How Do Insurers Manage Credit Risk Exposure of Corporate Bond Portfolios? An Analysis Based on Background Risk

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Abstract

This study examines the effect of background risk on the risk taking behavior in the corporate bond market by a group of institutional investors. We find that insurers with higher volatilities in underwriting income and underwriting cash flows have lower credit risk exposure in their corporate bond portfolios. Further, consistent with the dynamic version of the background risk theory, insurers with more persistent underwriting income/cashflow shocks and with tighter financing constraints are less aggressive in credit risk taking. Insurers exposed to higher background risk suffer less in their investment performance during the recent financial crisis. Our evidence suggests that background risk plays a role in explaining the inter-connection between seemingly unrelated risks across different sectors of the financial market.

1. Introduction

Financial institutions often hold large investment portfolios in addition to running their main business in various segments of the financial market. For example, insurers' main line of business is to underwrite life or property policies, collect premiums, and manage claim payouts. In the meantime, they typically hold large fixed-income portfolios. Investment banks' main business is to advice corporate clients on securities issuance, restructuring, and M&A activities, but they often have proprietary trading desks that bet large amount of firm capital. At some financial institutions, investment activities generate a large proportion of profit as well as a large amount of risk.[1]

How do financial institutions manage investment risk versus the risk they face in their main business is a prominent issue. Are these two types of risks managed independently regardless of each other, or managed as compliments or substitutes? At the firm level, these questions are part of the big issue on financial institutions' risk management practice that we strive to understand. While there is a large amount research on risk management at commercial banks, relatively little empirical research exists so far on risk management at non-bank financial institutions. At the market level, researchers have been trying to understand why seemingly unrelated segments of the financial market may suddenly act together, giving rise to financial contagion. Part of the answer may lie in the way institutions manage risk across market segments – although the risks of various market segments (i.e., the securities market an institution invests and the market segment it mainly operates in) may be unrelated, the risk-taking decisions of institutions across these segments may be dependent. Finally, the issue is also relevant from a policy-making or regulatory perspective. Consider the debate on regulating excessive risk taking in banks' proprietary trading activities. In order for the regulators to decide a proper limit on investment risk an institution should take, it is necessary to know what level of investment risk is considered proper or prudent given the business risk it already faces.

In this study, we provide an empirical assessment on how far one important finance theory goes in understanding the relation between the risk in financial institutions' investment activities

[1] For example, in 2007, during the depth of financial crisis, the profit reaped by the trading desks of Goldman Sachs, and the loss incurred at the trading desks of Morgan Stanley, respectively dominated the operating results of all other units of the two investment banks.

and the risk they face in their brick-and-mortar business. The theory in our spotlight is that of background risk. The gist of this theory is that investors facing more non-hedgeable background risk may behavior as if they were more risk averse when making investment decisions (e.g., Pratt and Zeckhauser 1987; Kimball, 1993; Gollier and Pratt 1996; Eekhoudt, Gollier, and Schlesinger 1996; Fei and Schlesinger 2008). There is a growing body of literature that documents how various forms of background risk - mainly related to labor income, entrepreneurial income, and housing - affect individual investors' investments (e.g., Guiso et al. 1996; Gakidis 1997; Heaton and Lucas; 2000b; Gentry and Hubbard, 1998; Yao and Zhang, 2005; Palia, Qi and Wu, 2007).[2]

The prediction of the background risk theory on financial institutions' investment risk-taking behavior is straightforward – institutions facing higher risk in their main business would invest more conservatively. However, so far there is little empirical research on this prediction. One hurdle is conceptual: the background risk theory is mainly developed in the framework of individual investors. For it to be applied to financial institutions, one must be willing to make proper assumptions on their risk-aversion properties.[3] Another hurdle is data availability – due to various reasons such as competition concerns, financial institutions are typically unwilling to disclose the revenue they generate and the risk they face in their investment activities. For example, investment banks guard the information on the risk and profitability of their proprietary trading business as top secret.

In this study, we take advantage of newly available data on the investment portfolios of insurance firms, and analyze how insurers manage their risk-taking in the corporate bond market in relation with the risk in their insurance business. In particular, we test the prediction of the static version of the background risk theory that the amount of credit risk an insurer takes is negatively related to the insurance business risk it faces, as well as the prediction from the dynamic version of the theory that the negative relation between investment risk and insurance business risk is moderated by insurers' ability to smooth business risk intertemporally. Finally, we also examine whether background risk has any impact on the valuation of corporate bonds.

[2]In addition, a contemporaneous study by Dimmock (2009) examines the effect of background risk on investment decisions by university endowments.

[3]Nonetheless, we can justify a proper risk-aversion assumption for financial institutions based on the same justifications the literature has used for corporate risk management, such as the need to protect the value of on-going concern of a firm, and the lack of diversification of investments by shareholders and human capital of managers and employees.

The investment portfolios of insurance firms typically consist of a rich set of financial securities, ranging from Treasuries, agency bonds, corporate bonds, asset-backed securities, stocks, as well as derivative instruments. Out of the entire spectrum of financial risks they take, we single out corporate credit risk for our analysis (while controlling for other sources of financial risk), for the following reasons. First, credit risk taking is an important investment decision that insurers face given their substantial stake in corporate bonds. Insurance companies invest significant amount of their assets in corporate bonds. Insurers' investment in corporate bonds is highest among all categories of financial assets they have invested. According to the Federal Reserve Flow of Funds Accounts report, at the end of 2008 insurance companies (both property and life insurance companies) invest over thirty-five percent of their assets in corporate bonds, which collectively account for thirty percent of the outstanding U.S. corporate bonds. Second, corporate credit risk is largely unrelated to the underwriting risk insurers face in their main business, while interest rate risk, another important source of risk in insurers' investment portfolios, is typically related. Thus, insurers' main business risk can be indeed viewed as background risk when insurers decide the amount of corporate credit risk to take.

There is a large dispersion on the level of credit risk exposure across insurers. Figure 1 plots the percentage holding by insurers on corporate bonds with S&P rating below A, over the period of 1996 through 2008. Insurers are sorted into deciles by the percentage holding of bonds rated below A in their corporate bond portfolios. Insurers in the topmost decile hold 94 percent of such bonds while insurers in the bottommost decile virtually none such bonds. To what extent such a wide dispersion in credit risk taking can be related to background risk is an interesting question we try to answer.[4]

In testing the effect of background risk on insurers' credit risk taking, we combine various sources of information to construct a comprehensive database on insurers' operating characteristics, their corporate bond holdings and trades, as well as characteristics of each bond, for a 13-year sample period from 1996 and 2008. To quantify background risk, we consider two comprehensive measures for insurers' aggregated risk taking in their underwriting business: the volatility of

[4]Despite the obvious importance of corporate bond holding and trading on the pricing corporate bonds, few studies empirically examine holding and trading characteristics of institutional investors. Few exceptions are Ellul, Jotikasthira, and Lundblad (2010) and Da and Gao (2009) while their emphasis is on trading activities of mutual funds and insurance companies when corporate bonds are downgraded to "junk" status.

underwriting income and the volatility of non-investment underwriting cash flows. We measure credit risk in corporate bonds by credit ratings and yield spreads of insurers' corporate bonds by insurers weighted by the value of individual bond holdings. Background risk is measured using ex ante data (relative to portfolio credit risk measures) to attenuate the potential endogeneity problem.

As mentioned earlier we test two versions of the background risk effect. The first is the static effect. Early theoretical development on background risk is typically in a static, one period setting. In this setting, the total amount of background risk matters. Subsequent studies analyze the problem in a multi-period setting and introduce the possibility of intertemporal smoothing. For example, Heaton and Lucas (1997) show that intertemporal smoothing enables investors to borrow and lend money to smooth out temporary, non-persistent shocks to labor income without significantly affecting their stock investment or consumption decisions. In other words, the ability of intertemporal smoothing is an important factor for determining the effect of background risk. Such ability is, in turn, affected by factors such as the persistence of background-risk shocks as well as borrowing constraints, short-sale constraints, and transaction costs (see, e.g., Aiyagari and Gertler 1991; Aiyagari 1994; Heaton and Lucas 1996; Heaton and Lucas 1997). We term the effect of intertemporal smoothing on the relation between background risk and investment decisions the "dynamic" effect. There is already strong evidence that financial constraints are important in understanding insurers' behavior. For example, many studies in the insurance literature document the cyclical pattern of underwriting profitability, and attribute such cyclicality to capacity constraints and financial constraints caused by capital market imperfection (Winter 1994; Gron 1994; Harrington and Niehaus 2000). Naturally, we conjecture that both the static and dynamic effects of background risk may be present.

