions for the firm's pension plan (e.g. inflated expected return for pension assets / higher raw discount rate for liabilities) when the FEE is bigger.

In the second group, plan characteristics, I control for those plan characteristics that could affect the expected return of plan assets and therefore the AEE. First I control for frozen plans (FROZEN - indicator variable equal to 1 if frozen, 0 otherwise). There is a number of reasons why firms choose to freeze their plans, for example to reduce volatility in funding obligations due to fluctuating equities markets, plan asset values and interest rates (Golumbic & Levine, 2014). Building on that, existing literature is suggesting that in some cases sponsors of frozen plans have incentives to keep their plans frozen in order to prevent more beneficiaries joining the plan and current beneficiaries accumulating more benefits, which would happen if the plan got out of the frozen status (Anantharaman, 2012), (Comprix & Muller, 2011). To keep

[19] Similar to FEEIMP from Anantharaman (2012).

the plan frozen actuaries may understate expected return for pension plan assets, essentially affecting AEE downwards.

I control for the percentage of the plan participants that are currently active workers[20] (Active % Employees) since young firms have a preference on stocks rather than bonds for their pension plan assets (Lucas & Zeldes, 2006) and therefore expect the variable to be associated to more volatile AEEs.

I control for sole plans (Sole Plan - indicator variable equal to 1 if the plan is the sole plan of a sponsor, 0 otherwise) as one might expect a sponsor to be able to manage (fund) better one plan only and, finally, I control for the size of the plan (Plan Size) which might affect AEEs in many different ways. On the one hand, actuaries might find it harder to issue inflated expected returns due to bigger plans receiving increased audit but at the same time one could also argue that firms with big plans exercise increased pressure on the plan's actuary, to get favoring assumptions, especially if the latter is also an employee of the firm (Kamiya & Milidonis, 2016), (Chtourou, Bedard, & Courteau, 2001), (Klein, 2002).

The last variable in the group of plan characteristics is ROA Plan. It is estimated by multiplying pension asset allocations with annual returns from relevant indices[21] (Equity, Debt, Real Estate and other industries) followed by summing the results of the multiplications. The result is an approximation of the annual pension assets' investment return that also takes into account pension asset allocation. ROA Plan is very likely to affect AEE of the next year as pension asset allocation and pension investment return in the current year are two determinants that actuaries would be expected to take into account before deciding an expected return for pension assets for the following year.

[20] Non-retired workers.
[21] For further details on how this variable is computed refer to Table 1 in the Appendix.

The third group of control variables, firm characteristics, controls for those firm characteristics that may potentially affect AEE. First I control for the size of the firm (Firm Size) as big firms ought to be more careful and accurate in their estimates and since the fees that big firms pay for professional advice are significantly higher it would be reasonable to expect more accurate estimations of the expected return (and hence less volatile AEEs). I control for leverage as highly leveraged firms have higher probability to sponsor underfunded plans (creditors have priority on firm funds). Therefore this type of sponsors in an attempt to decrease fund contributions towards their plans could signal their plan actuaries to assume inflated expected returns for the pension assets, resulting in bigger AEEs. I also control for the firm's return on assets (ROA Firm) as this variable is an indication of firm performance. Well performing firms have funds more readily available so it is easier for them to make cash contributions in their pension plans once needed. As the expected return on pension assets is usually inflated to reduce the amount of contributions that need to be done towards the pension plan this variable could be relevant. Last I control for the firm's credit risk by including an indicator variable, LowZscore, which is equal to 1 if the firm's Z score is below the 1.81 threshold, following Altman (1968). The Altman Z score was first introduced by Altman in 1968 who stipulated that firms with small Z-Score, specifically firms with Z score smaller than 1.81 are in the distress zone and have high risk to default in short period of time. Firms of this kind have bigger incentive of overstating expected returns on plan assets to reduce pension contributions as funds are not as readily available.

The fourth group of control variables, the actuarial characteristics, consists of one variable, Big 4 Auditor. It is an indicator variable which is equal to 1 if the auditor is one of the big 4 auditors (PWC, Deloitte, KPMG, Ernst & Young) and 0 otherwise. It has been found in the literature that bigger audit offices provide higher quality of audit due to the fact that they are less dependent from their clients and are less likely succumb to pressure in overlooking earnings, and possibly pension assumptions, manipulation (YU, 2007). Hence I include this variable in the models as I expect firms that buy services off a big 4 auditor to be associated with smaller and less volatile AEEs.

5. Methodology

5.1. Ordinary Least Squares and Panel Regression Model

To put the hypothesis of this paper to the test, I employ OLS and panel regressions. In the panel regressions I use fixed-effects at the firm (plan sponsor), actuarial firm, and actuary office levels. I justify using fixed effects in three different levels as I need to control for the unobserved time-invariant factors that might influence actuarial judgment, and consequently the AEE, that are present and change from firm to firm, from actuarial firm to actuarial firm and from actuary office to actuary office. For all regressions the errors are heteroscedasticity and cluster robust.

The equation of the OLS and panel regressions model is given below[22].

$$\begin{gathered} Actuarial\ Estimation\ Error_{t+1} = \\ a_0 + \alpha_1 * Actuarial\ Estimation\ Error_t + \alpha_2 * Funding\ \%\ Liabilities_t \\ + \alpha_3 * Transitions_t + \beta * Plan\ Characteristics_t + \gamma * Firm\ Characteristics_t \\ + \delta * Auditor\ Characteristics_t + \varepsilon * Actuary\ Characteristics_t + \eta_t + FE + \varepsilon_{t+1}. \end{gathered} \tag{5}$$

The element a_0 represents the intercept and *Funding % Liabilities* measures the proportion of pension liabilities covered by the pension assets at time *t*. The *Transitions* variable, that is the sum of *Green2Red, Orange2Red & Green2Orange*, is an indicator set to 1 if the

[22] In the OLS model the Fixed Effects (FE) element is missing.

corresponding plan fell from a higher (Green or Orange) to a lower (Orange or RED) funding category from time *t-1* to time *t*. The parameter η_t represents the year indicators while ε_{t+1} are error terms which are assumed to be heteroskedastic and auto correlated within clusters. Note that the *AEE* of time *t* is included as independent variable in the regression equation. That is to account for the fact actuaries could be making corrective assumptions in the next year, essentially affecting the *AEE* of *t+1*, based on their errors from the current year (time *t*).

5.2. Difference in Differences: First Regression Model

I exploit the fact that my sample includes data from both the pre-crisis (2007 and earlier) and the crisis years (2008 and later) and employ a difference in differences research design[23]. For that, I use a time (Crisis) and a treatment-control (Transitions = Green2Red + Orange2Red + Green2Orange) indicator variables to test if the increased number of plans falling to a lower category of financial strength level, after 2008, affects AEEs.

The difference in differences research design is based on two mutually exclusive groups of observations (treatment & control) of which the dependent variable (AEE) mean values are assumed to have parallel trends in time, in case no treatment takes place. It is further assumed that in the presence of some kind of treatment the dependent variable mean values do not have parallel trends in time. In this study, the treatment group consists of plans which dropped to a lower funding category from time *t-1* to time *t*, e.g. from Green (Safe) to Red (Critical), while the control group consists of all the remaining plans.

In total, I conduct three DD regressions which differ with respect to the control variables included in each as I progressively add control variables. In particular for the second regression I add to the model the variable LowZscore, which controls for the firm's credit risk,

[23] For details regarding these methods a nice read is that of Angrist & Pischke (2009).

while for the third regression I add the variable FEE which controls for the economic bonding of the actuary and the plan sponsor. In all three regressions I include an additional number of control variables based on firm, plan, actuarial and audit characteristics to control for the observable factors that could potentially affect AEEs. The equation of the DD model is provided below.

$$\begin{aligned} & Actuarial\ Estimation\ Error_{t+1} = \\ & a_0 + \alpha_1 * Actuarial\ Estimation\ Error_t + \alpha_2 * Crisis \\ & + \alpha_3 * Transitions_t + \alpha_4 * Transitions_t * Crisis + \alpha_5 * Funding\ \%\ Liabilities_t \\ & + \beta * Plan\ Characteristics_t + \gamma * Firm\ Characteristics_t \\ & + \delta * Auditor\ Characteristics_t + \varepsilon * Actuary\ Characteristics_t + \eta_t + \varepsilon_{t+1}. \end{aligned} \tag{6}$$

The element a_0 represents the intercept, *Crisis* is an indicator that takes the value 1 if the at time *t* the year is 2008 or later and *Transitions* is an indicator variable created by adding together the transition variables, *Green2Red, Orange2Red & Green2Orange* (for example Green2Red is an indicator set to 1, if from time *t-1* the corresponding plan is in the Green/Safe funding category and at time *t*, it fell in the Red/Critical funding category). The interaction of the *Crisis* and the *Transitions* variable measures the additional effect that the *Transitions* variable has on the dependent variable, due to the *Crisis* and, by definition, is the causal variable. *Funding % Liabilities* measures the proportion of pension liabilities covered by the pension assets at time *t*. The parameter η_t represents the year indicators while ε_{t+1} are error terms which are assumed to be heteroskedastic. It should be mentioned that *AEE* of time *t* is included as control variable in the regression equation in order to account for the fact actuaries could be making corrective assumptions for time *t+1*, essentially affecting the *AEE* of *t+1*, based on their errors from time *t*.

5.3. Difference in Differences: Second Regression Model

For the second DD regression model, I create a different time indicator, than in the first DD model, which I denote by PPA, and is equal to 1 if the year is 2006 or later. The treatment-control indicator is the same as in the first DD model (Transitions). I do that to investigate whether it was after 2006 that Transitions started having an effect on AEE. Since in 2006, Pension Protection Act law was voted into law defining the funding level categories and obliging firms in putting their DB pension plans in rehabilitation programs, once these become underfunded, this is a setting worth investigating. It should be noted that the Pension Protection Act law is a large document (consists of almost 400 pages of text) hence not all provisions in the act were enforced the date it was signed. However, I argue that as all provisions became known by the 17th of August 2006, when the Act was signed by President Bush, interested parties including corporate DB plan sponsors, had time to adapt to all the provisions of PPA, even those enforced at later dates. As a consequence I consider year 2006 to be the date that all the provisions in PPA became effective and build a model that captures the effects from the PPA enforcement based on this assumption.

In total, three DD regressions are run which differ with respect to the control variables contained in each. More specifically, for the second regression, the variable LowZscore is added as control variable on top of the variables already used in the first regression, to control for the firm's credit risk, while for the third regression the control variable FEE is further added, to account for the economic bonding of the actuary and the plan sponsor. In all three regressions additional number of control variables based on firm, plan, actuarial and audit characteristics are included to control for the factors that could potentially affect AEE of the next year. The equation of the second DD model follows.

$$
\begin{aligned}
&Actuarial\ Estimation\ Error_{t+1} = \\
&a_0 + \alpha_1 * Actuarial\ Estimation\ Error_t + \alpha_2 * PPA + \alpha_3 * Transitions_t \\
&+ \alpha_4 * PPA_t * Transitions_t + \alpha_5 * Funding\ \%\ Liabilities_t \\
&+ \beta * Plan\ Characteristics_t + \gamma * Firm\ Characteristics_t \\
&+\delta * Auditor\ Characteristics_t + \varepsilon * Actuary\ Characteristics_t + \eta_t + \varepsilon_{t+1}.
\end{aligned} \tag{7}
$$

The element a_0 represents the intercept, *PPA* is a time indicator that takes the value 1 if at time *t* the year is 2006 or later and *Transitions* is an indicator variable created by adding together the transition variables, *Green2Red, Orange2Red & Green2Orange*, and measures the proportion of plans that from time *t-1* to time *t* fell to a lower funding category. The interaction variable *(PPA*Transitions)* measures the additional effect of transitions on AEE of *t+1* after the 2006 landmark and by definition it is the causal variable of this regression model. *Funding % Liabilities* measures the proportion of pension liabilities covered by the pension assets at time *t.* The parameter η_t represents the year indicators while ε_{t+1} are error terms which are assumed to be heteroskedastic. It is important to mention that the *AEE* of time *t* is included as a control variable in the regression equation as well. This is done to account for the fact that actuaries could potentially be making corrective assumptions for time *t+1*, essentially affecting the *AEE* of *t+1*, by observing the estimation errors they made at time *t*.

6. Results

In this section I present descriptive statistics of the dependent and independent variables used in the three regression models of this paper (Tables 2, 3 & 4). Next I present results from the panel and OLS regression model (discussed in Section §5.1) in Tables 5, 6 & 7. Finally I present results from the two difference-in-differences regression models (discussed in Sections §5.2 and §5.3) in Tables 8 & 9.

6.1. Descriptive Statistics

In this section I present the descriptive statistics of key variables, winsorized at the 1% & 99% levels. In Table 2 descriptive statistics for the full sample are provided while in Table 3 the sample is split to a pre-crisis (2000-2007) and a crisis (2008-2011) subsample and descriptive statistics are provided for the two separately. In Table 4 the sample is split in two subsamples once more, in order to compare descriptive statistics for the years before the Pension Protection Act was voted into law (2000-2005) and the years after (2006-2011). In Table 1 variable definitions are provided.

6.1.1. Full Sample

Starting with Table 2, the AEE has a mean (median) value of -0.001179% (-0.001%) and a standard deviation of 2.46%, suggesting that, while on the negative side, the AEE is very volatile and so differentiation from zero is not possible. In other words there isn't enough evidence to suggest that actuaries change their expectation on pension asset returns from year to year. Moving on, the mean (median) value of Big Actuarial Firm is 0.64 (1) and the standard deviation 0.48 meaning that the top 5% actuarial firms, with respect to the number of clients, capture 64% of the market. The mean (median) value of FEE, the ratio of professional fees an actuary receives from a specific plan sponsor divided by all the professional fees the actuary earns in that year, is found to be 0.30 (0.02) and the standard deviation at 0.40. Even though very volatile, this essentially means that the average actuary gets 30% of his yearly professional fees by a single plan sponsor.

Next, the mean (median) value of Funding % Liabilities, giving the proportion of pension liabilities funded by pension assets, is 0.83 (0.80) and the standard deviation is 0.23, indicating that the average pension plan is adequately funded. Green, Orange and Red mean values represent the proportion of pension plans that are safe (Funding % Liabilities greater than 80%), endangered (Funding % Liabilities between 65% and 80%) and critical (Funding % Liabilities less than 65%) respectively. Exactly 50% of the plans are safe, 32% are endangered and 18% are in the critical category of funding. Transitions mean value shows the average proportion of pension plans that within 1-year period drop from a higher category of funding level (Green or Orange) to a lower one (Orange or Red). On average, within 1 year, 18% of all plans fall to a lower category of funding.

Next are frozen plans of which the mean value of 0.11 reveals that in any given year, the percentage of frozen plans is on average 11% while ROA Plan that is an estimation of the yearly return of pension assets has a mean value of 5.29%. Sole plans, i.e. plans from a single sponsor, account for 4% of the total number of plans in the sample. Leverage, i.e. the proportion of a firm's total assets that comes from debt, is on average 26.61% while ROA Firm, which accounts for a firm's yearly return on its total assets, is on average at 3.24%. Following Altman (1968), LowZscore measures the proportion of all the firms in the sample with a Z score smaller than 1.81, i.e. firms in the distress or bankrupt zone, and it is quite large, at 0.19. Last is the Big 4 Auditor indicator which measures the proportion of the market that is captured by the big 4 auditors all together. That is 0.56, meaning that there is probability 0.56 that a random plan in a random year is audited by one of the big 4 auditors.

6.1.2. Pre-Crisis (2000-2007) VS Crisis Sample (2008-2011)

In Table 3 the distribution of AEE in Panel A (years: 2000 – 2007) has a mean (median) value of -0.00131% (-0.001%) and a standard deviation of 2.82%. In Panel B the mean (median) value of AEE is -0.00091% (-0.001%) and the standard deviation is 1.44%. In both cases the AEE cannot be differentiated from zero as mean values are very small and volatilities are quite big, however, after the crisis arrived, the volatility of AEEs decreased considerably. One potential explanation for this is that actuaries became more conservative and careful in their assumptions after the arrival of the 2008 global financial crisis.

Continuing with Table 3 the distribution of Big Actuarial Firm has remained almost the same before and after the crisis (63% VS 65%), indicating that plan sponsors that chose to trust their plan to big actuarial firms in the pre-crisis years continued to do so in the crisis years as well. There is an increase in the mean (median) value of FEE, defined as ratio of professional fees an actuary receives from a plan sponsor divided by the sum of all fees the actuary earns in a year, from 0.239 (0) to 0.5928 (0.7), meaning that actuaries, after year 2008, received a much bigger proportion of their yearly revenue from a single plan sponsor. This suggests that the economic bonding between actuaries and plan sponsors strengthened after 2008.

A drop is observed in the mean (median) percentage of Funding % Liabilities from 0.8612 (0.8) to 0.7463 (0.7) meaning that the average funding level of pension plans dropped considerably when the crisis arrived. As expected, the average number of Green (Safe) plans decreased, from 57% to 32.5%, in the crisis years whereas the mean number of Orange (Endangered) and Red (Critical) plans moved upwards, from 28.2% to 40.7% and from 15% to 27% respectively. To sum this up, the mean value of the Transitions variable, i.e. the proportion of plans that fall to lower category of funding level within a year, increased from 14.55% to 27.2% in the crisis years. This essentially means that the average number of plans of which the funding level dropped to a lower category within one year period went up significantly after 2008. There is an increase in the mean (median) percentage of frozen plans from 0.0644 (0) in the pre-crisis years to 0.2332 (0) in the crisis years when at the same time there is a drop in the mean (median) value of Active % Employees from 0.51 (0.5) to 0.42 (0.4) which suggests that many of the active workers in the pre-crisis years either lost their jobs or retired during the crisis years. ROA Plan mean value, estimating the yearly return of pension assets, dropped from 6.58% in the pre-crisis years to 3.47% in the crisis years suggesting that pension asset investments became far less profitable after 2008. Big 4 Auditor mean (median) value dropped from 0.626 (1) in the pre-crisis years to 0.393 (0) in the crisis years indicating that plan sponsors shifted to smaller auditors in the crisis, perhaps to save themselves some of the professional fees. The remaining independent variables' distributions do not vary significantly between the pre-crisis and the crisis years.

6.1.3. Pre-PPA (2000-2005) VS Post-PPA Sample (2006-2011)

In this section I present descriptive statistics contained in Table 4. The difference from the previous section (§6.1.2) is that, instead of splitting the sample at the 2008 landmark, I split the sample at the 2006 landmark with the reason being that in August 2006, Pension Protection Act (PPA), the first major reform of ERISA since 1974, was voted into law. The new rules that have been set into place have the potential to affect actuarial decision taking, mainly due to the introduction of the traffic light system that defines the health status of DB pension plans. In this section, only the distribution of key variables will be analyzed.

Starting with the dependent variable, Actuarial Estimation Error, its distribution in Panel A (Pre-PPA years), has a mean (median) value of -0.00104% (0%) and a standard deviation of 3.22%. In Panel B (Post-PPA years) the mean (median) value of AEE drops to -0.00131% (-0.001%) and the standard deviation to 1.38%. In both cases AEE cannot be differentiated from zero as mean values are small and volatilities large. There is however a noticeable decrease in the volatility of AEE in the post-PPA period.

Moving on to FEE, defined as the ratio of professional fees an actuary receives from a plan sponsor divided by the sum of all fees the actuary earns in a year, its mean (median) value changes from 0.2312 (0) to 0.4233 (0.2), meaning that actuaries, after year 2006, received a significantly bigger proportion of their revenue for the whole year from a single plan sponsor.

This means that the economic bonding of actuaries and plan sponsors was increased after year 2006.

A decrease in the mean (median) value of Funding % Liabilities from 0.8559 (0.8) in the pre-PPA years to 0.7948 (0.8) in the post-PPA years suggests the average funding level of DB pension plans dropped slightly after 2006. This is also seen, by the percentage of Green (Safe) plans that decreased, from 53.4% in the pre-PPA years, to 45.5% in the post-PPA years and the percentage of Orange (Endangered) and Red (Critical) plans that moved upwards, from 29.6% to 34.5% and from 17% to 20% respectively. A substantial increase is observed in the percentage of frozen plans from 3.88% in the pre-PPA years to 20.16% in the post-PPA years. This could be explained by the deteriorating financial strength level of DB pension plans in the recent years, as freezing a plan prevents further participants to join and stop the accumulation of benefits from current beneficiaries, however, this seems as a topic that could benefit from further investigation.

The mean (median) value of ROA Plan, estimating the yearly return of pension assets, dropped from 6.87% in the pre-PPA years to 4.47% in the post-PPA years arising concern as it implies that DB plan sponsors had to increase contributions after 2006 towards their plans to have adequate funds for the benefits that had to be paid out to participants. This could as well be the reason that so many plans froze after year 2006.

LowZscore, an indicator variable taking the value 1 if a sponsor’s Z-score is smaller than 1.81, which is an indication of a firm being close to bankruptcy, drops from 0.216 in the pre-PPA years to 0.159 in the post-PPA years and last, Big 4 Auditor mean (median) value drops from 0.686 (1) in the pre-PPA years to 0.406 (0) in the post-PPA years indicating that plan sponsors shifted to smaller auditors in the more recent years, perhaps to cut expenses.

6.2. Empirical Results: Do transitions of DB pension plans among different financial strength levels affect AEE?

In this section I investigate if, and to what extent, the transitions of DB pension plans to lower categories of financial strength level affect Actuarial Estimation Errors of the next year. In order to provide an answer to this empirical question, I present results from panel, OLS and diff-in-diff regressions.

6.2.1. Panel and OLS Regression Results

The OLS and panel regression models, given by Equation 4, Section §5.1, yield the results in Tables 5, 6 & 7. Table 5 corresponds to regression results with fewer control variables, but bigger sample size, while in Tables 6 & 7 I progressively add LowZscore, which controls for the sponsor's credit risk, and FEE, that controls for the economic bonding of actuaries and plan sponsors. The results in Tables 6 & 7 essentially test the validity of the results in Table 5. The first three columns of Tables 5, 6 & 7 contain results from panel regressions with fixed effects taken at the firm, actuarial firm and actuarial office levels while the last column contains results from a pooled OLS regression.

Starting with Table 5, the coefficient of variable Transitions is positive and statistically significant at 1% level in all four cases. This result suggests that when DB pension plans fall to a lower funding category, for example from Green/Safe at time *t-1* to Red/Critical at time *t*, then AEEs of the following period (time *t+1*) are bigger. This is an indication that actuaries adjust their estimates of pension assets return upwards the following year transitions occur. There are two scenarios that can potentially explain this result: The first is that plan sponsors invest more aggressively in risky assets after transitions to lower funding levels occur and this drives expected returns of pension assets upwards the following year. The second is that actuaries adjust the expected return of pension assets for the following year upwards to reduce the amount of contributions sponsors need to make to their plan. PPA stipulates that when DB pension plans take the endangered (ORANGE) or Critical (RED) status, sponsors need to put their plans in a rehabilitation program to improve their financial position within a time horizon of 10 years. This implies, among others, increased contributions from sponsors towards their plans[24]. Besides that, additional contributions are needed to cover the annual pension expense, which is the additional funds that firms need to set aside in pension assets to cover any additional benefits accrued by beneficiaries during the year. In order to reduce the annual pension expense, and hence the amount of fund contributions towards their DB pension plans, firms signal their plan's actuary to assume higher expected return on pension assets. Now since the pension asset allocations and returns is controlled for in the regression models, the second scenario is the most likely one in this case.

Other variables that consistently come up as statistically significant is the AEE of time *t* with a negative coefficient suggesting that, all other being equal, actuaries take corrective actions when giving estimates of the pension asset returns of the next period to make up for the error of the previous period. Funding % Liabilities is also consistently statistically significant with a negative coefficient which means that, all else being equal, actuaries adjust their estimates for pension assets upwards when the funding level of pension plans is lower, an obligation reducing assumption. My view for this result is the same as in the case of transitions: actuaries adjust their expectations for pension asset returns upwards when the funding level of pension plans is lower, same result when transitions occur, to mitigate the need of sponsors having to make increased fund contributions to improve the financial strength of their plan.

[24] For more info on DB pension plan rehabilitation refer to Purcell (2006) and Topoleski (2014).

6.2.2. Difference-in-Differences First Model Regression Results

In the previous section (§6.2.1), I analyzed the results of Panel and OLS regressions and found that pension plans that drop to lower categories of financial strength are the cause of bigger actuarial estimation errors in the following year, an obligation reducing assumption. In this section I take the analysis to the next level by employing a diff-in-diff approach[25] to investigate if the increased number of plans falling to lower categories of financial strength (transitions) also strengthen the results (i.e. make AEE bigger). In the recent crisis years the average funding level of pension plans fell significantly and moreover the number of plans falling to lower funding categories (transitions) almost doubled[26]. Hence I test whether the results of the previous section (§6.2.1) are stronger after the 2008 landmark.

To use diff-in-diff, I separate the sample to sponsors of which the plan fell to lower funding categories (the treatment sample: *Transitions = 1*) and sponsors of which the plan did not fall to lower funding categories (the control sample: *Transitions = 0*). In this manner I am able to estimate the additional effect that the bigger number of transitions have had on AEE after the crisis, if any, and whether this additional effect is statistically significant.

The difference-in-differences regression model is given by Equation 5 in Section §5.2 and yields the results in Table 8. Table 8 consists of results from three regression runs. The difference between the three regression runs is the number of control variables included in each model which increases as we move to the right. The results from the diff-in-diff model are very interesting. The coefficient of the interaction variable (Transitions * Crisis) is positive and statistically significant at 1% level in all cases. This suggests that the additional number of plans falling to lower categories of funding level after the crisis affect AEE of the next year.

[25] For details about this identification method refer to Section §4.2 or see Angrist & Pischke (2009).
[26] Compared to the pre-crisis years. For more info refer to Table 3 in the Appendix.

However the coefficient of Transitions alone, even though positive, is not statistically significant meaning that before the Crisis when plans fell to lower categories of financial strength, AEE of the next year was not significantly affected. Put differently the results discussed in this section suggest that actuaries started adjusting the assumptions for the expected pension asset returns upwards, after the 2008 landmark. Other variables that consistently come up as statistically significant are the AEE of time *t* and the overall funding level of pension plans (Funding % Liabilities) both with negative coefficients. Discussion for these is provided in the previous section (§6.2.1).

6.2.3. Difference-in-Differences Second Model Regression Results

In the previous two sections (§6.2.1 & §6.2.2), I analyzed the results of panel, OLS and diff-in-diff regressions and found that pension plans dropping to weaker categories of funding level are associated with bigger actuarial estimation errors in the following year. This finding though was only found to be statistically significant after the 2008 landmark, when the crisis arrived. In this section I employ a different diff-in-diff model to test whether it is after 2006, when Pension Protection Act (PPA) law was introduced, that transitions to lower categories of financial strength affect AEE of the next year. This is done as after year 2006, when PPA was voted into law, plan sponsors are obliged to place their plans to a rehabilitation program, to improve their funding level, once they (the plans) drop to a lower category of financial strength. When such situations occur, plan sponsors have bigger motive to overstate the expectations of pension asset returns for the next year as this would imply that lower contributions towards their plans would need to be made. This would also drive AEE of the following year upwards.[27] Hence in this section, I test whether the findings of the previous two sections (§6.2.1 & §6.2.2) are stronger after the 2006 landmark. It should be noted that

[27] Explanation is provided in Section §6.2.1.

even though PPA was voted into law in August 2006, not all provisions in the Act were enforced the very same day, with some taking years to be enforced. However, as all provisions became known by the 17th of August 2006, when the Act became a law, interested parties including corporate DB plan sponsors, had time to adapt to all the provisions, even those enforced at later dates.

As in the first diff-in-diff model I separate the sample to sponsors of which the plan fell to lower funding categories (the treatment sample: *Transitions = 1*) and sponsors of which the plan did not fall to lower funding categories (the control sample: *Transitions = 0*). The time indicator (*PPA*) is though different this time, being equal to 1 when the year is 2006 or later and zero otherwise.

The second difference-in-differences regression model is given by Equation 6 of Section §5.3 and yields the results in Table 9. Table 9 contains results from three regression runs. The difference between the three regression runs is the number of control variables included in each model which increases as we move to the right. The first column contains results from the base model, in the second column I additionally control for the sponsors credit risk (LowZscore) and in the third column also control for the economic bonding of actuaries and plan sponsors (FEE).

The results follow the same pattern as in the first diff-in-diff model in the sense that the coefficient of the interaction variable (Transitions * PPA) is positive and statistically significant at 1% level in all three cases. This suggests that the additional effect of Transitions on the AEE of the next year is important only after 2006, when PPA was voted into law. However the coefficient of Transitions alone, even though positive, is not statistically significant meaning that before PPA when plans fell to lower categories of financial strength, AEE of the next year was not significantly affected. Other variables that consistently come up as statistically significant are the AEE of time *t* and the overall funding level of pension plans (Funding % Liabilities) both with negative coefficients. Discussion for these results is provided in Section §6.2.1.

7. Conclusions

In this paper I use a new measure for actuarial estimation errors in pension funding assumptions, the Actuarial Estimation Error. The Actuarial Estimation Error (AEE), developed by Papakyriakou (2016), is defined as the difference between the Expected Return (ER) of pension plan assets for two consecutive years (for example $AEE_t = ER_t - ER_{t-1}$). Using data spanning 2000 - 2011 from Defined Benefit (DB) pension plans of publicly traded firms in the US, I employ a difference-in-differences research design as my main identification method and find that when the funding level of DB pension plans falls significantly, enough for the plan to drop to a lower funding category, then Actuarial Estimation Errors of the following year become significantly bigger, an obligation reducing assumption. Put differently when DB pension plans funding level drops to a lower category, meaning that the plan takes the endangered or critical status, sponsors are obliged, among other things, to increase pension contributions in an attempt to improve the financial condition of their plan. The amount of contributions further increases as firms need to also set some funds aside to cover the additional benefits that plan participants accumulate during the year, namely the pension expense or cost. When actuaries assume bigger expected returns for pension assets, pension expense decreases. It is my view that actuaries adjust their expectations for pension asset returns upwards, this is what bigger Actuarial Estimation Error implies, to decrease the need for bigger contributions. It should be noted the findings of this study only hold for the later years of the sample, i.e. after 2006 when Pension Protection Act was voted into law or after 2008 when the global financial crisis arrived. Which of the two landmarks is the correct one, however, is an interesting topic for further research.

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Appendix

Table 1: Variable Definitions

Variable	Definition & Source
Actuary	
Actuarial Estimation Error	The difference between the expected return (ER) of DB pension plan assets for two consecutive years (for example $AEE_t = ER_t – ER_{t-1}$ or $AEE_{t+1} = ER_{t+1} – ER_t$).
Expected Return of Pension Assets	The Expected Return of Pension Assets return is estimated by dividing the Expected Change in Pension Assets Value (Compustat item -1*PPRPA) by the Total Pension Assets at the end of the previous period (Compustat Item PPLAO) and then multiplying the result with 100.
Big Actuarial Firm	Indicator variable set to 1 if, in a specific year, the actuarial firm belongs to the top 5% actuarial firms with respect to the number of clients, set to 0 otherwise. Number of clients is found from the number of entries corresponding to the same Actuarial Firm in Form 5500, Schedule B.
FEE	Professional fees received by actuary from each plan sponsor client in a particular year / Sum of all fees received by that actuary from all plan sponsor clients in that year. Professional fees is given by Form 5500, Schedule H, Part II, Item 2i (1).
Plan	
Funding % Liabilities	Measures the funding level of DB pension plans. Estimated from the ratio of pension plan assets (Compustat item PPLAO) divided by the projected benefit obligations of the same plan (Compustat item PBPRO).
Green	Indicator variable set to 1 if Funding % Liabilities is above 0.8; set to 0 otherwise.
Orange	Indicator Variable set to 1 if Funding % Liabilities is below 0.8 but above 0.65; set to 0 otherwise.
Red	Indicator variable set to 1 if Funding % Liabilities is below 0.65; set to 0 otherwise.
Green2Red	Indicator variable set to 1 at time t, if at time t-1 a plan had the GREEN (SAFE) status but at time t it fell to the RED (CRITICAL) status.
Green2Orange	Indicator variable set to 1 at time t, if at time t-1 a plan had the GREEN (SAFE) status but at time t it fell to the ORANGE (ENDANGERED) status.
Orange2Red	Indicator variable set to 1 at time t, if at time t-1 a plan had the ORANGE (ENDANGERED) status but at time t it fell to the RED (CRITICAL) status.
Transitions	Defined as the sum of Green2Red, Green2Orange & Orange2Red.
FROZEN	Indicator variable set to 1 if for a specific year a plan is frozen. Given by Form 5500 Part II, Item 8a.

Active % Employees	The proportion of active employees (Form 5500, Part II, Item 7a) amongst all plan beneficiaries (Form 5500, Part II, Item 7f).
Sole Plan	Indicator variable set to 1 if the plan is the only plan of a sponsor. Given by Form 5500 Part I, Item A (2).
Plan Size	Natural logarithm of [1+total plan assets (Compustat item PPRPA)].
ROA Plan	Approximates the Real Return of DB Pension Plan Assets. Weighted average return estimated by multiplying annual returns for the S&P 500 (DataStream item S&PCOMP), Barclays Capital Aggregate Bond (DataStream item LGAGGBD), MSCI Real Estate (DataStream item M2USR2$) and S&P Commodities (DataStream item GSCITOT) to the proportion of DB plan assets in invested in Equity (Compustat item PNATE), Debt (Compustat item PNATD), Real Estate (Compustat item PNATR) and Other Investments (Compustat item PNATO) respectively and then adding the results together.
Firm	
Firm Size	Natural logarithm of [1+Total Firm Assets (Compustat item AT)].
Leverage	Long-term debt (Compustat item DLTT) + Debt in current liabilities (Compustat item DLC) / Total Firm Assets (Compustat item AT).
ROA Firm	Income before extraordinary items (Compustat item IB) + Periodic Pension Cost (PPC) / Total Firm Assets (Compustat item AT).
LowZscore	Indicator variable set to 1 if the Altman Z Score for the particular plan sponsor (firm) is below the 1.81 threshold; set to 0 otherwise. Altman Z Score is estimated by 1.2 * [Current Firm Assets (Compustat item ACT) – Current Firm Liabilities (Compustat item LCT)] / Total Firms Assets (Compustat item AT) + 1.4 * Retained Earnings (Compustat item RE) / Total Firm Assets (Compustat item AT) + 3.3 * Operating Income After Depreciation (Compustat item OIADP) / Total Firm Assets (Compustat item AT) + 0.6 * [Firm Stock Price (Compustat item PRCC_F) * Number of Shares Outstanding (Compustat item CSHO)] / [Debt in Current Liabilities (Compustat item DLC) + Long Term Debt (Compustat item DLTT)] + 0.99 * Total Sales (Compustat item SALE) / Total Firm Assets (Compustat item AT).
Auditor	
Big 4 Auditor	Indicator variable set to 1 if the benefit plan is audited by one of the big 4 audit firms. Audit firm is Form 5500, Schedule H, Item 3c.