We find strong evidence for the static effect of background risk on insurers' corporate bond portfolios. The average credit rating of insurers' corporate bond holdings is positively related to volatilities in underwriting income and in non-investment cash flows, and the average credit spread of insurers' corporate bond holdings is inversely related to background risk. In other words, insurers with greater background risks prefer bonds with higher credit ratings and lower credit spreads (both indicative of lower credit risk). The result is robust after we control for various firm characteristics as well as the amount of risk insurers take in other parts of their investment portfolios, namely government bonds and equities.

We further perform two sets of analysis on the dynamic effect of background risk. First, we decompose the shocks to underwriting income and underwriting cash flows into persistent and temporary components. Our results show that persistent shocks have a significant impact on the level of credit risk insurers take. Secondly, we look at the effect of financing constraints in shaping the relation between background risk and investment risk. Insurers with tighter financing constraints have less ability to smooth shocks to their underwriting business. As a result, their investment risk-taking is more sensitive to their business risk. Three types of insurers by nature are more likely to have financing constraints: small firms, mutual insurers, and firms not affiliated with any large parental group.[5] We find that indeed for these insurers the effect of background risk on credit risk taking is stronger.

Our results are robust to alternative measures of background risk based on firm specific operational characteristics, including the percentage of business in long-term liability sectors (i.e., the long-tail business), the level of diversification across business sectors and geographic locations, and firm financial leverage. We find that firms with high leverage, operating more in the long tail business and less diversified in their underwriting business take less credit risk; such background risk effects are further stronger for firms facing greater financing constraints.

Finally, we examine the background risk effect during the recent financial crisis, when many financial institutions suffer large losses in the credit market. If insurers subject to higher background risk invest more conservatively, these insurers may suffer less during the crisis. We find that this is indeed the case. During 2007 and 2008, while insurers as a whole suffer investment losses, those with higher underwriting income volatility turn out to have substantially better investment performance (i.e., lower losses) than those lower underwriting income volatility.

In sum, the evidence is consistent with the effect of background risk on the investment decisions by financial institutions. While we do not expect background risk to explain the full link between insurers' credit risk taking and the business risk they face, our findings are consistent with the predictions from both the static and dynamic versions of the background risk theory. Our contribution

[5]This is because small firms have obvious disadvantage in financing their liabilities, mutual companies are less efficient in accessing the capital market than stock companies (Lamm-Tennant and Starks 1993; Harrington and Niehaus 2000), and finally, insurers unaffiliated with any parental groups cannot receive subsidies from other insurers.

to the empirical literature on background risk is to extend the test to the financial institutions. We also contribute to the literature on risk management of financial institutions, by showing substitutive effect in risk taking between insurers' investment portfolios and their main business. Such findings may have interesting implications in understanding why interconnections between various segments of the financial market may arise. To highlight, even though the risks from these market segments may be unrelated during "normal time", if the dependency in risk-taking decisions of financial institutions in these segments turns out to be strong, financial contagion could arise.

The remainder of the paper is organized as follows: Section 2 discusses the literature related to background risk. Section 3 discusses the data and our measures of credit risk for corporate bond portfolios. Section 4 provides empirical evidence on the relation between bond portfolio risk and background risk. Section 5 concludes.

2. Related Literature on Background Risks

Economic decisions are often made in the presence of multiple risks and in markets that are less than complete. Background risks are risks agents simultaneously face, not under their control, when they make decisions of endogenous risk taking. Conventional wisdom suggests that independent risks are substitutes for each other – adding a zero mean background risk to wealth should increase risk aversion to other independent risks. However, risk aversion is not sufficient to guarantee this. Pratt and Zeckhauser (1987), Kimball (1993), and Gollier and Pratt (1996), among others, are the most important works introducing the appropriate conditions, namely proper risk aversion, standard risk aversion, and risk vulnerability, for greater risk aversion in presence of independent background risks.[6] All these studies consider the background risk effect in the single-period framework.

Another group of studies analyze the effect of background risk in a multi-period setting and introduce the possibility of intertemporal smoothing. For example, Heaton and Lucas (1996) show that intertemporal smoothing enables investors to borrow and lend money to smooth out tempo-

[6]These studies provide definitions for proper risk aversion (Pratt and Zeckhauser 1987, page 145), standard risk aversion (Kimball 1993, page 593), and risk vulnerability (Gollier and Pratt 1996, page 1112). The effect of non-independent background risks are explored in Doherty and Schlesinger (1983) and and Fei and Schlesinger (2008))

rary, non-persistent shocks to labor income without significantly affecting their stock investment or consumption decisions. In other words, intertemporal smoothing ability is an important factor for determining the effect of background risk. Such ability is, in turn, affected by factors such as the persistence of background-risk shocks, as well as borrowing constraints, short-sale constraints, and transaction costs (see, e.g., Aiyagari and Gertler 1991; Aiyagari 1994; Heaton and Lucas 1996, 1997). There is strong evidence in the insurance literature, that financial constraints are important in understanding insurers' behavior. Studies document the cyclical pattern of underwriting profitability, and attribute such cyclicality to capacity constraints caused by capital market imperfection (Winter 1994; Gron 1994; Harrington and Niehaus 2000). Time-varying underwriting profitability in the insurance industry make investment decisions of insurance companies an ideal subject in testing the dynamic effect of background risk.

The literature so far has focused on two specific sources of background risk faced by investors. The first is the labor income risk. Bodie, Merton and Samuelson (1992) show that the presence of non-tradable stochastic future labor income reduces investors' demand for risky financial assets. Koo (1998) suggests that investors will take a smaller fraction of risky assets in their portfolio when they have liquidity constraints and uninsurable income risk. In addition, Heaton and Lucas (2000a) calibrate labor income risk with personal income data. They show that both labor income risk and the positive correlation between labor income and risky asset return tend to reduce investments in risky assets.

Housing ownership is another source of background risk. Cocco (2004) analyzes the impact of a housing decision on investors' portfolio choice. He points out a "crowding out" effect where housing investments constrain investors' investments in stocks. He also demonstrates that housing liquidation cost reduces the investor's incentive to invest in stocks. Yao and Zhang (2005) obtain similar results by modeling the portfolio choice of investors with both rental and house ownership options.

A small number of studies have empirically examined the effect of background risk on investors' portfolio choices. Guiso, Jappelli and Terilizzesse (1996) analyze the impact of labor income risk on portfolio choices using Italian household data. They find a significant negative effect of subjective income risk on household investment in stocks. Similarly, Heaton and Lucas

(2000b) examine the U.S. data and find that proprietary income risk reduces the share of risky assets in an investor's portfolio. In a more recent study, Angerer and Lam (2006) find permanent labor income risk significantly reduces the share of risky assets in investors' portfolio, while transitory income risk has little effect. In addition, Yao and Zhang (2005) find owning a business or real estate asset has a significant negative effect on a homeowner's stock market participation. These studies, however, focus on individual investors. In addition, Dimmock (2009) analyze the effect of background risk on the investments of university endowment funds. The impact of background risk on portfolio choices of financial institutions is not explored in existing literature.

3. Data and Methodology

3.1. Data and Sample

Our property liability insurers sample comes from the National Association of Insurance Commissioners (hereafter, the NAIC database) database for the period 1995 through 2007 (corresponding to insurers' corporate bond portfolios from 1996 to 2008). The NAIC database provides insurers' comprehensive demographic and detailed financial statements information for more than 3000 property liability insurers in the U.S. In addition, the above information is provided by the NAIC database at both insurance group level and individual insurer level. Our analysis is performed at individual insurer level as not all insurance groups disclose their combined financial statements to NAIC and some holding companies are not covered by the database because they are not insurance firms. Specifically, we require the NAIC firm code to be no less than 10000 to remove insurer groups. Following prior studies such as Cummins, Dionne, Gagne, and Nouira (2007), we eliminate firms with negative surplus, assets, losses or expenses. We also require that i) sample insurers are not reinsurance companies by requiring direct premium written to be positive, and ii) sample insurers have total assets no less than USD1 million. The resulting insurer sample contains 21513 firm-year observations and 2,290 unique firms for the 13-year period.