Table 2: Descriptive Statistics (2000-2011)

This table presents the descriptive statistics of all the variables (dependent and independent) used in every model of this paper. Each variable falls under one of the four categories based on Actuary, Plan, Firm, and Audit characteristics. The Actuarial Estimation Error (AEE) is defined as the difference between the expected return (ER) of DB pension plan assets for two years in a row (for example $AEE_t = ER_t – ER_{t-1}$). Big Actuarial Firm is an indicator variable set to 1 if, for a specific year, the actuarial firm belongs to the top 5% actuarial firms with respect to the number of clients, set to 0 otherwise. FEE is the ratio of professional fees that an actuary receives from a plan sponsor divided by the sum of all the fees the actuary receives in that year. Green, Orange & Red are indicator variables set to 1 if the funding level of a pension plan is above 80%, between 65% and 80% & below 65% respectively; set to 0 otherwise. Green2Red, Orange2Red & Green2Orange are transition variables set to 1 if in the previous period the funding category of the corresponding pension plan was specified by the left part of the transition variable and in the current period it fell in the funding category specified by the right part of it. Funding % Liabilities is the percentage of pension liabilities funded by the pension assets. Frozen is an indicator variable set to 1 if for a specific year a plan is frozen, set to 0 otherwise. Active % Employees is the proportion of active employees amongst all plan beneficiaries. Plan Size and Firm Size are computed by the natural logarithm of unity plus the worth, in millions, of plan and firm assets respectively. Sole Plan is an indicator variable set to 1 if a plan is the only plan of a sponsor, set to 0 otherwise. ROA Plan is an estimate of pension assets actual return. Leverage is the ratio of long and short-term firm debt divided by the worth of firm assets in millions. ROA Firm is given by the ratio of the firm income before extraordinary items and pension expense divided by the worth of firm assets in millions. LowZscore is an indicator variable set to 1 if the Z score of the firm (plan sponsor) is below the 1.81 threshold, set to 0 otherwise. Big 4 Auditor is an indicator variable set to 1 if the benefit plan is audited by one of the big 4 audit firms, set to 0 otherwise. All variables are winsorized at 1% & 99% levels.

Variable	Obs.	Mean	Std Dev.	p25	p50	p75
Actuary						
Actuarial Estimation Error	4018	-0.1179	2.468284	-0.6	-0.1	0.31
Big Actuarial Firm	4369	0.64	0.48	0	1	1
FEE	3065	0.30	0.40	0	0.02	0.66
Plan						
Funding % Liabilities	4446	0.83	0.23	0.68	0.80	0.93
Green	4446	0.50	0.50	0	0	1
Orange	4446	0.32	0.47	0	0	1
Red	4446	0.18	0.39	0	0	0
Transitions	4446	0.18	0.39	0	0	0
Frozen	4459	0.11	0.32	0	0	0
Active % Employees	4354	0.49	0.23	0.33	0.50	0.66
Plan Size	4457	5.01	2.00	3.53	4.92	6.45
ROA Plan	2839	0.0529	0.126636	0.03	0.08	0.12
Sole Plan	4459	0.04	0.20	0	0	0
Firm						
Firm Size	4444	7.72	1.95	6.41	7.73	8.98
Leverage	4436	0.2661	0.205575	0.12	0.23	0.36
ROA Firm	4443	0.0324	0.086399	0.01	0.03	0.07
LowZscore	3158	0.19	0.39	0	0	0
Auditor						
Big 4 Auditor	4430	0.56	0.50	0	1	1

Table 3: Descriptive Statistics [Pre-Crisis (2000-2007) VS Post-Crisis (2008-2011)]

This table compares the descriptive statistics (Pre-Crisis Years VS Crisis Years) across all the variables (dependent and independent) used in every model of this paper. Each variable falls under one of the four categories based on Actuary, Plan, Firm, and Audit characteristics. The Actuarial Estimation Error (AEE) is defined as the difference between the expected return (ER) of DB pension plan assets for two years in a row (for example $AEE_t = ER_t – ER_{t-1}$). Big Actuarial Firm is an indicator variable set to 1 if, for a specific year, the actuarial firm belongs to the top 5% actuarial firms with respect to the number of clients, set to 0 otherwise. FEE is the ratio of professional fees that an actuary receives from a plan sponsor divided by the sum of all the fees the actuary receives in that year. Green, Orange & Red are indicator variables set to 1 if the funding level of a pension plan is above 80%, between 65% and 80% & below 65% respectively; set to 0 otherwise. Green2Red, Orange2Red & Green2Orange are transition variables set to 1 if in the previous period the funding category of the corresponding pension plan was specified by the left part of the transition variable and in the current period it fell in the funding category specified by the right part of it. Funding % Liabilities is the percentage of pension liabilities funded by the pension assets. Frozen is an indicator variable set to 1 if for a specific year a plan is frozen, set to 0 otherwise. Active % Employees is the proportion of active employees amongst all plan beneficiaries. Plan Size and Firm Size are computed by the natural logarithm of unity plus the worth, in millions, of plan and firm assets respectively. Sole Plan is an indicator variable set to 1 if a plan is the only plan of a sponsor, set to 0 otherwise. ROA Plan is an estimate of pension assets actual return. Leverage is the ratio of long and short-term firm debt divided by the worth of firm assets in millions. ROA Firm is given by the ratio of the firm income before extraordinary items and pension expense divided by the worth of firm assets in millions. LowZscore is an indicator variable set to 1 if the Z score of the firm (plan sponsor) is below the 1.81 threshold, set to 0 otherwise. Big 4 Auditor is an indicator variable set to 1 if the benefit plan is audited by one of the big 4 audit firms, set to 0 otherwise. All variables are winsorized at 1% & 99% levels.

	Pre-Crisis Period						Post-Crisis Period					
Variable	**Obs.**	**Mean**	**Std Dev.**	**p25**	**p50**	**p75**	**Obs.**	**Mean**	**Std Dev.**	**p25**	**p50**	**p75**
Actuary												
Actuarial Estimation Error	2735	-0.131	2.823712	-0.6	-0.1	0.4	1283	-0.091	1.44389	-0.6	-0.1	0.23
Big Actuarial Firm	3111	0.6316	0.48244	0	1	1	1258	0.651	0.476833	0	1	1
FEE	2508	0.239	0.371104	0	0	0.4	557	0.5928	0.416633	0.14	0.7	1
Plan												
Funding % Liabilities	3161	0.8612	0.23786	0.71	0.8	1	1285	0.7463	0.170476	0.64	0.7	0.83
Green	3161	0.57	0.50	0	1	1	1285	0.3253	0.468666	0	0	1
Orange	3161	0.2822	0.450136	0	0	1	1285	0.407	0.491467	0	0	1
Red	3161	0.15	0.36	0	0	0	1285	0.27	0.44	0	0	1
Transitions	3161	0.1455	0.352684	0	0	0	1285	0.2724	0.445354	0	0	1
Frozen	3168	0.0644	0.245492	0	0	0	1291	0.2332	0.423002	0	0	0

Active % Employees	3115	0.5137	0.226659	0.37	0.5	0.7	1239	0.4254	0.227229	0.26	0.4	0.6
Plan Size	3167	4.914	2.004599	3.41	4.8	6.4	1290	5.2526	1.985032	3.94	5.2	6.71
ROA Plan	1662	0.0658	0.101456	0.03	0.1	0.1	1177	0.0347	0.153616	0.03	0.1	0.14
Sole Plan	3168	0.0458	0.209019	0	0	0	1291	0.0387	0.193025	0	0	0
Firm												
Firm Size	3156	7.5822	1.959647	6.26	7.6	8.9	1288	8.0579	1.870204	6.82	8	9.16
Leverage	3152	0.2782	0.215258	0.13	0.2	0.4	1284	0.2363	0.176166	0.11	0.2	0.33
ROA Firm	3156	0.0337	0.086322	0.01	0	0.1	1287	0.0294	0.086547	0.01	0	0.07
LowZscore	2242	0.1989	0.399284	0	0	0	916	0.1703	0.376106	0	0	0
Auditor												
Big 4 Auditor	3152	0.626	0.483953	0	1	1	1278	0.3928	0.488564	0	0	1

Table 4: Descriptive Statistics [Pre-PPA (2000-2005) VS Post-PPA (2006-2011)]

This table compares the descriptive statistics (Pre-Crisis Years VS Crisis Years) across all the variables (dependent and independent) used in every model of this paper. Each variable falls under one of the four categories based on Actuary, Plan, Firm, and Audit characteristics. The Actuarial Estimation Error (AEE) is defined as the difference between the expected return (ER) of DB pension plan assets for two years in a row (for example $AEE_t = ER_t - ER_{t-1}$). Big Actuarial Firm is an indicator variable set to 1 if, for a specific year, the actuarial firm belongs to the top 5% actuarial firms with respect to the number of clients, set to 0 otherwise. FEE is the ratio of professional fees that an actuary receives from a plan sponsor divided by the sum of all the fees the actuary receives in that year. Green, Orange & Red are indicator variables set to 1 if the funding level of a pension plan is above 80%, between 65% and 80% & below 65% respectively; set to 0 otherwise. Green2Red, Orange2Red & Green2Orange are transition variables set to 1 if in the previous period the funding category of the corresponding pension plan was specified by the left part of the transition variable and in the current period it fell in the funding category specified by the right part of it. Funding % Liabilities is the percentage of pension liabilities funded by the pension assets. Frozen is an indicator variable set to 1 if for a specific year a plan is frozen, set to 0 otherwise. Active % Employees is the proportion of active employees amongst all plan beneficiaries. Plan Size and Firm Size are computed by the natural logarithm of unity plus the worth, in millions, of plan and firm assets respectively. Sole Plan is an indicator variable set to 1 if a plan is the only plan of a sponsor, set to 0 otherwise. ROA Plan is an estimate of pension assets actual return. Leverage is the ratio of long and short-term firm debt divided by the worth of firm assets in millions. ROA Firm is given by the ratio of the firm income before extraordinary items and pension expense divided by the worth of firm assets in millions. LowZscore is an indicator variable set to 1 if the Z score of the firm (plan sponsor) is below the 1.81 threshold, set to 0 otherwise. Big 4 Auditor is an indicator variable set to 1 if the benefit plan is audited by one of the big 4 audit firms, set to 0 otherwise. All variables are winsorized at 1% & 99% levels.

	Pre-PPA Period						**Post-PPA Period**					
Variable	**Obs.**	**Mean**	**Std Dev.**	**p25**	**p50**	**p75**	**Obs.**	**Mean**	**Std Dev.**	**p25**	**p50**	**p75**
Actuary												
Actuarial Estimation Error	1994	-0.104	3.216211	-0.7	-0	0.5	2024	-0.131	1.380777	-0.6	-0.1	0.2
Big Actuarial Firm	2376	0.6486	0.477518	0	1	1	1993	0.6237	0.484583	0	1	1
FEE	1914	0.2312	0.366021	0	0	0.4	1151	0.4233	0.433415	0	0.2	1
Plan												
Funding % Liabilities	2416	0.8559	0.251909	0.69	0.8	1	2030	0.7948	0.186761	0.67	0.8	0.9
Green	2416	0.5335	0.498978	0	1	1	2030	0.4557	0.498153	0	0	1
Orange	2416	0.2959	0.45656	0	0	1	2030	0.3448	0.475429	0	0	1
Red	2416	0.1705	0.376175	0	0	0	2030	0.1995	0.399729	0	0	0
Transitions	2416	0.185	0.388391	0	0	0	2030	0.1788	0.383294	0	0	0

Frozen	2420	0.0388	0.193261	0	0	0	2039	0.2016	0.401271	0	0	0
Active % Employees	2374	0.5269	0.22339	0.39	0.5	0.7	1980	0.4426	0.230047	0.28	0.4	0.61
Plan Size	2419	4.819	1.997445	3.29	4.7	6.3	2038	5.241	1.989452	3.9	5.2	6.71
ROA Plan	971	0.0687	0.128686	-0	0.1	0.2	1868	0.0447	0.124808	0.03	0.1	0.11
Sole Plan	2420	0.0463	0.210136	0	0	0	2039	0.0407	0.197657	0	0	0
Firm												
Firm Size	2413	7.4835	1.961704	6.15	7.5	8.8	2031	8.0011	1.889413	6.74	8	9.15
Leverage	2411	0.2851	0.214777	0.14	0.3	0.4	2025	0.2435	0.191668	0.11	0.2	0.33
ROA Firm	2413	0.0281	0.086849	0.01	0	0.1	2030	0.0375	0.085603	0.01	0	0.07
LowZscore	1720	0.2169	0.412227	0	0	0	1438	0.1592	0.366035	0	0	0
Auditor												
Big 4 Auditor	2408	0.6865	0.464027	0	1	1	2022	0.4065	0.491307	0	0	1

Table 5: Panel and OLS regressions (No LowZscore, No FEE, Years 2000-2011)

In this table I present the results of the panel and OLS regression models, controlling for firm, plan, audit and actuary characteristics. The Actuarial Estimation Error (t+1) is defined as the expected return of pension assets for the following year (time *t+1*) minus the expected return of pension assets for the current year (time *t*). The remaining variables are described in Table 1. Fixed-effects, year indicators and robust clustered standard errors are used. For brevity considerations the coefficients of year indicators are not shown. All variables are winsorized at 1% & 99% levels. I denote statistical significance at the 1% (***), 5% (**) level and 10% (*) level.

	(1) Actuarial Estimation Error (t+1)	(2) Actuarial Estimation Error (t+1)	(3) Actuarial Estimation Error (t+1)	(4) Actuarial Estimation Error (t+1)
Actuarial Estimation Error (t)	-0.323***	-0.304***	-0.311***	-0.299***
	(0.0267)	(0.0257)	(0.0309)	(0.0276)
Funding % Liabilities (t)	-0.618	-0.804***	-1.024***	-0.686***
	(0.428)	(0.206)	(0.227)	(0.187)
Transitions (t)	0.317***	0.405***	0.378***	0.412***
	(0.0939)	(0.0786)	(0.0969)	(0.0811)
Frozen (t)	-0.433**	-0.0632	-0.0697	-0.103
	(0.175)	(0.0843)	(0.117)	(0.0846)
Active % Employees (t)	0.275	-0.0738	-0.0299	-0.0473
	(0.415)	(0.125)	(0.180)	(0.163)
Sole Plan (t)	-0.684**	-0.0581	0.0690	-0.0566
	(0.331)	(0.134)	(0.236)	(0.156)
Plan Size (t)	-1.452***	-0.00547	-0.00178	0.000235
	(0.291)	(0.0342)	(0.0390)	(0.0297)
ROA Plan (t)	-0.690	-0.928	-0.727	-0.680
	(0.749)	(0.771)	(0.766)	(0.802)
Firm Size (t)	0.0802	-0.00291	-0.00679	-0.0162
	(0.152)	(0.0240)	(0.0307)	(0.0260)
Leverage (t)	-0.108	-0.166	-0.112	-0.146
	(0.586)	(0.151)	(0.183)	(0.147)
ROA Firm (t)	-0.425	-0.459	-0.522	-0.537
	(0.630)	(0.585)	(0.547)	(0.444)
Big Actuarial Firm (t)	0.109	0.376***	0.362***	0.0320
	(0.150)	(0.0968)	(0.137)	(0.0586)
Big 4 Auditor (t)	0.0503	0.0157	0.0799	0.0128
	(0.108)	(0.0603)	(0.0682)	(0.0571)
Constant	7.425***	0.585*	1.166***	0.851**
	(1.241)	(0.307)	(0.350)	(0.376)
N	2585	2585	2585	2585
R^2	0.338	0.263	0.264	0.262
Year Indicators	Yes	Yes	Yes	Yes
Fixed Effects	Firm Level	Actuary-Firm Level	Office Level	No

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Panel and OLS regressions (No FEE, Years 2000-2011)

In this table I present the results of the panel and OLS regression models, controlling for firm, plan, audit and actuary characteristics. The Actuarial Estimation Error (t+1) is defined as the expected return of pension assets for the following year (time *t+1*) minus the expected return of pension assets for the current year (time *t*). The remaining variables are described in Table 1. Fixed-effects, year indicators and robust clustered standard errors are used. For brevity considerations the coefficients of year indicators are not shown. All variables are winsorized at 1% & 99% levels. I denote statistical significance at the 1% (***), 5% (**) level and 10% (*) level.

	(1) Actuarial Estimation Error (t+1)	(2) Actuarial Estimation Error (t+1)	(3) Actuarial Estimation Error (t+1)	(4) Actuarial Estimation Error (t+1)
Actuarial Estimation Error (t)	-0.331***	-0.323***	-0.331***	-0.307***
	(0.0350)	(0.0374)	(0.0457)	(0.0348)
Funding % Liabilities (t)	-0.222	-0.816***	-0.984***	-0.869***
	(0.568)	(0.251)	(0.291)	(0.221)
Transitions (t)	0.387***	0.486***	0.465***	0.465***
	(0.112)	(0.119)	(0.114)	(0.0953)
Frozen (t)	-0.241	-0.00503	-0.0497	0.0131
	(0.188)	(0.0938)	(0.131)	(0.0979)
Active % Employees (t)	-0.151	-0.0937	-0.110	-0.0337
	(0.402)	(0.146)	(0.201)	(0.193)
Sole Plan (t)	-0.917*	-0.228	-0.467	-0.170
	(0.505)	(0.255)	(0.312)	(0.268)
Plan Size (t)	-1.953***	-0.0185	-0.0545	-0.00119
	(0.369)	(0.0471)	(0.0580)	(0.0475)
ROA Plan (t)	-0.330	-0.902	-0.604	-0.546
	(1.122)	(1.093)	(1.240)	(1.110)
Firm Size (t)	0.300*	0.00865	0.0387	-0.0175
	(0.167)	(0.0370)	(0.0487)	(0.0471)
Leverage (t)	0.333	-0.238	-0.192	-0.214
	(0.679)	(0.224)	(0.300)	(0.235)
ROA Firm (t)	-0.168	-0.174	-0.254	-0.253
	(0.647)	(0.605)	(0.579)	(0.506)
Big Actuarial Firm (t)	0.220	0.364***	0.363**	0.0474
	(0.176)	(0.126)	(0.151)	(0.0732)
Big 4 Auditor (t)	0.0451	0.0200	0.0294	0.00189
	(0.139)	(0.0779)	(0.0869)	(0.0688)
LowZscore (t)	-0.0348	0.0588	-0.0245	0.0985
	(0.182)	(0.0786)	(0.118)	(0.117)
Constant	8.350***	0.484	1.026**	1.018***
	(1.473)	(0.337)	(0.454)	(0.328)
N	1828	1828	1828	1828
R^2	0.348	0.263	0.270	0.259
Year Indicators	Yes	Yes	Yes	Yes
Fixed Effects	Firm Level	Actuary-Firm Level	Office Level	No

Standard errors in parentheses

* p < 0.1, ** p < 0.05, *** p < 0.01

Table 7: Panel and OLS regressions (Full Model, Years 2000-2011)

In this table I present the results of the panel and OLS regression models, controlling for firm, plan, audit and actuary characteristics. The Actuarial Estimation Error (t+1) is defined as the expected return of pension assets for the following year (time *t+1*) minus the expected return of pension assets for the current year (time *t*). The remaining variables are described in Table 1. Fixed-effects, year indicators and robust clustered standard errors are used. For brevity considerations the coefficients of year indicators are not shown. All variables are winsorized at 1% & 99% levels. I denote statistical significance at the 1% (***), 5% (**) level and 10% (*) level.

	(1) Actuarial Estimation Error (t+1)	(2) Actuarial Estimation Error (t+1)	(3) Actuarial Estimation Error (t+1)	(4) Actuarial Estimation Error (t+1)
Actuarial Estimation Error (t)	-0.318***	-0.317***	-0.317***	-0.297***
	(0.0497)	(0.0511)	(0.0631)	(0.0435)
Funding % Liabilities (t)	-0.172	-0.589***	-0.686*	-0.717***
	(0.674)	(0.220)	(0.390)	(0.257)
Transitions (t)	0.262*	0.319**	0.306**	0.368***
	(0.151)	(0.130)	(0.127)	(0.135)
FEE (t)	-0.140	-0.0272	-0.0558	0.0671
	(0.118)	(0.0684)	(0.0938)	(0.0961)
Frozen (t)	-0.139	0.0552	0.0596	0.0564
	(0.258)	(0.141)	(0.191)	(0.126)
Active % Employees (t)	-0.849*	-0.113	-0.190	0.0718
	(0.446)	(0.174)	(0.259)	(0.228)
Sole Plan (t)	-0.582	-0.0165	-0.188	0.0858
	(0.581)	(0.118)	(0.255)	(0.212)
Plan Size (t)	-2.066***	-0.0796	-0.0836	-0.0322
	(0.486)	(0.0567)	(0.0719)	(0.0545)
ROA Plan (t)	0.678	-0.652	-0.512	-0.378
	(1.306)	(1.192)	(1.579)	(1.200)
Firm Size (t)	0.478**	0.0600	0.0645	-0.00196
	(0.202)	(0.0411)	(0.0665)	(0.0559)
Leverage (t)	0.343	0.0567	0.0764	-0.0126
	(0.660)	(0.234)	(0.353)	(0.287)
ROA Firm (t)	0.222	0.150	0.0683	-0.121
	(0.771)	(0.775)	(0.670)	(0.606)
Big Actuarial Firm (t)	0.250	0.303**	0.351*	-0.0204
	(0.163)	(0.142)	(0.185)	(0.0912)
Big 4 Auditor (t)	0.0635	0.0296	0.0842	0.0698
	(0.165)	(0.0976)	(0.109)	(0.0838)
LowZscore (t)	-0.152	0.0111	0.00923	0.153
	(0.235)	(0.105)	(0.147)	(0.155)
Constant	7.879***	0.450	0.842	0.860**
	(1.811)	(0.433)	(0.594)	(0.396)
N	1185	1185	1185	1185
R^2	0.367	0.278	0.275	0.273
Year Indicators	Yes	Yes	Yes	Yes
Fixed Effects	Firm Level	Actuary-Firm Level	Office Level	No

Standard errors in parentheses
* p < 0.1, ** p < 0.05, *** p < 0.01

Table 8: Difference-in-Differences First Model Regression Results: Years 2000-2011
In this table I present the results of the difference-in-differences regression model, controlling for firm, plan, audit and actuary characteristics. The Actuarial Estimation Error (t+1) is defined as the expected return of pension assets for the following year (time *t+1*) minus the expected return of pension assets for the current year (time *t*). The remaining variables are described in Table 1. Year indicators and robust standard errors are used. For brevity considerations the coefficients of year indicators are not shown. All variables are winsorized at 1% & 99% levels. I denote statistical significance at the 1% (***), 5% (**) level and 10% (*) level.

	(1) Actuarial Estimation Error (t+1)	(2) Actuarial Estimation Error (t+1)	(3) Actuarial Estimation Error (t+1)
Actuarial Estimation Error (t)	-0.299***	-0.307***	-0.302***
	(0.0273)	(0.0344)	(0.0433)
Crisis	0.00762	-0.0308	-0.155
	(0.0609)	(0.0764)	(0.103)
Funding % Liabilities (t)	-0.430**	-0.477**	-0.266
	(0.187)	(0.221)	(0.251)
Transitions (t)	0.110	0.142	0.179
	(0.158)	(0.191)	(0.216)
Transitions (t) * Crisis	0.948***	0.960***	0.978***
	(0.185)	(0.221)	(0.279)
Frozen (t)	-0.125	0.0148	0.0381
	(0.0851)	(0.0981)	(0.128)
Active % Employees (t)	-0.100	-0.0435	0.0214
	(0.165)	(0.194)	(0.228)
Sole Plan (t)	-0.0665	-0.159	0.0577
	(0.160)	(0.271)	(0.214)
Plan Size (t)	-0.00389	-0.0273	-0.0666
	(0.0302)	(0.0476)	(0.0539)
ROA Plan (t)	-0.637***	-0.903***	-0.934**
	(0.246)	(0.309)	(0.430)
Firm Size (t)	-0.00764	0.0114	0.0379
	(0.0262)	(0.0467)	(0.0544)
Leverage (t)	-0.0855	-0.193	0.0187
	(0.149)	(0.236)	(0.287)
ROA Firm (t)	-0.478	-0.272	-0.0204
	(0.444)	(0.507)	(0.601)
Big Actuarial Firm (t)	-0.0267	-0.0318	-0.0865
	(0.0601)	(0.0749)	(0.0951)
Big 4 Auditor (t)	-0.0172	-0.0223	0.0309
	(0.0583)	(0.0703)	(0.0861)
LowZscore (t)		0.0925	0.165
		(0.118)	(0.155)
FEE (t)			0.220**
			(0.0993)
Constant	0.160	0.152	-0.129
	(0.208)	(0.239)	(0.268)
N	2585	1828	1185
R^2	0.217	0.214	0.216

Standard errors in parentheses
* p < 0.1, ** p < 0.05, *** p < 0.01

Table 9: Difference-in-Differences Second Model Regression Results: Years 2000-2011

In this table I present the results of the difference-in-differences regression model, controlling for firm, plan, audit and actuary characteristics. The Actuarial Estimation Error (t+1) is defined as the expected return of pension assets for the following year (time *t+1*) minus the expected return of pension assets for the current year (time *t*). The remaining variables are described in Table 1. Year indicators and robust standard errors are used. For brevity considerations the coefficients of year indicators are not shown. All variables are winsorized at 1% & 99% levels. I denote statistical significance at the 1% (***), 5% (**) level and 10% (*) level.

	(1) Actuarial Estimation Error (t+1)	(2) Actuarial Estimation Error (t+1)	(3) Actuarial Estimation Error (t+1)
Actuarial Estimation Error (t)	-0.298***	-0.307***	-0.301***
	(0.0274)	(0.0347)	(0.0439)
PPA	0.256***	0.218***	0.227***
	(0.0598)	(0.0764)	(0.0825)
Funding % Liabilities (t)	-0.475***	-0.510**	-0.304
	(0.178)	(0.206)	(0.243)
Transitions (t)	0.231	0.275	0.296
	(0.175)	(0.212)	(0.236)
Transitions (t) * PPA	0.716***	0.708***	0.657**
	(0.198)	(0.237)	(0.291)
Frozen (t)	-0.159*	-0.0204	0.00872
	(0.0847)	(0.0974)	(0.127)
Active % Employees (t)	-0.0421	-0.000720	0.0842
	(0.164)	(0.195)	(0.228)
Sole Plan (t)	-0.0486	-0.158	0.0407
	(0.159)	(0.268)	(0.208)
Plan Size (t)	-0.00410	-0.0200	-0.0586
	(0.0303)	(0.0482)	(0.0546)
ROA Plan (t)	-0.552**	-0.821***	-0.778*
	(0.243)	(0.306)	(0.428)
Firm Size (t)	-0.0170	-0.00537	0.0150
	(0.0261)	(0.0475)	(0.0555)
Leverage (t)	-0.0664	-0.160	0.0559
	(0.149)	(0.237)	(0.290)
ROA Firm (t)	-0.552	-0.323	-0.0956
	(0.442)	(0.505)	(0.601)
Big Actuarial Firm (t)	-0.0159	-0.0169	-0.0511
	(0.0601)	(0.0754)	(0.0954)
Big 4 Auditor (t)	0.0276	0.0217	0.0879
	(0.0584)	(0.0708)	(0.0866)
LowZscore (t)		0.0930	0.170
		(0.118)	(0.156)
FEE (t)			0.144
			(0.0937)
Constant	0.0553	0.0629	-0.197
	(0.204)	(0.231)	(0.263)
N	2585	1828	1185
R^2	0.221	0.217	0.219

Standard errors in parentheses
* p < 0.1, ** p < 0.05, *** p < 0.01

Chapter 3: Scheduled Sovereign Rating Announcements and local stock markets

Abstract

In June 2013, as a result of EU regulation *No 462/2013 of the European Parliament and of the Council (EU, 2013)* sovereign rating announcements became scheduled events. Reasons included, among others, making the information transmission process from CRAs to local governments safer, increasing confidentiality and preventing leakage of information documented in the literature. Michaelides et al. (2015) find evidence consistent with information leakage in the stock markets of downgraded, low institutional quality countries. In this paper I examine the impact of this change in regulation, on the potential leakage of information. Given the scheduled nature of announcements and the expected market anticipation of such announcements, I use a news analytics database to build a surprise measure as captured by news articles to examine associated market reactions to positive and negative surprises. First I find that markets respond positively to unscheduled upgrades, regardless of surprise. The positive reaction is documented on the announcement day or later. Second, when positive surprises are considered, stock markets react positively at the time of the announcement but also later. Finally I find that markets do not respond to downgrades, scheduled or unscheduled, and negative surprises before or after official sovereign rating announcements. A likely explanation of the last result is given in the findings of Bhattacharya et al. (2000) who state that unrestricted insider trading drives stock market prices to their correct level, fully incorporating imminent news, before the official public announcement. This line of argument could also indicate that the phenomenon of leakage of information, as documented by Michaelides et al. (2015), may still be present but may have shifted further backwards in time.

1. Introduction

The literature on the impact of Sovereign Ratings announcements on rated countries' economies is not new. Findings include the increase of volatility in stock returns, in CDS spreads, in bond yields and interest rates prior to, or after, sovereign rating announcements (Afonso, Furceri, & Gomes, 2012), (Brooks, Faff, Hillier, & Hillier, 2004), (Kaminsky & Schmucler, 2002), (Hill & Faff, 2010), (Norden & Weber, 2004), (Martell, 2005), etc.

A recent study by Michaelides et al. (2015) finds evidence of information leakage taking place in the period prior to sovereign debt rating changes when credit rating agencies consult with local government officials. In particular, the authors find statistically and economically significant negative daily abnormal stock index returns prior to downgrade announcements from the three big Credit Rating Agencies (CRAs), namely Fitch, Moody's and Standard & Poor's, indicating information leakage. In addition the authors employ Transparency International's corruption perception index to classify countries (and events) in two groups: high and low corruption. Using this classification as an indication of institutional quality (IQ), where higher corruption implies lower IQ and the opposite, the authors find that their results are much more pronounced in countries of lower IQ as the impact of downgrades on local stock market indices, for such countries, is much bigger. In their concluding remarks, Michaelides et al. (2015) propose taking corrective action by imposing an upper bound on the communication window between CRAs and government officials, suggesting 48 hours as an option to consider. Current regulations in EU require CRAs to give rated entities at least 24 hour notice before official rating announcement, however, there is no regulation set for an upper bound. As a result several days, and sometimes weeks, could separate consultation from public announcement, a situation, potentially allowing information leakage to occur.

In 2013, the European Union (EU, 2013) in an attempt to improve the transparency and quality of sovereign debt ratings of EU member states imposed stricter rules on credit rating agencies. More specifically since the beginning of 2014 CRAs are obliged, among others, to set up a calendar indicating when they will rate EU Member States. Such ratings are limited to three per year for unsolicited sovereign ratings. Deviations are permitted only under exceptional circumstances and subject to providing sufficient explanations. Moreover, the ratings of EU Member States are to be published on Fridays after the close of business and at least one hour before the opening of trading venues in the EU. This is done to avoid situations of market disruption after official sovereign debt rating announcements. In addition, investors and EU Member States are to be informed of the underlying facts and assumptions made for each rating in order to facilitate a better understanding of credit ratings for EU Member States. As of June 2013, when the new the regulation went into effect, CRAs decided to preschedule sovereign debt ratings for all countries, and not just EU Member States, on Fridays. Hence the regime of unscheduled sovereign debt rating announcements has changed, since beginning of 2014[28], to scheduled events.

In this paper I investigate if the findings of Michaelides et al. (2015), that there is information leakage prior to official announcements of sovereign debt ratings announcements, remained unchanged after the European Union passed the June 2013 regulation for Credit Rating Agencies. Since Michaelides et al. (2015) use data from 1988-2012, their study does not capture the effect, if any, of the new regulation on information leakage. It is therefore an empirical question whether the information leakage, taking place in the years preceding the change, was reduced, eliminated or remained unaltered after June 2013. Existing literature

[28] The new regulation entered into force in June 2013 obliging CRAs to preschedule announcements once per year for the following year. For 2014 prescheduled announcement dates were released in December 2013.

on news announcements finds that volatility for stock prices, option prices, CDS spreads, exchange rates etc. usually resolves (increases) after scheduled (unscheduled) announcements (Jiang, Konstandinidi, & Skiadopoulos, 2012), (Ederington & Ha Lee, 1996), (Bomfim, 2003). However findings for the period preceding a scheduled announcement are not always in the same direction, with some studies finding an increase in volatility (Lucca & Moench, 2015), (Bauwens, Ben Omrane, & Giot, 2005) and some other studies finding a decrease (Bomfim, 2003), (Jiang, Konstandinidi, & Skiadopoulos, 2012).

In this study I classify sovereign rating announcements based on whether they are scheduled or not, as the new regulation from the EU permits CRAs to make unscheduled announcements as well. I use the sample of unscheduled announcements to test for leakage. I also test for anticipation of the rating change direction by using the sample of scheduled announcements. For this purpose, I combine the sample of scheduled announcements with Thompson Reuters Marketpsych Sentiment Index (TRMI Sentiment) which captures all country-specific news around sovereign rating announcements. More specifically, TRMI sentiment is an index that scores the content of each story relevant to a country of interest on a normalized scale between -1 and 1. Put differently, TRMI Sentiment “transforms” news articles based on their general tone and specific word choice into an index between -1 to +1 that is positively correlated with the actual market sentiment. This transformation aims to capture macro-related information, other general news relevant to each country and also feelings such as joy or fear that can potentially affect stock market reactions (Stambaugh, Yu, & Yuan, 2012). Further robustness tests, such as classifying the sample of countries (sovereign rating announcements) in groups of high and low institutional quality, in the same manner as Michaelides et al. (2015), are scheduled in a future version of this paper.

Using all sovereign debt rating announcements (scheduled + unscheduled) from the big 3 Credit Rating Agencies, namely Fitch, Moody's and Standard & Poor's, from June 2013 to April 2016, local daily stock market data from January 2012 to April 2016 and TRMI data from June 2013 to April 2016, I employ a short-horizon event study analysis and find that markets respond positively to good news, for example an unscheduled upgrade, upon and after announcement only. This finding is also supported by the relevant literature (Bomfim, 2003), (Reisen & Von Maltzan, 1999). I also find that markets do not respond to downgrades, scheduled or unscheduled, and negative surprises before or after the announcement. Even though unexpected, the last finding is not unheard of. For example, Bhattacharya et al. (2000) find that unrestricted insider trading drives stock market prices to their correct level, fully incorporating news before their official public release. This line of argument could also indicate that the phenomenon of leakage of information, as documented by Michaelides et al. (2015), may still be present but may have shifted further backwards in time.