Our corporate bonds sample comes from schedule D of the NAIC data and the Fixed Investment Securities Database (hereafter, the FISD database) from 1996 to 2008.[7] Schedule D of insurance

[7] In the study, we use the lagged financial data to construct background risk measures and other control variables.

companies' annual reports classifies bonds into eight categories based on the nature of the issuer. For each of the category, it further classifies bonds into 4 different types based on whether the bonds have collaterals and the risk of the bonds.[8] The database provides detailed information on every bond holding for each insurer at the end of each year, including par value of bonds and fair value of bonds.[9]

The FISD database provides pricing data for all of the U.S. corporate bonds maturing in 1990 or later. It provides comprehensive information on each bond issuance and each issuer, such as coupon rate, coupon frequency, maturity, offering amount, and the country of an issuer.

We merge bonds in schedule D with bonds in the FISD database by their CUSIP. [10] We select sample bonds following Campbell and Taksler (2003). In the eight types of bonds, we consider public utilities, industrial and miscellaneous bonds that are not backed by other loans as our sample corporate bonds. We also restrict our sample to fixed-rate U.S. dollar bonds that are noncallable, nonputtable, nonsinking funds, and nonconvertible. Finally, we remove AAA-rated bonds because the NAIC data for these issues are found by prior studies to have errors (Elton et al. 2000, 2001, Campbell and Taksler, 2003).

Panel A of Table 1 shows the number of unique corporate bonds during the sample selection process. For the period of 1996 through 2008, combining corporate bonds reported in Schedule D of the NAIC database and the FISD database, we obtain 46,247 unique bonds. The enforcement of fixed-rate and other restrictions further reduce the number of bonds. We obtain a final sample corporate bonds with 30,436 unique corporate bonds.

Thus financial statement data lag the corporate bond data by 1 year.

[8]See Appendix A for details of Schedule D classifications.

[9]Schedule D of insurance companies' annual statements contains six parts. Part 1 shows all long-term bonds owned by insurers at the end of each year; part 2 shows all preferred stocks and common stocks owned at the end of each year; part 3 shows all long-term bonds and stocks acquired during the year and held at the end of the year; part 4 shows all long-term bonds and stocks sold, redeemed or otherwise disposed of during the year; part 5 showing all long-term bonds and stocks acquired during the year and fully disposed of during the same year; part 6 shows valuation of share of subsidiary, controlled or affiliated companies. In our analysis, we use the information from Part 1.

[10]The Schedule D data provided by National Association of Insurance Commissioners (NAIC) differs from a conventionally used bond transaction database, known as the NAIC Schedule D data reconciled by Mergent. The Mergent version data consists of all 1995 to 2003 bond transactions by property and liability insurance companies, life insurance companies, and health maintenance organizations (HMOs). See Hong and Warga (2000) and Campbell and Taksler (2003) for the details of this database. There are two limitations associated with the Mergent version of schedule D data. First, it does not include the identity of the insurance companies which trade the bonds. Second, it has all the trading data, but does not have the year-end holding information. In other words, the Mergent version of Schedule D does not include Part 1 information from the original Schedule D data.

Panel B of Table 1 provides summary information of insurers' corporate bond holdings for each sample year. The number of bonds ranges from 5,398 (year 1996) to 7,202 (year 1999). An average insurer holds 21 corporate bonds in 1996 and 34 bonds in 2008. The invested assets in corporate bonds also increased from \$66.42 billion to \$108.23 billion. Insurance firms invested mostly in investment grade bonds (about 95% of corporate bond investment) rather than junk bonds. We also find that insurance firms tend to hold short term and median term bonds. For example, on average, insurers hold 48% in bonds due in five years, 41% of bonds due in 5 to 10 years, and only 11% on bonds longer than 10 years. Such tendency to hold bonds less than 10 years has been more obvious in recent years.

3.2. Credit Risk Measures

We evaluate the amount of credit risk taken by property liability insurance companies using the average credit ratings and credit spreads of corporate bonds held by insurers.

The first measure of credit risk taking is the average bond rating for an insurer's bond portfolio. The FISD database provides bond rating made by four rating agents: Duff & Phelps' rating, Fitch rating, Moody's rating, and S&P rating. While each rating agent uses its own scale system, there is a general consensus on the equivalent scale comparison. Based on the rating scale comparison, we convert the letter bond ratings into numerical rating scheme ranging from 3(D) to 27(AAA).[11] Higher numerical rating indicates lower credit risk. The rating schemes of different rating agencies are provided in Appendix B. We primarily rely on the S&P rating in our analysis. Each year, we obtain the rating of a bond assigned by S&P closest to the year end. When S&P rating is not available, Moody's rating, Fitch rating, and Duff & Phelps' rating (in this order) are alternatively used. With credit rating of each corporate bond, we calculate the holding-weighted average of all corporate bond ratings as the credit rating of the portfolio.

$$Rating_{i,t} = \sum_{j=1}^{N} w_{i,j,t} * Rating_{j,t} \qquad (1)$$

[11]The rating scheme here inverts the number ratings provided in the FISD database, where, in items of S&P rating scheme, 1=AAA,, 25=D, 26=SUSP, and 27=NR. We exclude bonds with SUSP and NR ratings.

Our second measure of credit risk taking is the average credit yield spreads of insurer bond portfolios involves three steps. Its estimation involves three steps. In the first step, we compute the yield of each bond held in the sample at the end of each year. Specifically, we estimate bond yield with the following equation (e.g., Fabozzi 2003):

$$P_{j,t} = \sum_{j=1}^{N} \frac{C}{(1 + r_{j,t})^{\upsilon}(1 + r_{j,t})^{t-1}} + \frac{M}{(1 + r_{j,t})^{\upsilon}(1 + r_{j,t})^{n-1}} \tag{2}$$

where $P_{j,t}$ is the fair market value of the bond j at the end of year t.[12] υ is the ratio of days between year end and next coupon to days in six-month period, C_j is the coupon payment, M_j is the face value of the bond, and n is the number of remaining coupon payment. $r_{j,t}$ is the yield to maturity of the bond during the 6-month period. Doubling $r_{j,t}$, we obtain the annual yield to maturity of the bond at time t. In the second step, following Collin-Dufresne and Goldstein (2001) and Campbell and Taksler (2003), we match each corporate bond with a treasury bond that has the closest remaining time to maturity. For the benchmark Treasuries, we use the CRSP Fixed Term indexes, which provide monthly yield data for notes and bonds of 1, 2, 5, 6, 10, 20, and 30 target years to maturity and use a linear interpolation scheme to estimate the entire yield curve. The credit spread is the yield to maturity on each bond in the sample and its spread over the closest benchmark U.S. treasury at the end of a year.

$$Spread_{i,t} = r_{j,t} - r_t^B \tag{3}$$

where $r_{j,t}$ is the estimated yield to maturity of corporate bond j at the end of year t, and r_t^B is the estimated yield to maturity of Treasury bond that at the end of year t.

3.3. Background Risk Measures

Background risk of investment portfolios of insurance companies stems from the uncertainty of their underwriting business, jointly determined by firm operating and financial leverages. We

[12] The Schedule D data provides the fair market value for each holding in insurers' bond portfolios. For bond transactions, we use the actual costs (the buying price) and consideration (the selling price) for their fair market values.

assess the background risk of an insurer based on the uncertainty of the insurer's profitability or cash flow from its underwriting business. To be specific, the first measure of background risk is the standard deviation of each insurer's underwriting income per dollar of the insurer's total assets:

$$UIVOL_{i,t} = Std(\frac{\text{Underwriting Income}_{i,t}}{\text{Total Assets}_{i,t}}) \tag{4}$$

where underwriting income is from the income statement;[13] total invested assets are from the balance sheet. In each year t from 1996-2008, we use the prior 10 year data of an insurer to estimate its standard deviation of underwriting income scaled by total invested assets. We name this measure UIVOL of year t-1. Firms with fewer than 5-year observations over the past 10-year period are excluded. This background risk measure lumps up various sources of insurer underwriting exposures in a single measure.