The contribution of this study is on many levels. First I show that the findings of Michaelides et al. (2015), that there are economically and statistically significant negative abnormal stock index returns prior to sovereign debt rating downgrades have changed after the new regulations on CRAs were imposed by the European Union in June 2013. The findings of the present study suggest that the new regulation has either put an end to the destabilizing effect of leakage before official sovereign rating downgrades or that it has shifted it further backwards in time.[29] Second I develop a surprise measure that compares the market sentiment before and after an event, to test whether the content of the announcement meets market expectations, and use it to investigate whether a surprise on the market (positive or negative) causes abnormal market reactions (similar to upgrades or downgrades). Third I

[29] Further analysis to provide a more accurate answer is scheduled for a future version of this paper.

build on past literature to explain the results. Literature finds large excess returns before scheduled announcements, indicating informed trading prior to announcement (Lucca & Moench, 2015), (Bernile, Hu, & Tang, 2015). The results of this study oppose literature findings as I document most of the significant market reaction after scheduled upgrades.

The remaining of this paper is structured as follows. In Section 2 I provide the Institutional background and develop the hypotheses. In Section 3 I describe the sample, in Section 4 the methodology and in Section 5 I present the results. In Section 6 I conclude.

2. Institutional Background and Hypotheses

In the years preceding 2013, Credit Rating Agencies (CRAs) rated sovereigns at a time of their own choosing. Before official announcements, rated entities were given a time window during which they could, if asked by the CRA, provide additional information, pose questions to CRAs or, give arguments and place objections on the content of the announcement. In the EU, a 2009 regulation on CRAs (EU, 2009) required CRAs to provide the rated entity at least a 12-hour window to study the content of the announcement and then, if it wished, revert back. Despite the fact that a lower bound for consultation was stipulated by EU (2009), an upper-bound was not, giving the opportunity, in case consultation time was long, for information leakage to occur causing a destabilizing effect in local stock markets as documented by Michaelides et al. (2015).

In 2013 the EU imposed stricter regulations on CRAs in order to improve the transparency and quality of sovereign ratings and to reduce overreliance on CRAs (EU, 2013). In this framework, CRAs are now obliged, among other things, to set up a calendar indicating when they will rate EU Member States. Such ratings are limited to three per year for unsolicited sovereign ratings. Deviations are permitted only under exceptional circumstances and subject to providing sufficient explanations. Moreover, the ratings are to be published on Fridays after the close of business and at least one hour before the opening of trading venues in the EU to avoid situations of market disruption after official sovereign debt rating announcements. As of June 2013, when the new regulation entered into force, CRAs decided to preschedule sovereign debt ratings for all countries, and not just EU Member States, starting from the 1st of January 2014, on Fridays. In addition, the minimum notice period that CRAs were obliged to give to sovereigns to study and negotiate the content of forthcoming announcements was amended from 12 hours to 24 hours. An upper communication window was not enforced meaning that the hazard of leakage of information in local stock markets still remains in place.

2.1. Hypothesis Development

The unbounded communication window between CRAs and local government officials allows the possibility of leakage of information before an imminent downgrade or upgrade. In addition CRAs have the discretion of also making unscheduled changes in sovereign ratings, if sufficient explanations are provided, in the same manner as in the period preceding the 2013 regulation change. However, the fact that the European Securities and Markets Authority (ESMA) has since 2011 undertaken a supervisory role of CRAs operating within the EU, with the number of CRAs registered with ESMA continually growing (ESMA, 2015), has likely reduced the phenomenon of information leakage prior to official sovereign rating changes. Moreover, the case of unscheduled announcements has been thoroughly investigated by Michaelides et al. (2015), albeit in the period preceding the 2013 regulation change (EU, 2013) which introduced scheduled announcements. As a result the present paper concentrates most attention on scheduled announcements.

Provided that after June 2013 CRAs need to preschedule up to three announcements per sovereign for subsequent years, for example scheduled events for 2014 were announced in

December 2013, local markets have sufficient time to start building expectations regarding imminent scheduled sovereign rating announcements. For this purpose I construct a surprise measure classifying events as having a positive, negative or no surprise based on a market sentiment index.[30] Studies in the literature, e.g. (Stambaugh et al., 2012), document that it possible to generate profits from buying and selling equity following periods of high sentiment, a finding that justifies the use of a surprise measure. I anticipate that when market expectations for scheduled announcements are met then there would be no surprise which would lead to no significant market reaction. Similarly when market expectations are exceeded (fall short) I expect positive (negative) surprise and significant positive (negative) market reaction the few days following the announcement. The hypotheses follow.

Hypothesis 1: When market expectations fall behind the content of scheduled announcements then a significant negative stock market reaction will take place the days following the official announcement.

Hypothesis 2: When market expectations are surpassed by the content of scheduled announcements then a significant positive stock market reaction will take place the days following the official announcement.

Hypothesis 3: When market expectations for scheduled announcements are met then no significant stock market reaction will take place the days following the announcement.

[30] For more info on TRMI Sentiment please refer to Introduction and Data sections.

3. Data and descriptive statistics

3.1. Sovereign Rating Announcements

In this study I use the sample of sovereign debt rating announcements from the big 3 CRAs, namely, Fitch, Moody's and Standard & Poor's from June 2013 to April 2016. As there are two types of announcements that is sovereign rating changes, where the debt rating of a country is upgraded or lowered, and rating affirmations, where the rating of a sovereign is repeated / not changed, I use two sets of sovereign rating announcements (also called events). The first set is smaller in size, henceforth the small dataset, and consists of the union of sovereign debt rating changes (Upgrades + Downgrades) while the second set is larger in size, referred to as large dataset hereafter, and includes all sovereign rating announcements (Upgrades + Downgrades + Affirmations), by the big 3 CRAs, namely Fitch, Moody's and Standard & Poor's from June 2013 to April 2016. It should be noted that none of the two datasets includes announcements of sovereign debt rating outlook changes.[31] The purpose of employing two datasets of sovereign rating announcements is to address concerns that the small number of events in the small dataset is driving the results. On the other hand the rating affirmations (included in the large but not the small dataset) are expected to have a much milder effect than rating upgrades or downgrades (included in both datasets) which implies that the results of the large dataset are expected to be less significant, still on the same direction, compared to the those of the small dataset.

Both datasets consist scheduled and unscheduled rating announcements, however scheduled announcements have a slightly more limited timespan, from January 2014 to April 2016. It is important to mention that the dates of scheduled announcements for a calendar

[31] Announcements of sovereign rating outlook changes will be incorporated in the data in a future version of this paper.

year are decided and released to public at an earlier stage, usually at the end of the previous calendar year. Each of the big 3 CRAs rates from 50 – 80 sovereigns, for years 2014 – 2016, and schedules up to three announcements per sovereign since 2014. Unscheduled announcements, after 2014, remain possible but only in exceptional circumstances and subject to appropriate explanations (EU, 2013).

The big 3 CRAs use letters to grade the debt of sovereign entities they rate. Moreover, the lettering of S&P and Fitch differs from that of Moody's. To make the ratings comparable, I transform letter grades from the big 3 CRAs to numeric values and store them in Table 1. For finding the changes in sovereign debt ratings I compare consecutive letter grades for each country. In this paper I examine how local stock markets respond to sovereign rating announcements by matching the union of announcements with daily returns for each country's local currency stock market index and the world MSCI index from DataStream. The DataStream sample starts from January 2012, since estimation data are also needed, and ends in May 2016. After removing duplicate events (i.e., rating changes on the same day) and events without equity data, the union of rating changes in the small dataset is reduced to 183 (79 upgrades and 104 downgrades) from 55 countries (Table 2, Panel A). The corresponding numbers for the large dataset are 976 sovereign rating announcements (77 upgrades, 102 downgrades and 797 affirmations) from 76 countries (Table 3, Panel A).

Rating changes of the same sovereign announced around the same time probably have smaller effect on local market returns because the reasons driving CRAs to downgrade or upgrade are mostly common. I would expect that first announcement to have a bigger impact on the stock market compared to announcements occurring in the immediate future. I account for that by following prior literature (e.g., Martell, 2005) constructing a "first-mover" filter (FMF) to exclude rating announcements too close to one another. In particular, the FMF filter removes from the small (large) dataset of sovereign rating changes (announcements) all changes (announcements) that are preceded by other changes (announcements) by any CRA the previous twenty one trading days. Applying this filter results to a sample of 85 downgrades (from an initial 103) and 64 upgrades (from an initial 79) from 53 countries for the small dataset (Table 2, Panel B) and a sample of 73 downgrades (from an initial 102), 56 upgrades (from an initial of 77) and 634 affirmations (from an initial of 797) from 72 countries for the large dataset (Table 3, Panel B).

3.2. Daily stock market data

In this paper, I use equity data from DataStream. Whenever available, I employ the Morgan Stanley Capital International (MSCI) index, but there are cases I take other local stock market indices, when the MSCI is not available. One requirement I have set is that each sovereign rating announcement should have at least 100 daily (non-zero returns) observations in the window starting from trading day -270 and ending in trading day +20 relative to the day of event. If this requirement is not satisfied the event is taken out of the sample. Applying this filter results in 3 more events taken out from the small dataset, leaving 146 rating changes of which 83 are downgrades and 63 are upgrades from 53 countries (Table 2, Panel C). The corresponding numbers for the large dataset are 556 sovereign rating announcements which break down to 71 downgrades, 55 upgrades and 430 affirmations from 72 countries (Table 3, Panel C).

3.2.1. Thomson Reuters Marketpsych Indices (TRMIs)

Thomson Reuters in collaboration with Marketpsych LLC developed an algorithm to identify news stories from Thomson Reuters News Feed Direct, Factiva News, and other third party news sources and construct daily indices for the content (TRMI Sentiment) of news related to the country of interest. Because the TRMIs are based on all the news related to a country, on a daily basis, news unrelated to downgrades are also captured by the indices.

For each country the TRMI Sentiment is based on an algorithm that reads the content of each article and gives it a score on a scale between -1 and +1. Overall, the TRMI Sentiment classifies and then ranks news stories on a scale between -1 to +1 depending on their tone and specific word choice. This classification aims to not only capture macro-related information but also feelings such as joy or fear that could potentially affect stock market returns (e.g., Stambaugh et al., 2012).

3.3. News analysis

In order to investigate whether it is the news, and not leakage, upsetting the stock markets around sovereign rating announcements I use the TRMI (Thomson Reuters Marketpsych Indices) Sentiment, following Michaelides et al. (2015)[32], to capture the content of economic, political and other country-level news around those announcements.

3.3.1. Surprise Factor (Based on TRMI Sentiment)

Each sovereign rating announcement is classified in one of three groups of surprise based on the overall cumulative abnormal sentiment at day +2 relative to event day 0. I estimate cumulative abnormal sentiment by adding consecutive abnormal sentiments starting from day 0. Abnormal sentiments, in the testing period (0, +2), are estimated by subtracting from raw sentiment the average raw sentiment from estimation period (-10, -2). I then take the sample of cumulative abnormal sentiment on day +2 for all events and sort it in ascending sequence, starting from the smallest value. Next I classify events as negatively surprised (Surprise=-1), if cumulative abnormal sentiment on day + 2 is below the 40th percentile, as positively

[32] Michaelides et al. (2015) was the first paper to use and validate TRMI data.

surprised (Surprise=+1) if it is above the 60th percentile and as unsurprised (Surprise=0) if it is in-between the 40th and 60th percentiles of the sorted, in ascending sequence, sample.

The concept behind the surprise measure is simple. Since the beginning of 2014, CRAs have to preschedule some or all of their sovereign rating announcements at the beginning of the year to adhere to the new regulations imposed by the EU. As a result of the scheduled nature of sovereign rating announcements markets have time to start building expectations about the content of forthcoming announcements. The purpose of the surprise measure is to capture how accurately the market anticipates the content of forthcoming scheduled announcements by the big 3 CRAs. It is further used to test whether any surprises (positive or negative) are associated to significant market reactions the few days following the announcements. In this paper I employ a small (Upgrades + Downgrades) and a large sample (Upgrades + Downgrades + Affirmations) of sovereign rating announcements that span from June 2013 to April 2016. For each of the samples I provide an illustration of the distribution of sovereign rating announcements classified into distinct groups of Cumulative Abnormal Sentiment (i.e. surprise groups) in Figures 1 and 2 of the Appendix.

4. Methodology

The present study examines the impact of a new EU regulation for CRAs (EU, 2013) on the, documented by the literature, leakage of information before official sovereign rating announcements. On this topic, Michaelides et al. (2015) find statistically and economically significant daily abnormal local stock market index returns prior to official sovereign rating announcements from big 3 Credit Rating Agencies, during the period 1988 - 2012, which the authors attribute to information leakage. The reason the present study revisits the results of Michaelides et al. (2015) is that the new regulation, that was enforced in June 2013, essentially changed the nature of sovereign rating announcements, of CRAs operating within the EU, from unscheduled to scheduled. Hence the purpose of the present study is to examine whether the findings of Michaelides et al. (2015) persist after the new regulation was enforced.

In order to examine the impact of sovereign debt rating announcements on local stock market index returns I employ a short-horizon event study analysis where I regress each country's major stock market index returns on the world MSCI return index over the (estimation) period [-270, -21] relative to event day 0. More specifically I use the following time-series regression model:

$$\boldsymbol{R_{it} = a_i + \beta_i R_{Wt} + \varepsilon_{it}} \qquad (1)$$

Then for every event I calculate, over the event period [-20, +20], the abnormal returns which are defined as the difference of the actual (raw) and expected returns of the local stock market index.

$$\boldsymbol{AR_{it} = R_{it} - \widehat{a}_i - \widehat{\beta}_i R_{Wt}} \qquad (2)$$

I obtain cumulative abnormal returns (hereafter CARs) by summing abnormal returns over the time interval the CAR is covering.

$$\boldsymbol{CAR_i[t_1, t_2] = AR_{it1} + \cdots + AR_{it2}} \qquad (3)$$

I take upgrades (equivalently positive surprise announcements) and downgrades (negative surprise announcements) separately and test the statistical significance of average abnormal returns (*AARs*) by employing a number of different tests. First, I take the cross-sectional variation of abnormal returns in the event window by assuming that AR_{it} are independent and identically distributed random variables following the normal distribution with mean zero and variance σ^2. I use s_t as an estimator for σ, with N being the number of events, to define the first test statistic for average abnormal returns (ARs).

$$\boldsymbol{Z = \sqrt{N}\frac{AAR_t}{S_t} \sim t_{N-1}} \tag{4}$$

Where

$$\boldsymbol{AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{it}} \tag{5}$$

And

$$\boldsymbol{s_t = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(AR_{it} - AAR_{it})^2}} \tag{6}$$

In a similar manner I define the test statistic for CAARs.

$$\boldsymbol{Z = \sqrt{N}\frac{CAAR_i[t_1, t_2]}{s} \sim N(0, 1)} \tag{7}$$

Where CAAR stands for Cumulative Average Abnormal Return and is defined as follows.

$$CAAR_i[t_1, t_2] = \frac{1}{N}\sum_{i=1}^{N} CAR_i[t_1\,, t_2] \tag{8}$$

Standard Deviation for CAARs is provided below.

$$s = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(CAR_i[t_1\,, t_2] - CAAR_i[t_1, t_2])} \tag{9}$$

The test statistics defined by Equations 4 and 7 use an event-induced variance estimated by using ARs or CARs from all events in the estimation period. Still there is another way to account for event-induced variance by standardizing abnormal returns in the event window. Proposed by Boehmer, Masumeci, & Poulsen (1991), the new method takes the ratio of event window Abnormal Returns (*AR_i*) by the times series standard deviation (*s_i*) of Abnormal Returns in the estimation period [-270,-21] of the corresponding event. More details are provided below.

$$\overline{AR_i} = \frac{1}{250}\sum_{i=1}^{250} AR_{it} \tag{10}$$

$$\overline{s_i} = \sqrt{\frac{1}{249}\sum_{i=1}^{250}(AR_{it} - AR_i)^2} \tag{11}$$

Standardized Abnormal Returns are then estimated.

$$SAR_{it} = \frac{AR_{it}}{\bar{s_i}} \tag{12}$$

Finally, the test statistic of Boehmer et al. (1991) is given by the following equation.

$$T_{BMP} = \sqrt{N}\frac{ASAR_t}{s} \tag{13}$$

Where

$$ASAR_t = \frac{1}{N}\sum_{i=1}^{N} SAR_{it} \tag{14}$$

And

$$s = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(CAR_i[t_1, t_2] - CAAR_i[t_1, t_2])} \tag{15}$$

Moving on, the test statistic of Kolari and Pynnonen (2010), which I use as the base case, is an extension of Equation 13 that also takes into consideration the cross-sectional correlation of abnormal returns in the estimation period [-270, -21].

$$T_{KP} = T_{BMP}\sqrt{\frac{1-\bar{r}}{1+(N-1)\bar{r}}} \tag{16}$$

The coefficient $\bar{r}$ is the average of sample cross-correlations of the estimation period residuals (abnormal returns).