The second background risk measure is the volatility of underwriting cash flow per dollar of the insurer's total assets:

$$UCVOL_{i,t} = Std(\frac{\text{Underwriting Cash Flow}_{i,t}}{\text{Total Assets}_{i,t}}) \tag{5}$$

where underwriting cash flow is cash from underwriting, reported in the cash flow statement.[14] We apply the same procedure to estimate UIVOL in gauging UCVOL.

The use of prior 10-year underwriting income and underwriting cash flows to calculate the volatility is to attenuate the endogeneity problem, which may arise if both underwriting risk and credit risk taking are jointly and contemporaneously determined by factors unobservable to an econometrician. Such unobservable influence per se is not necessarily anything against the background risk theory. But without controlling for such factors one may introduce correlations between the explanatory variables (background risk measures) and the error terms, giving rise to

[13] Underwriting income is the net underwriting gain or loss reported in the statement of income of insurers' statutory annual statements. It is computed as the premiums earned deducting i) losses incurred, ii) loss expenses incurred, iii) other underwriting expenses incurred.

[14] Reported in the cash flow statement of insurers' statutory annual statement, cash from underwriting is computed as premiums collected net of reinsurance net of loss and loss adjustment expenses paid and underwriting expenses paid, plus other underwriting incomes. Operating cash flow for insurers also includes investment income. Thus we use cash from underwriting, instead of operating cash flow, to construct our background risk measure

difficulty in statistical inference. Using lagged background risk measures avoids this issue.

3.4. Control Variables

We include a rich set of control variables to isolate the influence of insurers' firm characteristics and other alternative factors on the background risk effect. Larger firms, firms having longer history, and having better underwriting performance may have more rooms to accommodate greater investment risks, thus diluting the impact of background risks. We therefore include firm size, firm age, and price index as control variables. Moreover, insurers face investment risks other than credit risks. Here we consider four additional investment risks: systematic risk of insurers' investments in common stocks, interest rate risk of insurers' Treasury bonds, agency bonds, and corporate bonds, percentage investment in government bonds, and percentage investment in stocks. Financial, insurers' organization may also affect their investment choice. To be specific,

- LGSIZE: the logarithm of the total book value of assets at the end of each year, obtained from insurers' balance sheets.
- LGAGE: the logarithm of firm age, computed as the difference between the reporting year and the year when the firm is founded.
- PROFIT: underwriting profit, measured as the ratio of an insurer's earned premiums to its incurred losses. Price index measures an insurer's profitability.
- DURATION: the Macaulay duration for an insurer's bond portfolio. percentage of common stocks in total invested assets.[15] The inclusion of bond duration is to control for an insurer's interest rate risk.
- BETA: the average beta of an insurer's equity portfolio weighted by year end's fair market value of each stock holding.[16]

[15]Schedule D, Part 1 of insurers' annual statements reports insurers' year-end positions in treasury bonds, agency bonds, and municipal bonds, in addition to corporate bonds (See Appendix 1 for details). We exclude structured bonds, callable, puttable, convertible, foreign and euro bonds. We obtain bond features, such maturity and coupon information, from the FISD database.

[16]Schedule D, Part 2 (Section 2) of insurers' annual statements reports all common stocks owned by an insurer at

- GOVINV: the ratio of investment in government bonds to total invested assets.
- STKINV: the ratio of investment in stocks to total invested assets.
- NONSTK: dummy variable that equals to one if an insurer is a mutual, reciprocal company, or affiliated with Llyods of London, and zero if it is a stock insurer.
- NONAFF: indicator equal to one if an insurer is a stand-alone company (not affiliated with any insurance group or in a single-insurer group) and zero if it is affiliated with a group having more than one member firm.

3.5. Summary Statistics

Panel A of Table 2 shows the time-series averages of summary statistics credit risk, background risk, and control variables for two samples. The left is so called "PL Insurer Universe", which includes all property liability insurers covered in the NAIC database that meet our requirements specified in section 3.1. The right is so called "Sample Insurers" which include insurers with covered by both the NAIC data and the FISD data. The time series average of cross-sectional mean (median) of bond rating is 21.80 (22.02), corresponding to a letter rating of S&P rating of A-. This is consistent with the general consensus that insurers are prudent and they typically invest in highly rated bonds. The time-series means of credit spread is 2.13% with a minimum of 0.92% and a maximum of 24.78%. In terms of background risk measures, mean UIVOL for all insurers is 4.62%, while mean UIVOL for our sample insurers is 3.77%. Also, the mean UCVOL is 9.15% for the insurer universe while it is 7.27% for sample firms. The result shows that sample firms are slight less volatile than insurer universe. This is consistent with univariate results for firm size and age where sample firms typically are larger and older than PL universe firms – the average book value of assets for firms in PL insurer universe is USD641.41 million while that of sample firms is USD859.03 million; the average age of PL universe firms is 44.72 years while that of sample insurer is 47.29 years. Except the above, the univariate statistics for price index,

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year end. We use daily stock returns within a calendar year to estimate the year-end equity beta of a stock. To account for the effect of nonsynchronous trading, we estimate the market model for each using market returns up to five daily leads and five daily lags, in addition to the contemporaneous term. Following Dimson (1979), the stock beta is the sum of the estimated coefficients on leads, lags, and contemporaneous market returns.

equity beta, duration of bond portfolios, investment in government bonds and stocks, and insurers' organization forms for the two samples are quite similar.

Panel B of Table 2 reports the correlation coefficients among bond portfolio risk and insurer characteristics. Our two proxies for bond portfolio risk are highly negatively correlated: the correlation between bond portfolio rating and credit spread is -0.56: insurers of highly rated corporate bond portfolios (i.e., good rating scores based on our number rating schedule) have a low credit spread. Without any surprise, our two proxies for background risk are highly positively correlated: the correlation between UIVOL and UCVOL is 0.70. The correlation between credit risk measures and background risk proxies are in line with the background risk hypothesis: the correlation between bond rating and UIVOL (UCVOL) is 0.20 (0.18) and the correlation between portfolio credit spread and UIVOL (UCVOL) is -0.15 (-0.16).

Several side results are also worth to mention. Firm size is inversely related to bond rating. In other words, large insurers, potentially less risk averse, tend to invest in bonds with lower rating scores. Also, rating is inversely correlated with bond duration (correlation = -0.19). In words, insurers owning higher rated corporate (lower credit risk) bonds tend to hold shorter term bonds (lower interest rate risk). It is possible that the same factor (e.g., insurers' risk appetite) is driving insurers' credit risk and interest rate risk taking. Lastly, the correlations among credit risk measures and insurer equity beta and price index are low.

4. Results

4.1. Static Background Risk Effect

We start the analysis by looking at the average credit ratings and spreads across decile bond portfolios sorted by background risk. In each year, we sort firms into deciles based on year t-1 UIVOL or UCVOL and compute averaged ratings and credit spreads of each decile portfolio. To account for serial correlations across decile portfolio returns, we apply the Newey-West (1987) procedure with a 2-year lag when computing the t-statistics for the difference in D10 and D1 portfolios.

Reported in Table 3, there is a wide spread for background risk measures across decile portfolios. For example, the average UIVOL is 0.60% for D1 insurers (with the lowest background risk) while it is 12.06% for D10 insurers (with the highest background risk). Accordingly, the average corporate bond portfolio number rating for insurers in the D1 portfolio is 19.15 while that for D10 insurers is 22.88. The difference of 3.73 (t=12.83) is statistically significant at the 1 percent significance level. The difference is economically significant as well – 19 corresponds to a BBB rating for S&P and 23 corresponds to A+. Based on the definition of S&P ratings, insurers in the lowest background risk group on average hold lower medium grade bonds while insurers in the highest background risk group hold upper medium grade bonds. Moreover, the average yield spread for the D1 group is 2.54% while that for the D10 group is 2.05%. The difference of -0.49% (t=-3.25) in yield spreads between D10 and D1 groups is significant at the 1 percent significance level. We obtain similar results when sorting insurers using UCVOL. These results provide preliminary supports to the background risk effect hypothesis.

Further, we perform panel regressions to examine the effect of background risk on credit risk taking of property and liability insurance companies. We include fixed firm and time effects in the regression by including firm dummies and year dummies in the regressions. Moreover, as our sample firms come from the same industry for multiple years, the residuals may be correlated across firms and/or across time. We follow Petersen (2006) to allow for correlation of residuals using the two-way clustering method. The models are specified as following:

$$Rating_{i,t} = \alpha + \beta^1 \mathbf{X}_{i,t-1} + \mu_i^1 + v_t^1 + \varepsilon_{i,t}^1 \tag{6}$$

$$Spread_{i,t} = \alpha + \beta^2 \mathbf{X}_{i,t-1} + \mu_i^2 + v_t^2 + \varepsilon_{i,t}^2 \tag{7}$$

where Spread$_{i,t}$ (Rating$_{i,t}$) is the yield spread (credit rating) of bond portfolios of insurer i at the end of year t; X$_{i,t-1}$ is a vector of insurer i's background risk measure and other firm characters in year t-1; μ_i^k(k=1,2) is a firm-specific intercept; v_t^k(k=1,2) is the time-specific intercept; $\varepsilon_{i,t}^k$ (k=1,2) is a random error term assumed to be possibly heteroskedastic and correlated within firms and years.

The results are reported under "total background risk" of table 4. We consider nine control variables and their definitions are provided in section 3.4. Panel A shows the coefficients of regressions of credit ratings. The coefficient on UIVOL is 1.72 (t=3.93), significant at the 5% level; the coefficient on UCVOL is 0.62 (t=3.15). The results suggest that firms with greater background risk tend to hold corporate bonds with higher ratings. Similarly, Panel B of Table 4 shows insurers' background risk is negatively related to insurers' corporate bond yield spread. For instance, the coefficients on UIVOL and UCVOL are -0.73 (t=-2.33) and -0.53 (t=-2.32) respectively. The evidence indicates that background risk has significant influence on insurer credit risk taking, even after controlling for insurer characteristics and other investment risks taken by insurers.

A few control variables also have significant impact on insurers' corporate bond credit risk taking. DURATION is negatively related to portfolio rating and positively related to portfolio yield spread. Insurers taking more interest rate risk also take more on credit risk. Moreover, stock investment is negatively related to credit rating and positively related to yield spread. That is, if insurers invest more in stocks, they would take more risk in corporate bond. From the relationship among different invested assets, the results suggest that insurers have their own risk preference and such preference is reflected in both credit risk taking and other type of investments.

4.2. Intertemporal Smoothing - the Dynamic Background Risk Effect

4.2.1. Persistent versus Idiosyncratic Shocks

As discussed in the early sections, not all background risks would affect asset allocation in the same way when the dynamic effect is considered. Lucas (1994) shows that uninsurable idiosyncratic risk has little impact on consumption allocation in a long-horizon model as agents can diversify their idiosyncratic risk through borrowing or lending. Despite that later studies show the extent of trade to smooth the uninsurable idiosyncratic risk is constrained by borrowing constraints, short-sale constraints, and transaction costs (see, e.g., Aiyagari and Gertler 1991; Aiyagari 1994; Heaton and Lucas 1996; Heaton and Lucas 1997), we expect insurers experiencing more systematic or permanent shocks will be more risk averse in their corporate bond risk taking as persistent shock are most difficult to smooth.

We measure the persistence of shocks to underwriting income and underwriting cash flows by the first order auto-regressive (AR(1)) coefficient in firm-specific time series regressions. Use the underwriting income (UI) measure as an example. We perform AR(1) regressions using data from year t-9 through t for firm i:

$$UI_{i,t-k} = \alpha_i + \beta_{i,t}^{UI} UI_{i,t-k-1} + \varepsilon_{i,t-k} (k = 0\ through\ 9) \tag{8}$$

where $\beta_{i,t}^{UI}$ measures the persistence of the underwriting income shock.[17] A higher value of $\beta_{i,t}^{UI}$ indicates more persistent shock, which is more difficult to smooth. Based on Equation (8), we decompose total underwriting risk to the variance of a persistent shock and the variance of an idiosyncratic shock. That is,

$$Var(UI_{i,t}) = \beta_{i,t}^2 Var(UI_{i,t-1}) + Var(\varepsilon_{i,t}) \tag{9}$$

As long as UI is a stationary process, we consider $\beta_{i,t}$*UIVOL as the measure for persistent background risks.

The last two columns in Panel A of Table 4 reports the effects of permanent background risk on bond credit ratings. The coefficient on $\beta_{i,t}^{UI}$*UIVOL is 2.52 (t=2.64), significant at one percent level; the coefficient on $\beta_{i,t}^{UC}$*UCVOL is 1.35 (t=2.57), also significant at one percent level. Note the significance levels for permanent background risk measures are larger than those for total background risk measures. The last two columns in Panel B of Table 4 show the effects of permanent background risk on bond yield spread. The results are consistent with what we find in Panel A. These results confirm our hypothesis that persistent shocks have a greater impact on insurers' credit risk taking.

4.2.2. The Effect of Financing Constraints

Financing constraints limit firms' ability to smooth background risk shocks. Therefore insurers' credit risk taking would be more sensitive to background risk when it is harder or more expensive for them to raise money. We examine this effect here.

There is a large literature on financing constraints, part of which focusing on the measurement

[17]The mean of $\beta_{i,t}^{UI}$ across all sample firm-year observations is 0.24 with a standard deviation of 0.35. The mean and standard deviation of $\beta_{i,t}^{UI}$ are similar. We exclude observations when the absolute values of their $\beta_{i,t}^{UI}$ and $\beta_{i,t}^{UC}$ are close to 1.

of financing constraints. A popular measure is the KZ index advocated by Kaplan and Zingales (1997), Lamont, Polk and Saa-Requejo (2001) and Baker, Stein and Wurgler (2002). However, the KZ index is developed for industrial firms. We suspect that financial institutions, such as insurance firms, have different relationship between accounting variables and their financial status. As a result, we do not use the KZ index to measure financing constraints for insurers.

Rather, we use three proxies for financing constraints. The first one is based on firm size. The role of firm size is similar to the wealth effect on individuals' investment. Like wealthy people have more money to invest and tend to invest more on risky assets, large firms have more to invest and may prefer to take more risk in investment. We construct a dummy variable, SMALL, that equals to one for the bottom quintile insurers sorted by book total assets and zero for other quintiles. We expect small firms have more financial constraints and the background risk effect on bond portfolio credit risk is stronger.

The second is based on the ownership. Lamm-Tennant and Starks (1993) find that stock insurers have a better access to the capital market relative to mutual insurers. Similarly, Harrington and Niehaus (2002) present evidence that mutual insurers have higher ex ante target capital to liability ratios than stock insurers. In addition, the capital to liability ratio is more sensitive to income for mutual insurers than for stock insurers. Enlighten by these findings, we hypothesize that stock insurers have less financing constraints than mutual insurers. We construct a dummy variable NONSTK to proxy for ownership structure. NONSTK equals to 1 for mutual insurers and 0 for stock insurers.

The third proxy for financing constraint is group affiliation. An insurance company can be a stand-alone firm or a member of a conglomerate group. Insurers affiliated with a conglomerate group are more likely to have access to the internal capital market of the conglomerate, which helps reduce external financing constraints. We construct a dummy variable, NONAFF, to proxy the status of affiliation. NONAFF equals to 1 for stand-alone insurers and 0 otherwise.

The results are reported in Table 5. Panel A shows that firm size and affiliation have significant impact on the relationship between background risk and credit rating. For instance, the coefficient on UIVOL*SMALL is 1.12 (t=2.06) and the coefficient on UIVOL*NONAFF is 2.04 (t=2.13). That is, the effect of background risk on credit rating is stronger for small firms and non-affiliated firms. Moreover, Panel B shows that firm size and affiliation have significant impact on the relationship between background risk and yield spread. We find that the coefficients on the interaction terms based on firm size and affiliation are significantly negative, suggesting small firms or non-affiliated firms tend to hold corporate bonds with lower yield spreads. Finally, we do not find evidence that ownership structure affects background risk effect.