For robustness, the test statistic proposed by Brown and Warner (1980) is used as well.

$$T_{BW} = \frac{AAR_t}{\bar{s}} \qquad (17)$$

For the BW test statistic I need to estimate the standard deviation of average abnormal returns in the estimation period [-270, -21] as follows.

$$\bar{s} = \sqrt{\frac{1}{249}\sum_{i=1}^{250}(AAR_t - \overline{AAR})^2} \qquad (18)$$

Where

$$\overline{AAR} = \frac{1}{250}\sum_{i=1}^{250} AAR_t \qquad (19)$$

The formula for the standard deviation for Cumulative Average Abnormal Return (CAAR) between times t_1 and t_2 is provided below.

$$s^* = \sqrt{(t_2 - t_1 + 1}\,\bar{s} \qquad (20)$$

5. Results

In this section I discuss descriptive statistics of the small and large datasets of sovereign rating announcements after these are classified in smaller subgroups, in order to study their properties (Tables 2, 3 & 4). I then proceed to discuss how the results of event studies conducted (Tables 5, 6, 7 & 8) compare to expectations given by this paper's hypotheses.

5.1. Descriptive Statistics

In this study I use two sets of sovereign rating announcements.[33] In Table 2 Panel A, I present descriptive statistics of the small dataset of sovereign rating changes, which comprises of the union of scheduled and unscheduled debt rating upgrades and downgrades between June 2013 and April 2016 by the big 3 CRAs, namely, Fitch, Moody's and Standard & Poor's. In total, the small dataset consists of 183 events of which 104 are downgrades and 79 are upgrades from a number of 55 countries. Similarly, in Table 3 Panel A, I present descriptive statistics of the large dataset of sovereign rating announcements, which comprises of scheduled and unscheduled debt rating upgrades, downgrades and affirmations, from June 2013 to April 2016, by the big 3 CRAs. In total, the large dataset comprises of 976 events of which 102 are downgrades, 77 are upgrades and 797 are rating affirmations from 76 countries.

According to Michaelides et al. (2015), multiple ratings of the same sovereign entity, within short period of time, are unlikely to have the same impact on local stock market returns. Moreover, a number of studies from the literature, e.g. (Jiang, Konstandinidi, & Skiadopoulos, 2012), (Ederington & Ha Lee, 1996), (Afonso, Furceri, & Gomes, 2012), (Kaminsky & Schmucler, 2002), (Gande & Parsley, 2003), (Arezki, Candelon, & R.Sy, 2011) and more,

[33] For more details about the two datasets refer to Section §3.1

document spillover effects from news announcements of neighboring countries which further strengthens the argument of Michaelides et al. (2015). To address this concern, I adopt a First Mover Filter (FMF), similar to Michaelides et al. (2015), which deletes all sovereign rating announcements that are preceded by other sovereign rating announcements, from the same or different CRA, in the previous 21 trading days. Overall, after imposing the FMF filter, the total number of events for the small dataset drops to 149 of which 85 are downgrades and 64 are upgrades from 53 countries (Table 2, Panel B). The total number of announcements remaining in the large dataset after applying the FMF filter is 763 of which 73 are downgrades, 56 are upgrades and 634 are rating affirmations from 72 countries.

Last I impose a liquidity filter. Illiquid markets are unlikely to be informative around a sovereign debt rating event in the same degree as liquid markets (Chae, 2005), (Chordia, Roll, & Subrahmanyam, 2008) & (Zheng & Bulkley, 2014). The liquidity filter takes out sovereign rating announcement events that have less than 100 non-zero returns over the interval [-270, +20] of trading days around the event. Overall, the liquidity filter leaves in the small dataset of sovereign rating announcements 146 events, of which 83 are downgrades and 63 are upgrades from 53 countries (Table 2, Panel C). In the large dataset, the total number of events after applying the liquidity filter is 556, of which 71 are downgrades, 55 are upgrades and 430 are affirmations from 72 countries (Table 3, Panel C).

One of this study's innovations is the introduction of the surprise factor that separates the sample of events based on the element of surprise. The new measure is based on the TRMI sentiment index and there are four possible categories by which each event in the sample is classified: Negative Surprise, No Surprise, Positive Surprise and Unclassified. The Unclassified category includes all these events for which the TRMI sentiment index is not available. I provide descriptive statistics for the small sample (Upgrades + Downgrades) in

Table 4, Panel A and for the large sample (Upgrades + Downgrades + Affirmations) in Table 4, Panel B. In the former case, out of the 146 events, 50 are classified with a negative surprise, 27 are classified with no surprise, 50 have a positive surprise and 19 events are unclassified. The corresponding numbers for the large sample of events are 176, 90, 176 and 114.

5.2. Empirical Results: Do stock markets around the world move around official sovereign debt rating announcements after June 2013?

In this section I test whether the findings from Michaelides et al. (2015) that there is statistically and economically significant negative (positive) daily abnormal local stock market index returns prior to official downgrade (upgrade) announcements from big 3 Credit Rating Agencies, during the period 1988 -2012, continue to hold after June 2013. The reason this study revisits the results by Michaelides et al. (2015) is a new regulation imposed by the EU (EU,2013) on CRAs operating within the European Union, essentially changing the nature of sovereign rating announcements of EU member states[34] from unscheduled to scheduled.

To provide an answer to the empirical question posed above, I take Cumulative Average Abnormal Returns (CAARs) before, at and after sovereign debt rating changes dated after June 2013 and store them in Table 5. The sample of events used to produce the results discussed in this section is scheduled or unscheduled sovereign debt rating downgrades or upgrades (small dataset) that span from June 2013 to April 2016. Unlike the results from Michaelides et al. (2015), the results from the present study do not show any significant market reaction prior, at, or post downgrade events. Even though unexpected, results do not

[34] CRAs responded by prescheduling the sovereign rating announcements of all the countries that they rate, not just EU member states.

come as a complete surprise. A recent study by Chung et al. (2012) finds that CRAs tend to release credit watches when the credit quality of rated entities deteriorates thus allowing rated entities time to correct deficiencies and prevent downgrades. Furthermore Bannier & Hirsch (2010) state that credit watches is a tool that CRAs use to abstain rated entities from risk-augmenting actions. They continue to say that CRAs role has been enhanced from purely informational about the credit quality of rated entities to a more active monitoring function. It is perhaps possible that the absence of significant market reaction around downgrades is attributed to old news leading to the downgrade where sovereigns were given the opportunity to take corrective measures in preventing the imminent downgrade, when they were put on watchlist, but failed subsequently to do so. This is an interesting topic that would be worth investigating further in a future version of this paper.

The results for upgrades are different. More specifically I find that CAARs at and around upgrades are positive and statistically significant in some instances, e.g. CAAR[-1, +1] = 0.425% with p-value < 0.05; CAAR[0, +1] = 0.361% with p-value < 0.05, and that after a few trading days there is some correction where CAARs become negative, e.g. CAAR[+3, +10] = -0.6% with p-value < 0.1. The last finding can be attributed to overreaction of the market around the announcement.

It should be noted that to test the robustness of my methodology and results I also run the same analysis using a sample of sovereign rating announcements similar to that of Michaelides et al. (2015), ranging from 1988 – 2012, and the results are almost identical to that of Michaelides et al. (2015).

5.3. Empirical Results: Does the scheduled nature of sovereign debt rating announcements affect the destabilizing effect of leakage prior to announcement?

In the previous section (§5.2) I revisited the results of Michaelides et al. (2015) and redone their analysis, for the period June 2013 – April 2016, following a regulation change which was introduced in June 2013 and required CRAs operating within the EU to preschedule sovereign rating announcements of the countries they rate since the beginning of 2014.

In this section I test the robustness of the results discussed in the previous section (§5.2), finding no evidence of abnormal market reaction prior to official sovereign debt rating changes, by breaking down the sample of sovereign rating changes (upgrades + downgrades) to 2 smaller ones, unscheduled and scheduled events. Then I repeat the analysis of the previous section (§5.2) twice, once for each of the smaller samples, and store results in Table 6. Intuitively, the unscheduled nature of some announcements puts less attention by the media on the forthcoming announcement which increases the probability of leakage of information. Starting from the unscheduled sample of events (Table 6, Panel A) the results are mostly similar to those of the previous section (Table 5), with no significant market reaction before, at and after downgrades and some positive market reaction at and around upgrades followed by reversal the period after the event. Moving on to the scheduled events sample (Table 6, Panel B) results for downgrades remain the same as in the unscheduled case. CAARs are not statistically significant in any of the CAAR intervals indicating no significant market reaction before, at or after scheduled downgrades. Moving on, the results for scheduled upgrades are now different. At this instance, I do not find statistically significant CAARs at or after scheduled upgrades as in the cases of unscheduled and pooled samples of upgrades. Moreover I do not find statistically significant CAARs before scheduled upgrades.

Even though the results of this section are different than expected, there are studies in the literature that can potentially provide explanations. In particular, Bhattacharya et al. (2000), who use Mexican corporate data from July 1994 to June 1997, study the impact of corporate news events on stock prices in the Mexican stock market and find that insider trading prohibits corporate news announcements from influencing stock prices. In other words, the authors find that insider trading cause Mexican stock prices to fully incorporate information before its official release. Although Bhattacharya et al. (2000) study stock prices locally and during a diffent era, their findings are relevant and could potentially lend support to the argument of leakage of information before the official sovereign rating announcements, if their line of argument is accepted. However, due to the obvious differences of the present paper and that of Bhattacharya et al. (2000) it would be useful, in a future version of this paper, to conduct further analysis to investigate the argument of leakage in further depth. Another potential explanation of the results is that perhaps new EU regulation has increased the transparency of all events, scheduled and unscheduled, making them fully anticipated which explains why stock market prices do not react to sovereign debt rating changes before and on the date of official release.

5.4. Empirical Results: Does the element of surprise help explain stock market reactions around sovereign debt rating announcements?

In order to test this paper's hypotheses, I redo the analysis of the previous two sections (§5.2 & §5.3) for scheduled announcements spanning from January 2014 to April 2016. The element of surprise, which is one of this paper's innovations, is expected to play a key role in explaining stock market reactions after sovereign rating announcements according to this paper's hypotheses. In particular the effect is expected to be significantly more pronounced for scheduled announcements as in those cases the market has enough time to build expectations for the content of the forthcoming announcement. Instead of looking at CAARs of upgrades against downgrades I look at CAARs of events based on a surprise factor that is measured two days after the announcement. I classify events in three categories of surprise: negative, neutral and positive[35]. If there is no data to measure surprise then events remain unclassified and are excluded from the test sample. Since the surprise measure essentially splits the sample of sovereign rating announcements in three smaller testable samples, I run the analysis twice, one time for the small dataset (N=60) and one time of the large dataset (N=474) of sovereign rating announcements. I do that to test the robustness of my results and to address concerns that the small number of observations in the subsamples of the small dataset might be driving the results. I present results of the small dataset (Upgrades + Downgrades) in Table 7 and the results of the large dataset (Upgrades + Downgrades + Affirmations) in Table 8. Following the first hypothesis, I expect that announcements with a negative surprise to exhibit negative abnormal stock index returns the few days after the announcement. Similarly, following the second hypothesis, positive surprise announcements are expected to be associated with positive abnormal stock index returns in the post announcement period.

Starting with the small (large) dataset, I present events with negative surprise in Table 7 (8), Panel A. I do not find cases of CAARs that come up as statistically significant, before at or after announcement in contrast to expectations set forth by the first hypothesis. Despite the fact that news articles, as these are captured by the TRMI sentiment, document a negative

[35] For more details about the about the definition of the Surprise variable and the classification of events in categories based on Surprise refer to Section §3.3.

surprise at the announcement, the impact on stock markets is insignificant, suggesting that such news do not cause instability to local stock markets. There are three possible explanations for this result. The first is that investors do not regard sovereign rating related announcements, with content worse than expected, as relevant to stock market prices. Second, since the surprise measure is based on TRMI Sentiment, that is a proxy of all the news related to a country, perhaps it is capturing negative vibes from news unrelated to sovereign rating announcements which explains why stock markets remain unaffected. As this is a potential flaw of the surprise measure, a future version of this paper could include other "surprise" measures coming from other news sources that would be directly related to forthcoming sovereign rating announcements. The third possible explanation is that leakage of information is still happening, in the same manner as documented by Michaelides et al. (2015), but further back in time where informed investors have time to drive stock prices to the correct level long before the official announcement. This too is a scenario that is worth investigating further in a future version of this paper.

Events without (neutral) surprise are presented in Tables 7 and 8, Panel B. In the same manner as announcements with negative surprise, CAARs before at or post announcement are not significant in any case. This is in line with expectations from the third hypothesis. When markets are not surprised, having anticipated accurately the content of the scheduled announcement, then no abnormal reaction should be observed, at least, post the event.

Last I analyze events with positive surprise. Results for the small dataset are provided in Table 7, Panel C while results for the large dataset in Table 8, Panel C. Starting with Table 7C, one Cumulative Average Abnormal Return (CAAR) comes up as statistically significant: CAAR[-1, +1] = 0.669% with p-value < 0.05. Continuing with Table 8C, two CAARs come up as statistically significant: CAAR[-1, +1] = 0.296% with p-value < 0.01 and CAAR[0, +1] =

0.312% with p-value < 0.01. Results from both the small and large datasets indicate positive market reaction when the news are better than those anticipated and are in-line with the expectations of the second hypothesis. This essentially means that when news are better than expected, for example receiving an upgrade instead of an affirmation, markets respond positively at and post the announcement.

6. Conclusions

In this study I investigate whether the leakage of information that was documented prior to official sovereign ratings announcements, in years 1988 – 2012, by Michaelides et al. (2015) was resolved after the EU voted a law in 2013 which obliged CRAs to pre-schedule sovereign debt rating announcements. Reasons for the new law included, among others, making the information transmission process from CRAs to local governments safer, increasing confidentiality and preventing leakage of information as documented by Michaelides et al. (2015). Using data from June 2013 to April 2016 I find that stock markets respond positively to unscheduled upgrades, regardless of surprise. The positive reaction is documented on the announcement day or after that. Stock markets do not respond to scheduled upgrades and also don't respond to downgrades, scheduled or unscheduled. The fact that CRAs usually place sovereigns on watchlist, before downgrades but not upgrades, is one potential explanation as to why there is no stock market response around downgrades since markets, being fully efficient, anticipate such events, and reflect bad news in prices long before the official announcement. The absence of significant stock market response prior to scheduled sovereign rating upgrades can also be explained by anticipation. Due to the scheduled nature of such announcements, markets have enough time to incorporate anticipated good news into the stock prices before official release. In the results, I also find that stock markets react positively to positive surprise announcements, regardless of downgrade, upgrade or affirmation, at the time of the announcement. Finally, I do not document significant market reaction before, at or after negative (or no surprise) announcements. Even though news articles, captured by the TRMI sentiment, document a negative surprise at the announcement, stock markets perceive the negative surprises as non-events suggesting that the impact of such news is not enough to cause instability to local stock markets. A likely explanation is given by Bhattacharya et al. (2000) who state that unrestricted insider trading drives stock market prices to their correct level, fully incorporating news before their official public release. Their line of argument provides support to the argument that the leakage of information, as documented by Michaelides et al. (2015), may still be happening and may have shifted further backwards in time.

In the future this paper will be expanded to investigate further the reasons for which scheduled negative surprises and scheduled or unscheduled downgrades, do not exhibit any significant market reaction around the corresponding sovereign rating announcements. Since the findings in this paper are not conclusive, as both leakage and anticipation are both possible explanations to the results, I plan to experiment with different windows around sovereign rating announcements to test whether the leakage of information has shifted backwards in time or was eliminated after June 2013, when the new EU regulation for CRAs was introduced. I also plan to incorporate additional surprise measure(s) from news directly related to forthcoming sovereign rating announcements. In this manner I will test the results from the currently used surprise measure for robustness as its appropriateness is currently questionable. The fact that the currently used surprise measure is based on country specific and not event specific news could potentially mean that it is picking a lot of noise. Moreover, I plan to expand the sample of announcements to the end of year 2016 or later and classify countries (sovereign rating announcements) in groups of high and low institutional quality based on the Transparency International's perception corruption index. Michaelides et al. (2015) find that the abnormal stock market reaction preceding sovereign rating downgrades is significantly more pronounced in countries of lower institutional quality hence it is a setting worth investing in a future version of this paper as well.

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Appendix

Table 1: Letter to Numeric Grades Transformation Table for Credit Rating Agencies

Standard & Poor's	Fitch	Moody's	Numeric Grade
AAA	AAA	Aaa	1
AA+	AA+	Aa1	2
AA	AA	Aa2	3
AA-	AA-	Aa3	4
A+	A+	A1	5
A	A	A2	6
A-	A-	A3	7
BBB+	BBB+	Baa1	8
BBB	BBB	Baa2	9
BBB-	BBB-	Baa3	10
BB+	BB+	Ba1	11
BB	BB	Ba2	12
BB-	BB-	Ba3	13
B+	B+	B1	14
B	B	B2	15
B-	B-	B3	16
CCC+	CCC+	Caa1	17
CCC	CCC	Caa2	18
CCC-	CCC-	Caa3	19
CC	CC	Ca	20
C	C	C	21
FINANCIAL DISTRESS OR BANKRUPTCY			22

Table 2: Descriptive Statistics of Sovereign Rating Changes (*06/2013 – 04/2016*)

This table contains descriptive statistics of the sample of sovereign rating changes (upgrades and downgrades) from June 2013 to April 2016. The scheduled sample consists of announcements of which the date, although not the content, was decided and released to public at an earlier stage. In contrast the unscheduled sample consists of announcements that occurred unexpectedly. It should be noted that since Credit Rating Agencies (CRAs) began scheduling sovereign rating announcements since the beginning of 2014 the descriptive statistics for the scheduled sample only span from January 2014 to April 2016. In panel A all the sovereign rating changes from the big 3 CRAs (Fitch, Moody's, Standard & Poor's) having equity data are included. In panel B I apply the first mover filter (FMF) and exclude all sovereign rating changes that are preceded by other sovereign rating changes in the previous 21 trading days. The last filter imposed (Liquidity) takes out of the sample all rating changes that have less than 100 non-zero returns in the period -270 to +20 relative to the event.