4.3. Alternative Measures of Background Risks

We have been using the standard deviations of underwriting income or cash flow to measure background risk in the above analysis. In this section, we perform robustness check by measuring background risk using other proxies. The four additional measures are selected based on the business characteristics of insurance industry. The first proxy is insurers' leverage ratio (LEVERAGE). For insurers, the leverage ratio is not just a financial ratio. More importantly it measures the total liability coming from insurance underwriting business to the total assets. The second proxy is the percentage of long tail insurance business (LONG). The longer the claim tail, the higher the background risk. The other two measures are diversification across insurance lines (HERFL) and across states (HERFS). The details on the construction of these variables are provided in Appendix B.

Table 6 looks into the effect of alternative background risk on credit risk taking. Firm size, long tail business, and business-line diversification has significant impact on both credit ratings and yield spreads. For instance, the coefficient on leverage is 0.45 (t=2.65) in the credit rating regression, while it is -0.25 (t=-2.11) in the yield spread regression. In untabulated tables, we find that the correlations among the four proxies are quite low. Thus, we include all of them in the regressions and still find leverage, long tail, and Herfindale index of business lines are significant in the rating regressions, while only leverage and long tail are significant in the yield spread regressions. The evidence suggests that the alternative proxies capture different components of overall background risk.

Table 7 examines the impact of financing constraints on background risk effects. As geographic herfindale index does not show any relationship with credit risk taking, we do not include it in this table. While the results varies for different background risk measures, in general, we find firm size has strong impact on the role of background risk on credit risk taking. Consistent with intertemporal smoothing hypothesis, we find that the effect of background risk is stronger for very small firms.

4.4. Background Risk and Investment Performance During the Financial Crisis

The heart of the background risk effect is that investors with greater background risk would be more conservative in investments. The recent financial crisis offers us a unique opportunity to see if the background risk effect truly exists. Risky investments experience substantial losses during the financial crisis. If background risk has an effect on firm investments, we would see high background risk firms, who are prudent in investments, have lower losses during the crisis period. The realized capital gains/losses are readily reported in insurance companies' income statements, allowing us to perform a quick analysis on the effect of background risk on investment performance.

We perform a regression analysis to test the crisis effect. The sample period spans from 2001 to 2009. As shown in Figure 3, insurers' realized capital gain ratios are negative in 2007 and 2008 while they are positive in all other years. As a result, to see the effect of financial crisis on the background risk effect, we construct a NONCRISIS dummy, equal to zero for 2007 and 2008 and one otherwise. The regression includes the measure of background risk and the interaction of background risk measures with the NONCRISIS dummy. The coefficient on the background risk measure captures the effect of background risk on investment performance in the crisis period while the coefficient on the interaction stands for the the differential effects in the non-crisis period and the crisis period. Consistent with regressions in prior sections, the regression includes firm size, firm age, the group dummy, and the stock ownership dummy as control variables and it considers firm fixed effects.

The results are presented in Table 8. The first column shows the result when underwriting income volatility is used to gauge background risk. The coefficient on UIVOL is 2.98 (t=3.29), suggesting a significant relation between background risk and investment performance during crisis period. We also find that the coefficient on UIVOL*NONCRISIS is -2.70 (t=-3.39), suggesting a significant difference in the background risk effect on investment performance between the crisis and non-crisis periods. We obtain similar results when other background risk measures are used. The evidence support that insurers exposed to higher background risk suffer less in their investment performance during the recent financial crisis.

5. Conclusions

Insurance companies hold a substantial stake in the corporate credit market. This study presents empirical evidence on an important economic prediction that variability of insurers' underwriting business, which is typically uncorrelated with risk of insurers' investment portfolios, affects insurers' credit risk taking behavior. Using data on property and liability insurance firms for the period between 1996 and 2007, we document empirical evidence that that insurers facing greater background risk take less credit risk. A further interesting finding is that the background risk effect is stronger for insurers facing more persistent underwriting business shocks, and for insurers facing tighter financing constraint, such as those not affiliated with insurance groups or having mutual ownership. Moreover, we find insurers exposed to greater background risk, potentially more conservative in their investment practice, suffer less in their investment performance during the recent financial crisis. These results are in support of the theory on background risk.

Recognizing the fact that background risk takes effect among institutional investors is important. Background risk is potentially a mechanism for the inter-connection among various sectors of the financial market, and especially for strong downside correlations among various financial businesses. This can be understood in light of recent turmoil in the financial markets, when financial institutions rush to unwind risk-taking behavior in one corner of the industry when they face heightened risk in another corner, even though during "normal periods" of time the performance of such business are much uncorrelated.

Appendices

A. Bond Classifications by Schedule D

We obtain property/liability insurers' corporate bond holding information from schedule D of the National Association of Insurance Commissioners data (NAIC data). Schedule D classifies bonds into eight different types based on the nature of issuer:

- Government bonds, including US Government bonds and Other Government bonds
- States, Territories and Possessions bonds
- Political Subdivisions of States, Territories and Possessions bonds
- Special Revenue, Special Assessment Obligations of agencies and authorities of governments and their political subdivisions bonds
- Unaffiliated Public Utilities bonds,
- Unaffiliated Industrial and Miscellaneous bonds,
- Credit Tenant Loans, and,
- Parent, Subsidiaries and Affiliates Bonds.

For each bond category, schedule D future provides four sub-classifications based on the nature of bonds:

- Bonds not backed by other loans. These are bonds without collaterals or with non-financial assets as collaterals.
- Loan-backed bonds. These are asset backed bonds that are backed by loans other than mortgages, such as home equity loans, auto loans, credit card receivables, student loans, and other loans.
- Collateralized mortgage obligations. These are bonds backed by mortgages.

- Other structured securities. These are other types of structured securities that do not belong to asset-backed bonds or collateralized mortgage obligations.

We use the following procedures to select our sample corporate bonds:

- Choose unaffiliated public utilities, unaffiliated industrial and miscellaneous bonds as our initial corporate bonds sample

- Only include ”bonds not backed by other loans” from the four types of different loans. The reason is that the other three kinds of bonds are structured bonds whose pricing is complicated and whose risk is difficult to evaluate

- Require sample bonds to have positive face value and fair value

- Exclude observations with obvious error in CUSIP

This results in a clean sample of 57,535 unique corporate bond issues from the NAIC SD database.

B. Corporate Bond Ratings

The following table summarizes rating grades of four rating agencies, S&P, Moody's, Fitch, and Duff&Phelps and the associated number ratings used in the analysis.

Number Rating	**S&P**	**Moody's**	**Fitch**	**Duff&Phelps**
27	AAA	Aaa	AAA	AAA
26	AA+	Aa1	AA+	AA+
25	AA	Aa2	AA	AA
24	AA-	AA3	AA-	AA-
23	A+	A1	A+	A+
22	A	A2	A	A
21	A-	A3	A-	A-
20	BBB+	Baa1	BBB+	BBB+
19	BBB	Baa2	BBB	BBB
18	BBB-	Baa3	BBB-	BBB-
17	BB+	Ba1	BB+	BB+
16	BB	Ba2	BB	BB
15	BB-	Ba3	BB-	BB-
14	B+	B1	B+	B+
13	B	B2	B	B
12	B-	B3	B-	B-
11	CCC+	Caa1	CCC+	
10	CCC	Caa2	CCC	CCC
9	CCC-	Caa3	CCC-	
8	CC	Ca	CC	
7	C	C	C	
6			DDD	
5			DD	DD
4			D	
3	D		D	
2	SUSP	SUSP	SUSP	SUSP
1	NR	NR	NR	NR

C. Definitions of Alternative Background Risk Measures

- LEVERAGE: the ratio of total liability to total assets.

- LONG: net premiums written (NPW) in long-tail lines of insurance divided by total NPW. We include auto liability, other liability, farm owners/homeowners /commercial multiple peril, medical malpractice, workers compensation, aircraft, and boiler and machinery as long-tail lines.