PANEL A (No Filters)			
Number of Observations	Scheduled	Unscheduled	Total
Downgrades	30	74	104
Upgrades	41	38	79
Total	71	112	**183**
PANEL B (FMF Filter)			
Number of Observations	Scheduled	Unscheduled	Total
Downgrades	28	57	85
Upgrades	32	32	64
Total	60	89	**149**
PANEL C (FMF & LIQUIDITY Filters)			
Number of Observations	Scheduled	Unscheduled	Total
Downgrades	28	55	83
Upgrades	32	31	63
Total	60	86	**146**

Table 3: Descriptive Statistics of Sovereign Rating Announcements (*06/2013 – 04/2016*)

This table contains descriptive statistics of the sample of sovereign rating announcements (upgrades, downgrades and affirmations) from June 2013 to April 2016. The scheduled sample consists of announcements of which the date, although not the content, was decided and released to public at an earlier stage. In contrast the unscheduled sample consists of announcements that occurred unexpectedly. It should be noted that since Credit Rating Agencies (CRAs) began scheduling sovereign rating announcements since the beginning of 2014 the descriptive statistics for the scheduled sample only span from January 2014 to April 2016. In panel A all the sovereign rating announcements from the big 3 CRAs (Fitch, Moody's, Standard & Poor's) having equity data are included. In panel B I apply the first mover filter (FMF) and exclude all sovereign rating announcements that are preceded by other sovereign rating announcements in the previous 21 trading days. The last filter imposed (Liquidity) takes out of the sample all rating announcements that have less than 100 non-zero returns in the period -270 to +20 relative to the event.

PANEL A (No Filters)			
Number of Observations	Scheduled	Unscheduled	Total
Downgrades	28	74	102
Upgrades	39	38	77
Affirmations	797	0	797
Total	864	112	**976**
PANEL B (FMF Filter)			
Number of Observations	Scheduled	Unscheduled	Total
Downgrades	20	53	73
Upgrades	24	32	56
Affirmations	634	0	634
Total	678	85	**763**
PANEL C (FMF & LIQUIDITY Filters)			
Number of Observations	Scheduled	Unscheduled	Total
Downgrades	20	51	71
Upgrades	24	31	55
Affirmations	430	0	430
Total	474	82	**556**

Table 4: Descriptive Statistics of Sovereign Rating Announcements (*06/2013 – 04/2016*)

This table contains descriptive statistics of the sample of sovereign rating announcements classified in four groups of surprise. I classify events as Negative Surprise, if cumulative abnormal sentiment (CAS) 2 days after the announcement is below the 40th percentile, as Positive Surprise if it is above the 60th percentile and as No Surprise if it is in-between the 40th and 60th percentiles of the sorted, in ascending sequence, sample. In case CAS data aren't available then announcements are registered under the No Data column. CAS 2 days after the event is estimated by summing Abnormal Sentiment of day 0 (event day), day 1 and day 2. Abnormal Sentiment (on days 0, 1 & 2) is estimated by subtracting from the raw sentiment the average raw sentiment in days -10 to -2 relative to the day of event (day 0). Panel A contains descriptive statistics for sovereign rating announcements (Upgrades & Downgrades) spanning from June 2013 to April 2016. Panel B contains descriptive statistics of sovereign rating announcements (Upgrades, Downgrades & Affirmations) spanning from June 2013 to April 2016.

PANEL A: NO AFFIRMATIONS					
Event / Surprise	Negative Surprise	No Surprise	Positive Surprise	No Data	Total
Downgrades	38	19	17	9	83
Upgrades	12	8	33	10	63
Total	50	27	50	19	**146**
PANEL B: AFFIRMATIONS INCLUDED					
Event / Surprise	Negative Surprise	No Surprise	Positive Surprise	No Data	Total
Downgrades	42	11	10	8	71
Upgrades	11	6	29	9	55
Affirmations	123	73	137	97	430
Total	176	90	176	114	**556**

Table 5: CAARS of Sovereign Rating Changes (06/2013 – 04/2016)

This table consists of Cumulative Average Abnormal Returns (CAARs) from the sample of sovereign rating changes (upgrades & downgrades) from June 2013 to April 2016. There are several CAARs over different windows which are estimated by summing together all Average Abnormal Returns in that window. Average Abnormal Returns on a relative (to the announcement) day are given by the mean of Abnormal Returns of all rating changes on that specific relative day. Abnormal Returns are in turn estimated by subtracting from the raw stock market return the estimated by the CAPM return. The estimation period used to come up with CAPM estimated returns is -270 to -21 days relative to the event.

Event Window	DOWNGRADES				UPGRADES			
	CAAR (%)	**N**	**P-VALUE**	**SS**	**CAAR (%)**	**N**	**P-VALUE**	**SS**
(-10, -1)	-0.026	83	0.907		-0.380	63	0.321	
(-10, -3)	-0.003	83	0.922		-0.340	63	0.281	
(-5, -1)	0.111	83	0.735		-0.174	63	0.454	
(-5, -2)	-0.026	83	0.835		-0.238	63	0.223	
(-5, -3)	0.135	83	0.630		-0.134	63	0.348	
(-2, -1)	-0.02	83	0.929		-0.04	63	0.867	
(-1, +1)	0.065	83	0.881		0.425	63	0.027	**
(-5, +5)	0.144	83	0.861		0.316	63	0.430	
(0, +1)	-0.072	83	0.467		0.361	63	0.012	**
(+2, +10)	0.211	83	0.599		-0.444	63	0.190	
(+3, +10)	0.340	83	0.414		-0.600	63	0.052	*

Table 6: CAARS of Unscheduled Sovereign Rating Changes (06/2013 – 04/2016)

This table consists of Cumulative Average Abnormal Returns (CAARs) from the sample of unscheduled sovereign rating changes (upgrades & downgrades) from June 2013 to April 2016. Unscheduled sovereign rating changes are announced unexpectedly by Credit Rating Agencies. There are several CAARs over different windows which are estimated by summing together all Average Abnormal Returns in that window. Average Abnormal Returns on a relative (to the announcement) day are given by the mean of Abnormal Returns of all rating changes on that specific relative day. Abnormal Returns are in turn estimated by subtracting from the raw stock market return the estimated by the CAPM return. The estimation period used to come up with CAPM estimated returns is -270 to -21 days relative to the event.

PANEL A: UNSCHEDULED								
Event Window	DOWNGRADES				UPGRADES			
	CAAR (%)	N	P-VALUE	SS	CAAR (%)	N	P-VALUE	SS
(-10, -1)	-0.0003	55	0.910		0.11	31	0.817	
(-10, -3)	0.0001	55	0.959		0.12	31	0.820	
(-5, -1)	-0.0003	55	0.913		-0.04	31	0.915	
(-5, -2)	-0.0019	55	0.466		-0.03	31	0.839	
(-5, -3)	0.0002	55	0.996		-0.03	31	0.814	
(-2, -1)	-0.0004	55	0.858		-0.01	31	0.917	
(-1, +1)	0.0003	55	0.995		0.38	31	0.080	*
(-5, +5)	-0.0012	55	0.721		0.59	31	0.189	
(0, +1)	-0.0013	55	0.387		0.39	31	0.039	**
(+2, +10)	0.0007	55	0.930		-0.51	31	0.342	
(+3, +10)	0.0020	55	0.737		-0.91	31	0.059	*

Table 6: CAARS of Scheduled Sovereign Rating Changes (01/2014 – 04/2016)

This table consists of Cumulative Average Abnormal Returns (CAARs) from the sample of scheduled sovereign rating changes (upgrades & downgrades) from January 2014 to April 2016. The date, although not the content, of scheduled sovereign rating announcements is known before the actual event day. Credit Rating Agencies started scheduling sovereign rating announcements in January 2014. There are several CAARs over different windows which are estimated by summing together all Average Abnormal Returns in that window. Average Abnormal Returns on a relative (to the announcement) day are given by the mean of Abnormal Returns of all rating changes on that specific relative day. Abnormal Returns are in turn estimated by subtracting from the raw stock market return the estimated by the CAPM return. The estimation period used to come up with CAPM estimated returns is -270 to -21 days relative to the event.

PANEL B: SCHEDULED								
Event Window	**DOWNGRADES**				**UPGRADES**			
	CAAR (%)	**N**	**P-VALUE**	**SS**	**CAAR (%)**	**N**	**P-VALUE**	**SS**
(-10, -1)	-0.01	28	0.959		-0.86	32	0.180	
(-10, -3)	-0.03	28	0.915		-0.79	32	0.166	
(-5, -1)	0.38	28	0.524		-0.31	32	0.383	
(-5, -2)	0.29	28	0.622		-0.44	32	0.129	
(-5, -3)	0.36	28	0.455		-0.24	32	0.289	
(-2, -1)	0.02	28	0.899		-0.07	32	0.771	
(-1, +1)	0.13	28	0.775		0.47	32	0.161	
(-5, +5)	0.66	28	0.441		0.05	32	0.921	
(0, +1)	0.04	28	0.921		0.33	32	0.136	
(+2, +10)	0.49	28	0.459		-0.38	32	0.367	
(+3, +10)	0.62	28	0.370		-0.30	32	0.392	

Table 7: CAARS of Scheduled Sovereign Rating Changes by Surprise (01/2014 – 04/2016)

This table consists of Cumulative Average Abnormal Returns (CAARs) from the sample of scheduled sovereign rating changes (upgrades & downgrades) from January 2014 to April 2016, classified by surprise. The date, although not the content, of scheduled sovereign rating announcements is known before the actual event day. Credit Rating Agencies started scheduling sovereign rating announcements in January 2014. I classify events as Negative Surprise (SURPRISE=-1), if cumulative abnormal sentiment (CAS) 2 days after the announcement is below the 40^{th} percentile, as Positive Surprise if it is above the 60^{th} percentile and as No Surprise if it is in-between the 40^{th} and 60^{th} percentiles of the sorted, in ascending sequence, sample. CAS 2 days after the event is estimated by summing Abnormal Sentiment of day 0 (event day), day 1 and day 2. Abnormal Sentiment (on days 0, 1 & 2) is estimated by subtracting from the raw sentiment the average raw sentiment in days -10 to -2 relative to the day of event (day 0).There are several CAARs over different windows which are estimated by summing together all Average Abnormal Returns in that window. Average Abnormal Returns on a relative (to the announcement) day are given by the mean of Abnormal Returns of all rating changes on that specific relative day. Abnormal Returns are in turn estimated by subtracting from the raw stock market return the estimated by the CAPM return. The estimation period used to come up with CAPM estimated returns is -270 to -21 days relative to the event.

PANEL A: NEGATIVE SURPRISE (SURPRISE = -1)				
Event Window	**CAAR (%)**	**N**	**P-VALUE**	**SS**
(-10, -1)	-0.514	20	0.539	
(-10, -3)	-0.266	20	0.688	
(-5, -1)	-0.514	20	0.456	
(-5, -2)	-0.265	20	0.585	
(-5, -3)	-0.3	20	0.568	
(-2, -1)	-0.248	20	0.546	
(-1, +1)	-0.087	20	0.822	
(-5, +5)	-0.734	20	0.347	
(0, +1)	0.137	20	0.762	
(+2, +10)	-0.622	20	0.228	
(+3, +10)	-0.546	20	0.249	

Table 7: CAARS of Scheduled Sovereign Rating Changes by Surprise (01/2014 – 04/2016)

This table consists of Cumulative Average Abnormal Returns (CAARs) from the sample of scheduled sovereign rating changes (upgrades & downgrades) from January 2014 to April 2016, classified by surprise. The date, although not the content, of scheduled sovereign rating announcements is known before the actual event day. Credit Rating Agencies started scheduling sovereign rating announcements in January 2014. I classify events as Negative Surprise (SURPRISE=-1), if cumulative abnormal sentiment (CAS) 2 days after the announcement is below the 40th percentile, as Positive Surprise if it is above the 60th percentile and as No Surprise if it is in-between the 40th and 60th percentiles of the sorted, in ascending sequence, sample. CAS 2 days after the event is estimated by summing Abnormal Sentiment of day 0 (event day), day 1 and day 2. Abnormal Sentiment (on days 0, 1 & 2) is estimated by subtracting from the raw sentiment the average raw sentiment of days -10 to -2 relative to the day of event (day 0).There are several CAARs over different windows which are estimated by summing together all Average Abnormal Returns in that window. Average Abnormal Returns on a relative (to the event) day are given by the mean of Abnormal Returns of all rating changes on that specific relative day. Abnormal Returns are in turn estimated by subtracting from the raw stock market return the estimated by the CAPM return. The estimation period used to come up with CAPM estimated returns is -270 to -21 days relative to the event.

PANEL B: NO SURPRISE (SURPRISE = 0)				
Event Window	**CAAR (%)**	**N**	**P-VALUE**	**SS**
(-10, -1)	-0.072	11	0.692	
(-10, -3)	0.251	11	0.881	
(-5, -1)	0.550	11	0.957	
(-5, -2)	0.414	11	0.977	
(-5, -3)	0.874	11	0.271	
(-2, -1)	-0.323	11	0.238	
(-1, +1)	0.414	11	0.850	
(-5, +5)	1.519	11	0.339	
(0, +1)	0.278	11	0.827	
(+2, +10)	0.306	11	0.567	
(+3, +10)	0.387	11	0.619	

Table 7: CAARS of Scheduled Sovereign Rating Changes by Surprise (01/2014 – 04/2016)
This table consists of Cumulative Average Abnormal Returns (CAARs) from the sample of scheduled sovereign rating changes (upgrades & downgrades) from January 2014 to April 2016, classified by surprise. The date, although not the content, of scheduled sovereign rating announcements is known before the actual event day. Credit Rating Agencies started scheduling sovereign rating announcements in January 2014. I classify events as Negative Surprise (SURPRISE=-1), if cumulative abnormal sentiment (CAS) 2 days after the announcement is below the 40th percentile, as Positive Surprise if it is above the 60th percentile and as No Surprise if it is in-between the 40th and 60th percentiles of the sorted, in ascending sequence, sample. CAS 2 days after the event is estimated by summing Abnormal Sentiment of day 0 (event day), day 1 and day 2. Abnormal Sentiment (on days 0, 1 & 2) is estimated by subtracting from the raw sentiment the average raw sentiment of days -10 to -2 relative to the day of event (day 0).There are several CAARs over different windows which are estimated by summing together all Average Abnormal Returns in that window. Average Abnormal Returns on a relative (to the event) day are given by the mean of Abnormal Returns of all rating changes on that specific relative day. Abnormal Returns are in turn estimated by subtracting from the raw stock market return the estimated by the CAPM return. The estimation period used to come up with CAPM estimated returns is -270 to -21 days relative to the event.

PANEL C: POSITIVE SURPRISE (SURPRISE = +1)				
Event Window	**CAAR (%)**	**N**	**P-VALUE**	**SS**
(-10, -1)	-0.383	19	0.782	
(-10, -3)	-0.568	19	0.619	
(-5, -1)	-0.118	19	0.929	
(-5, -2)	-0.423	19	0.533	
(-5, -3)	-0.303	19	0.622	
(-2, -1)	0.185	19	0.487	
(-1, +1)	0.669	19	0.0438	**
(-5, +5)	0.655	19	0.336	
(0, +1)	0.364	19	0.248	
(+2, +10)	1.122	19	0.222	
(+3, +10)	1.112	19	0.2000	

Table 8: CAARS of Scheduled Sovereign Rating Announcements by Surprise (01/2014 – 04/2016)

This table consists of Cumulative Average Abnormal Returns (CAARs) from the sample of scheduled sovereign rating changes (upgrades, downgrades & affirmations) from January 2014 to April 2016, classified by surprise. The date, although not the content, of scheduled sovereign rating announcements is known before the actual event day. Credit Rating Agencies started scheduling sovereign rating announcements in January 2014. I classify events as Negative Surprise (SURPRISE=-1), if cumulative abnormal sentiment (CAS) 2 days after the announcement is below the 40th percentile, as Positive Surprise if it is above the 60th percentile and as No Surprise if it is in-between the 40th and 60th percentiles of the sorted, in ascending sequence, sample. CAS 2 days after the event is estimated by summing Abnormal Sentiment of day 0 (event day), day 1 and day 2. Abnormal Sentiment (on days 0, 1 & 2) is estimated by subtracting from the raw sentiment the average raw sentiment of days -10 to -2 relative to the day of event (day 0).There are several CAARs over different windows which are estimated by summing together all Average Abnormal Returns in that window. Average Abnormal Returns on a relative (to the event) day are given by the mean of Abnormal Returns of all rating changes on that specific relative day. Abnormal Returns are in turn estimated by subtracting from the raw stock market return the estimated by the CAPM return. The estimation period used to come up with CAPM estimated returns is -270 to -21 days relative to the event.