- HERFL: this is the Herfindahl index that measures the concentration degree of an insurer. It is the sum of squared ratio of premium earned in a business line of an insurer to the total premium earned by the insurer. That is,

  $$HERFL_{it} = \sum(\frac{PE_{ijt}}{TPE_{it}})^2 \qquad \text{(B1)}$$

  where PE_{ijt} is the premium earned of insurer I in line j and year t, and TPE_{it} is the total premium earned by insurer I in year t. the business line classification j is based on the Best Average and Aggregates.

- HERFS: the sum of the squared percentages of insurance premiums written in each state to the total premiums written in all states by an insurer:

  $$HERFS_{it} = \sum(\frac{PW_{is}}{TPW_{it}})^2 \qquad \text{(B2)}$$

  where PW_{is} is premiums written in state s (s=1,2,,51) of insurer i, and TPW_{it} is total premium written for all sates. Herfindahl indices evaluate line and geographical diversifications. The higher the HERFS, the lower diversification exists.

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Table 1: Bond Sample Selection and Summary Statistics

The table describes the bond sample construction procedure and by-year statistics of bond characteristics. Panel A shows the procedure to obtain our sample corporate bonds. We begin our sample with corporate bond holding data from Schedule D of National Association of Insurance Commissioners (NAIC) annual statement files. We remove bonds with missing or zero par value and non-positive fair value. Then we merge bond issues in the NAIC Schedule D with bonds in the FISD. Finally, we delete bonds with enhancement, asset-backed, Yankee, Canadian, foreign currency. The number of bond issues in panel A is to count the distinct bonds in the sample period. Panel B presents characteristics of the corporate bond sample over time. It includes i) the number of distinct bonds, ii) the aggregate market value of bonds in our sample, iii) percentage of investment grade bonds, iv) percentage of speculative bonds, v) percentage of bonds with time to maturity fewer than 5 years, vi) percentage of bonds with time to maturity between 5 and 10 years, and vii) percentage of bonds with time to maturity longer than 5 years. All the percentages are computed in terms of market value. For all-year statistics, the number of bonds is the number of unique bond issues over the sample period. The rest statistics are the average of the numbers over time. The sample period is from 1996 to 2008.

Panel A: Bond Sample Construction Procedure

	Number of Bonds
Bonds after merging with the FISD data	46,247
Final sample of Fixed-rate US dollar bonds (noncallable, nonputtable, nonsinking fund, nonconvertible, non-asset-backed, non-credit enhancement, and non-AAA-rated)	30,436

Panel B: Corporate Bond Characteristics in Each Sample Year

Year	# of Bonds	# of Bonds Per Insurer	Bond Value (Billion)	% in Investment Grade	$\% \leq 5$ years	$5 < \% < 10$ years	$\% \geq 10$ years
1996	5398	21	66.42	96.28	36.2	50.56	13.24
1997	6104	22	72.78	96.45	39.23	48.65	12.12
1998	6742	23	79.21	96.42	42.86	44.79	12.35
1999	7202	24	83.05	95.88	44.61	43.58	11.81
2000	7113	26	86.68	96.52	50.03	39.09	10.88
2001	7078	28	97.05	95.64	47.35	41.47	11.19
2002	6862	31	98.3	94.62	46.6	42.06	11.33
2003	6488	36	86.41	94.22	45.27	41.61	13.11
2004	6623	36	108.23	95.51	47.48	40.94	11.57
2005	6227	35	103.23	95.12	52.19	38.58	9.23
2006	6036	35	104.41	95.21	53.51	36.72	9.77
2007	5943	34	102.86	94.84	55.6	35.66	8.74
2008	5705	34	97.27	96.33	58.23	34.5	7.26

Table 2: Summary Statistics of Insurer Characteristics

Panel A of this table shows the summary statistics of all insurers covered in the NAIC property-liability database (PC Insurer Universe) and insurers included in our sample that report their financial data and corporate bond holding (Sample Insurers). It presents the time-series averages of cross sectional statistics, including number of observations, mean, median, standard deviations, minimum, and maximum. RATING is the fair-value weighted average ratings of bonds held by an insurer. SPREAD is the fair-value weighted average spread (difference between the yield of the corporate bonds and the yield of benchmark portfolio) of bonds held by an insurer. UIVOL is the standard deviation of net underwriting gain (loss) in the prior 10 years scaled by invested assets in corporate bonds at the end of the prior year. UCVOL is the standard deviation of cash flow from underwriting in the prior 10 years scaled by invested assets in corporate bonds at the end of the prior year. SIZE is the total book value of assets in million dollars at the end of each year. AGE is firm age, computed as the difference between the year of reporting and the firm found year. PROFIT (the inverse of loss ratio) is the ratio of an insurer's earned premiums to incurred losses. BETA is the holding-weighted averaged beta for stocks held by each sample insurer. DURATION is the bond fair value-weighted average of durations of all government and corporate bonds held by each sample insurer. Panel B of the table reports the correlations among the variables. The sample period is from 1996 to 2008.

Panel A: Summary Statistics

	PL Insurer Universe						Sample Insurers					
	N	Mean	Median	Std	Min	Max	N	Mean	Median	Std	Min	Max
							Credit Risk Measures of Insurers Corporate Bond Portfolios					
RATING	–	–	–	–	–	–	1134	21.8	22.02	1.34	12.48	25.03
SPREAD (%)	–	–	–	–	–	–	1134	2.13	1.95	1.16	0.92	24.78
							Background Risk Measures					
UIVOL (%)	1819	4.62	3.09	4.39	0.54	17.75	1134	3.77	2.74	3.45	0.54	17.75
UCVOL (%)	1819	9.15	5.7	9.25	1.06	36.85	1134	7.27	4.96	7.12	1.06	36.85
							Control Variables					
SIZE	1710	641.41	73.58	3113.72	1.25	79616.95	1083	859.03	125.18	3632.39	2.07	79616.95
AGE	1596	44.72	27.27	40.75	1	209.45	1005	47.29	29.09	41.6	2.64	209.45
PROFIT	1509	1.54	1.42	0.57	0.52	4.94	1007	1.5	1.41	0.53	0.54	4.9
DURATION	1446	4.26	4.04	1.75	0.44	14.55	1073	4.36	4.18	1.51	0.85	12.43
BETA	854	0.87	0.89	0.33	-0.55	3.18	621	0.89	0.9	0.32	-0.48	3.13
GOVINV	1708	0.22	0.16	0.21	0	0.99	1083	0.18	0.14	0.15	0	0.84
STKINV	1709	0.14	0.08	0.17	0	0.93	1083	0.14	0.1	0.15	0	0.85
NONSTK	1710	0.34	0.08	0.41	0.08	1	1083	0.35	0.08	0.42	0.08	1
NONAFF	1710	0.33	0	0.47	0	1	1083	0.29	0	0.45	0	1

Panel B: Correlations across Variables

	RATING	SPREAD	UIVOL	UCVOL	SIZE	AGE	PROFIT	DUR	BETA	GOVINV	STKINV	NONSTK
PREAD	-0.56											
UIVOL	0.20	-0.15										
UCVOL	0.18	-0.16	0.70									
SIZE	-0.15	0.08	-0.18	-0.17								
AGE	-0.02	0.02	-0.09	-0.17	0.13							
PROFIT	0.01	0.04	0.04	0.00	-0.06	-0.03						
DUR	-0.19	-0.02	-0.17	-0.18	0.09	0.06	-0.06					
BETA	0.01	-0.02	-0.01	0.00	0.02	-0.02	-0.01	0.03				
GOVINV	0.2	-0.1	0.17	0.17	-0.12	-0.08	-0.01	-0.02	0.01			
STKINV	-0.15	0.12	-0.18	-0.24	0.20	0.32	0.02	0.12	0	-0.24		
NONSTK	0.13	-0.06	-0.04	-0.16	0.00	0.38	-0.03	0.03	0.05	0.01	0.22	
NONAFF	0.15	-0.03	0.11	0.00	-0.12	-0.01	0.11	-0.05	0.06	0.16	-0.03	0.31

Table 3: Bond Portfolio Credit Risk across Background Risk Deciles

This table reports the averages of bond portfolio rating and credit spread (in percentage) in year t as well as the background measures in year t-1, across deciles sorted by background risk measures in year t-1. The background risk measures are UIVOL and UCVOL and credit risk measures as defined in the same way as Table 2. When computing averages, we first average across firms in each insurer portfolio for each year, then average the cross-sectional means in each portfolio over time. We also report the differences of portfolio rating and credit spread between the top (D10) and bottom (D1) portfolio deciles. Inside the parentheses are the Newey-West (1987) adjusted t-statistics with a 2-year lag. The sample period is from 1996 to 2008.