PANEL A: NEGATIVE SURPRISE (SURPRISE = -1)				
Event Window	**CAAR (%)**	**N**	**P-VALUE**	**SS**
(-10, -1)	0.109	140	0.703	
(-10, -3)	0.238	140	0.269	
(-5, -1)	-0.077	140	0.924	
(-5, -2)	0.026	140	0.961	
(-5, -3)	0.052	140	0. 961	
(-2, -1)	-0.129	140	0.236	
(-1, +1)	-0.006	140	0.456	
(-5, +5)	0.331	140	0.288	
(0, +1)	0.097	140	0.789	
(+2, +10)	0.091	140	0.691	
(+3, +10)	-0.068	140	0.637	

Table 8: CAARS of Scheduled Sovereign Rating Announcements by Surprise (01/2014 – 04/2016)

This table consists of Cumulative Average Abnormal Returns (CAARs) from the sample of scheduled sovereign rating changes (upgrades, downgrades & affirmations) from January 2014 to April 2016, classified by surprise. The date, although not the content, of scheduled sovereign rating announcements is known before the actual event day. Credit Rating Agencies started scheduling sovereign rating announcements in January 2014. I classify events as Negative Surprise (SURPRISE=-1), if cumulative abnormal sentiment (CAS) 2 days after the announcement is below the 40th percentile, as Positive Surprise if it is above the 60th percentile and as No Surprise if it is in-between the 40th and 60th percentiles of the sorted, in ascending sequence, sample. CAS 2 days after the event is estimated by summing Abnormal Sentiment of day 0 (event day), day 1 and day 2. Abnormal Sentiment (on days 0, 1 & 2) is estimated by subtracting from the raw sentiment the average raw sentiment of days -10 to -2 relative to the day of event (day 0).There are several CAARs over different windows which are estimated by summing together all Average Abnormal Returns in that window. Average Abnormal Returns on a relative (to the event) day are given by the mean of Abnormal Returns of all rating changes on that specific relative day. Abnormal Returns are in turn estimated by subtracting from the raw stock market return the estimated by the CAPM return. The estimation period used to come up with CAPM estimated returns is -270 to -21 days relative to the event.

PANEL B: NO SURPRISE (SURPRISE = 0)				
Event Window	**CAAR (%)**	**N**	**P-VALUE**	**SS**
(-10, -1)	0.025	78	0.654	
(-10, -3)	-0.058	78	0.903	
(-5, -1)	0.207	78	0.3532	
(-5, -2)	0.178	78	0.305	
(-5, -3)	0.125	78	0.629	
(-2, -1)	0.083	78	0.483	
(-1, +1)	-0.084	78	0.418	
(-5, +5)	0.274	78	0.473	
(0, +1)	-0.113	78	0.301	
(+2, +10)	0.118	78	0.829	
(+3, +10)	0.089	78	0.857	

Table 8: CAARS of Scheduled Sovereign Rating Announcements by Surprise (01/2014 – 04/2016)

This table consists of Cumulative Average Abnormal Returns (CAARs) from the sample of scheduled sovereign rating changes (upgrades, downgrades & affirmations) from January 2014 to April 2016, classified by surprise. The date, although not the content, of scheduled sovereign rating announcements is known before the actual event day. Credit Rating Agencies started scheduling sovereign rating announcements in January 2014. I classify events as Negative Surprise (SURPRISE=-1), if cumulative abnormal sentiment (CAS) 2 days after the announcement is below the 40^{th} percentile, as Positive Surprise if it is above the 60^{th} percentile and as No Surprise if it is in-between the 40^{th} and 60^{th} percentiles of the sorted, in ascending sequence, sample. CAS 2 days after the event is estimated by summing Abnormal Sentiment of day 0 (event day), day 1 and day 2. Abnormal Sentiment (on days 0, 1 & 2) is estimated by subtracting from the raw sentiment the average raw sentiment of days -10 to -2 relative to the day of event (day 0).There are several CAARs over different windows which are estimated by summing together all Average Abnormal Returns in that window. Average Abnormal Returns on a relative (to the event) day are given by the mean of Abnormal Returns of all rating changes on that specific relative day. Abnormal Returns are in turn estimated by subtracting from the raw stock market return the estimated by the CAPM return. The estimation period used to come up with CAPM estimated returns is -270 to -21 days relative to the event.

PANEL C: POSITIVE SURPRISE (SURPRISE = +1)				
Event Window	**CAAR (%)**	**N**	**P-VALUE**	**SS**
(-10, -1)	-0.144	151	0.815	
(-10, -3)	-0.117	151	0.867	
(-5, -1)	-0.037	151	0.959	
(-5, -2)	-0.020	151	0.988	
(-5, -3)	-0.010	151	0.908	
(-2, -1)	-0.027	151	0.830	
(-1, +1)	0.296	151	0.005	***
(-5, +5)	0.306	151	0.141	
(0, +1)	0.312	151	0.0002	***
(+2, +10)	0.152	151	0.484	
(+3, +10)	0.203	151	0.356	

Figure 1: Distribution of Sovereign Rating Changes by Surprise (06/2013 – 04/2016)
This graph presents the distribution of sovereign rating changes (not including affirmations) with TRMI Sentiment data (N=127) that range from June 2013 to April 2016. The Cumulative Abnormal Sentiment (CAS), that is used to classify announcements into groups, is defined as the sum of the excess TRMI Sentiment, over the average TRMI Sentiment in the interval 10 days before to 2 days before the announcement, on days 0, 1 and 2 relative to the announcement. The groups of announcements marked with red have CAS below the 40th percentile (of the sorted sample of CASes) and are considered to have suffered a negative surprise (Surprise = -1). The groups of announcements marked with blue have CAS above the 60th percentile (of the sorted sample of CASes) and are considered to have experienced a positive surprise (Surprise = +1). All remaining announcements (marked with light grey) are those with CAS between the 40th and 60th percentile (of the sorted sample of CASes) and are considered to have had no surprise (Surprise = 0).

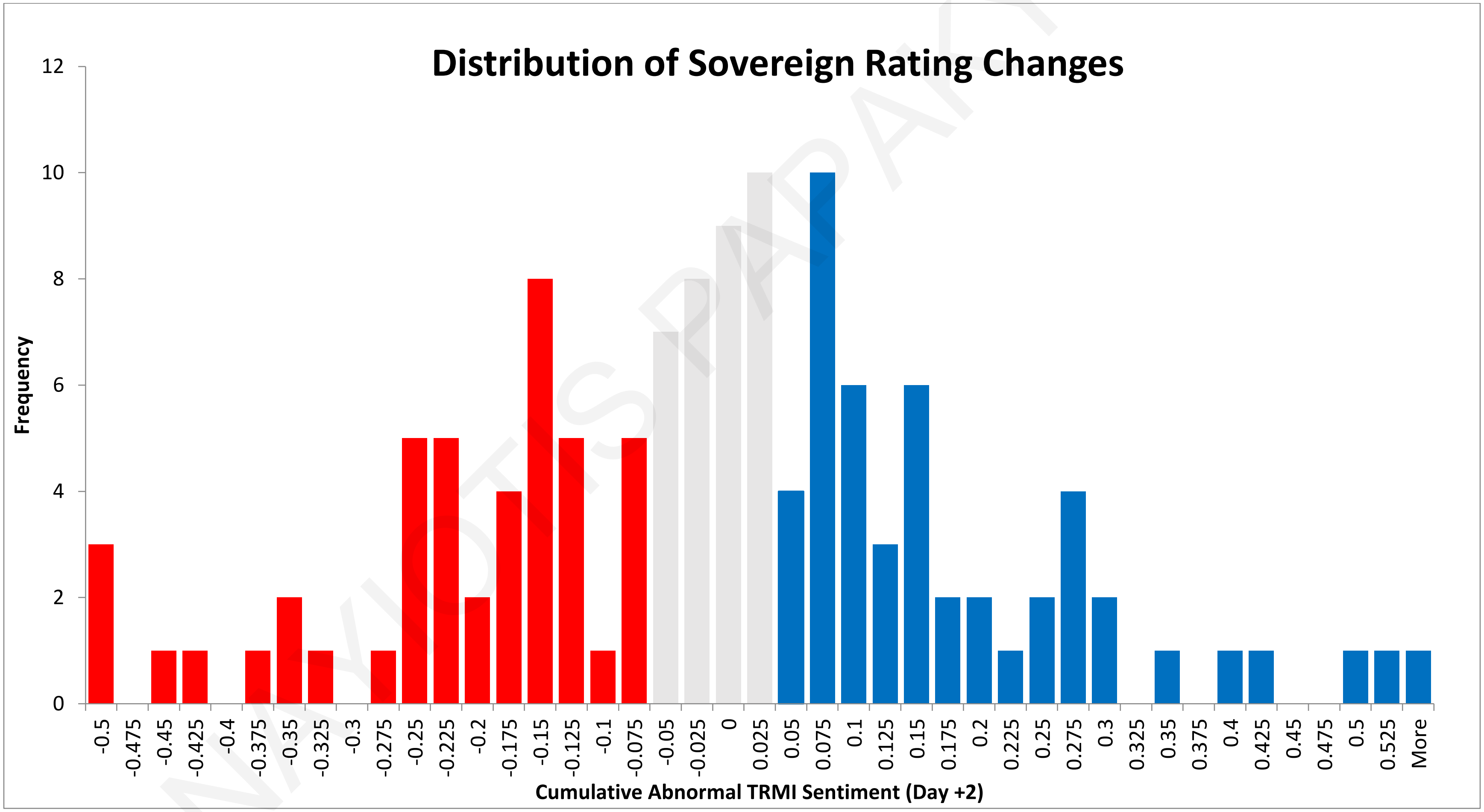
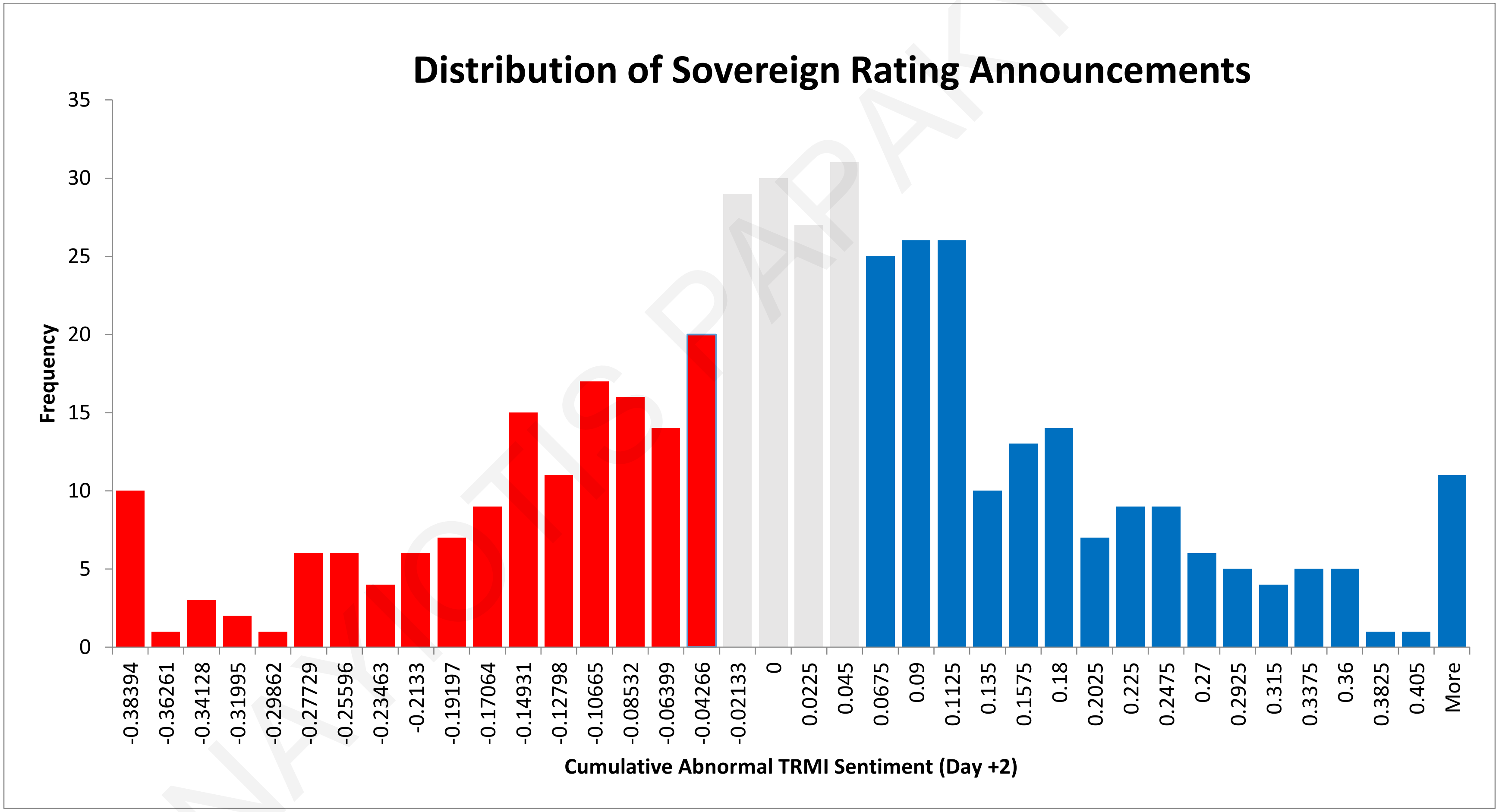


Figure 2: Distribution of Sovereign Rating Announcements by Surprise (06/2013 – 04/2016)
This graph presents the distribution of sovereign rating announcements (including affirmations) with TRMI Sentiment data (N=442) that range from June 2013 to April 2016. The Cumulative Abnormal Sentiment (CAS), that is used to classify announcements into groups, is defined as the sum of the excess TRMI Sentiment, over the average TRMI Sentiment in the interval 10 days before to 2 days before the announcement, on days 0, 1 and 2 relative to the announcement. The groups of announcements marked with red have CAS below the 40th percentile (of the sorted sample of CASes) and are considered to have suffered a negative surprise (Surprise = -1). The groups of announcements marked with blue have CAS above the 60th percentile (of the sorted sample of CASes) and are considered to have experienced a positive surprise (Surprise = +1). All remaining announcements (marked with light grey) are those with CAS between the 40th and 60th percentile (of the sorted sample of CASes) and are considered to have had no surprise (Surprise = 0).



Conclusions

This dissertation examines the important role of actuarial assumptions in corporate defined-benefit (DB) pension plans. Prior literature has raised concerns that actuaries do not always have the best interest of plan participants in mind when making pension funding assumptions, highlighting, compensation incentives and the overall financial strength level of pension plans as two factors compromising actuarial integrity. This dissertation also examines the effects of the EU regulation No 462/2013 of the European Parliament and of the Council, which obliges CRAs to preschedule sovereign rating announcements, on the leakage of information, documented by prior literature, in the stock markets of downgraded, low institutional quality countries.

In Chapter 1 I develop and use a new measure for actuarial estimation errors in pension funding assumptions. The new measure, the Actuarial Estimation Error (AEE), is defined as the difference between the expected return (ER) of DB pension plan assets for two consecutive years (for instance $AEE_t = ER_t - ER_{t-1}$). By using DB pension data, spanning 2000-2011, from publicly traded firms in the US I find that financially weaker DB pension plans are associated with bigger AEEs in the following year. A potential interpretation of this result is that actuaries inflate assumed expected returns of pension assets to reduce the pension expense and consequently the fund contributions plan sponsors need to make towards their plans in the next year. The results of this study support findings from existing literature claiming that there is association between the funding level of DB pension plans and pension funding assumptions. Last, results do not lend support to the findings from prior literature that actuarial compensation incentives affect actuarial integrity.

In Chapter 2, I use the AEE developed in Chapter 1, DB pension data from publicly traded firms in the US spanning 2000 – 2011, and the 2008 global financial crisis as an exogenous shock that transitions pension funds across different categories of financial strength to make inference. I find that DB pension plans dropping to a lower category of funding, by taking the endangered or critical status, are associated with significantly larger actuarial estimation errors in the following year, an obligation reducing assumption. When DB pension plans become financially weaker, their sponsors are obliged, among other things, to increase pension contributions in order to improve the financial condition of their plans. It is my view that, when this happens, actuaries adjust their expectations for pension asset returns upwards, which is what bigger AEE implies, to reduce the annual pension expense and mitigate the need for bigger contributions. Results are robust to actuarial compensation incentives and the overall financial strength level of pension plans. Last, findings only hold for the later years of the sample, i.e. after 2006 when Pension Protection Act was voted into law and after 2008 when the global financial crisis arrived.

In Chapter 3 I investigate whether the information leakage, found by Michaelides et al. (2015), to take place before official sovereign rating announcements in the years 1988 - 2012 was affected after the EU voted a law in 2013, which obliged CRAs to pre-schedule sovereign debt rating announcements, starting from January 2014. Using data from June 2013 to April 2016 and employing a short-horizon event study, I find that stock markets respond positively to unscheduled upgrades on and after the announcement day. Stock markets do not respond to scheduled upgrades and also don’t respond to downgrades, scheduled or unscheduled. The fact that CRAs place sovereigns on watchlist, when they intend to downgrade, could explain why there is no stock market response around downgrades. Markets, being fully efficient, anticipate forthcoming downgrades and reflect bad news in prices long before the official announcement. The absence of significant stock market response prior to scheduled sovereign rating upgrades can be explained by anticipation as well. The scheduled nature of such announcements, gives markets time to incorporate good news into the stock prices before official release. In the results, I also find that stock markets react positively to positive surprise announcements at the time of the announcement regardless of rating direction. Finally, I do not document significant market reaction before, at or after negative or no surprise announcements. Even though news articles, as captured by the TRMI sentiment, clearly document negative surprise at the time of the announcement, investors perceive the negative surprises as non-events in the sense that the impact of such news is not enough to cause major concern or instability to local stock markets. Past literature, e.g. Bhattacharya et al. (2000), finds that unrestricted insider trading causes prices to fully incorporate news before the official public release, a finding that could be particularly more pronounced for prescheduled announcements, potentially explaining this paper's results. Hence whether the leakage of information in the cases of negative sovereign rating announcements was eliminated or has shifted further back in time remains an open question to be answered by future research.