Rank	UIVOL (%)	RATING	SPREAD (%)	UCVOL (%)	RATING	SPREAD (%)
D1	0.60	19.15	2.54	1.15	19.32	2.60
2	1.09	19.99	2.40	2.04	20.23	2.48
3	1.56	20.35	2.25	2.84	20.70	2.29
4	2.00	21.04	2.20	3.62	21.02	2.22
5	2.46	21.86	2.14	4.45	21.64	2.16
6	2.99	21.85	2.18	5.46	21.88	2.13
7	3.67	21.95	2.16	6.79	21.85	2.16
8	4.60	21.90	2.14	8.76	21.88	2.17
9	6.20	22.12	2.18	12.28	22.27	2.17
D10	12.06	22.88	2.05	25.11	22.80	2.06
D10-D1		3.73	-0.49		3.48	-0.54
(t-stat)		(12.83)	(-3.25)		(13.62)	(-3.53)

Table 4: Background Risks on Bond Portfolio Credit Risk

This table reports the coefficients of panel regressions of bond portfolio credit risk measures on insurer background risk and control variables. Both aggregate and persistent background risk measures are used. The specific model is a fixed firm and fixed time effects model assuming cross-sectional and time-series correlations in the residual terms (Petersen, 2006). Panel A reports results when ratings are used as the dependent variable. Panel B reports results when credit spreads are the dependent variable. The t-statistics (adjusting for two-way clustering) are reported in the parentheses. The sample period is from 1996 to 2008. Note: *** $p<0.01$, ** $p<0.05$, * $p<0.10$

Panel A: Measuring Credit Risk using Average Ratings of Bond Portfolios

	Total Background Risk		Persistent Background Risk	
INTERCEPT	20.75***	20.67***	20.85***	20.62***
	(47.23)	(43.21)	(43.17)	(43.11)
UIVOL	1.72***			
	(3.93)			
UCVOL		0.62***		
		(3.15)		
$\beta_{i,t}^{UI}$*UIVOL			2.71***	
			(3.64)	
$\beta_{i,t}^{UC}$*UCVOL				1.40***
				(3.44)
LOGSIZE	0.06	0.07	0.05	0.04
	(0.99)	(1.12)	(0.74)	(0.82)
LOGAGE	0.11	0.11	0.11	0.11
	(0.82)	(0.84)	(0.80)	(0.80)
PROFIT	-0.05	-0.05	-0.04	-0.05
	(-1.05)	(-1.05)	(-1.01)	(-1.02)
DURATION	-0.04**	-0.03**	-0.04**	-0.03**
	(-2.03)	(-2.00)	(-2.02)	(-2.00)
BETA	0.02	0.03	0.02	0.03
	(0.45)	(0.43)	(0.53)	(0.56)
GOVINV	0.25	0.25	0.25	0.25
	(1.47)	(1.46)	(1.50)	(1.55)
STKINV	-0.63**	-0.63**	-0.63**	-0.63**
	(-2.11)	(-2.09)	(-2.12)	(-2.04)
NONSTK	0.23	0.24	0.23	0.24
	(1.40)	(1.41)	(1.40)	(1.41)
NONAFF	-0.11	-0.10	-0.11	-0.10
	(-1.27)	(-1.24)	(-1.28)	(-1.21)
FIRM DUMMIES	Yes	Yes	Yes	Yes
YEAR DUMMIES	Yes	Yes	Yes	Yes
N	9,154	9,154	9,154	9,154
Adj.R^2	0.65	0.65	0.68	0.68

Panel B: Measuring Credit Risk using Average Credit Spreads of Bond Portfolios

	Total Background Risk		Persistent Background Risk	
INTERCEPT	2.39***	2.26***	2.69***	2.57***
	(8.15)	(9.19)	(8.93)	(9.14)
UIVOL	-0.73**			
	(-2.33)			
UCVOL		-0.53**		
		(-2.32)		
$\beta_{i,t}^{UI}$*UIVOL			-2.28***	
			(-2.56)	
$\beta_{i,t}^{UC}$*UCVOL				-1.77***
				(-2.64)
LOGSIZE	-0.04	-0.02	-0.01	-0.01
	(-0.82)	(-0.93)	(-0.86)	(-0.73)
LOGAGE	0.14	0.13	0.11	0.12
	(1.61)	(1.49)	(1.59)	(1.52)
PROFIT	0.01	0.03	0.04	0.04
	(0.32)	(0.55)	(0.54)	(0.54)
DURATION	0.05**	0.04**	0.05**	0.05**
	(2.27)	(2.15)	(2.18)	(2.09)
BETA	0.01	0.01	0.02	0.02
	(0.16)	(0.09)	(0.18)	(0.12)
GOVINV	0.01	0.02	0.03	0.04
	(0.06)	(0.27)	(0.14)	(0.47)
STKINV	0.82**	0.67***	0.65***	0.65***
	(2.41)	(3.42)	(3.26)	(3.31)
NONSTK	-0.24*	-0.23**	-0.21**	-0.22**
	(-1.87)	(-2.37)	(-2.43)	(-2.50)
NONAFF	0.05	0.04	0.03	0.03
	(0.91)	(1.18)	(1.01)	(1.08)
	(8.15)	(9.19)	(8.93)	(9.14)
FIRM DUMMIES	Yes	Yes	Yes	Yes
YEAR DUMMIES	Yes	Yes	Yes	Yes
N	9,154	9,154	9,154	9,154
Adj.R^2	0.54	0.55	0.59	0.59

Table 5: Financing Constraints and Background Risk Effect

This table reports the coefficients of panel regressions of bond portfolio credit risk on insurer background risk and financing constraints. The specific model is a fixed firm and fixed time effects model assuming cross-sectional and time-series correlations in the residual terms (Petersen, 2006). We use three dummy variables to measure financing constraints. SMALL is a dummy variable that equals to one for the bottom quintile insurers sorted by total book assets and zero for other quintiles. NONSTK is a dummy variable which equals to 1 for mutual insurers and 0 otherwise. NONAFF is a dummy variable which equals to 1 for stand-alone insurers and 0 otherwise. Panel A reports results when credit ratings are used as the dependent variable. Panel B reports results when credit spreads are the dependent variable. The t-statistics (adjusting for two-way clustering) are reported in the parentheses. The sample period is from 1996 to 2008. Note: *** p<0.01, ** p<0.05, * p<0.10.

Panel A: Measuring Credit Risk using Average Ratings of Bond Portfolios

		UIVOL			UCVOL	
INTERCEPT	20.76***	20.74***	20.77***	22.73***	22.69***	22.63***
	(47.03)	(46.77)	(47.18)	(47.48)	(46.48)	(47.89)
BG	1.58*	1.98**	1.46*	0.53*	0.51*	0.48**
	(1.89)	(2.21)	(1.84)	(1.88)	(1.80)	(2.28)
BG*SMALL	1.12**			0.84**		
	(2.06)			(2.27)		
BG*NONSTK		0.61			0.67	
		(1.26)			(1.10)	
BG*NONAFF			2.04**			1.22**
			(2.13)			(2.14)
LOGSIZE	0.07	0.06	0.06	0.06	0.06	0.06
	(1.09)	(1.00)	(0.88)	(1.01)	(1.09)	(1.02)
LOGAGE	0.11	0.11	0.12	0.12	0.12	0.02
	(0.83)	(0.80)	(0.85)	(0.73)	(0.64)	(0.61)
PROFIT	-0.05	-0.05	-0.05	-0.04	-0.04	-0.04
	(-1.06)	(-1.05)	(-1.04)	(-1.30)	(-1.21)	(-1.26)
DURATION	-0.04**	-0.04**	-0.04**	-0.05**	-0.05**	-0.05**
	(-2.05)	(-2.03)	(-2.04)	(-2.25)	(-2.51)	(-2.36)
BETA	0.02	0.02	0.02	0.02	0.02	0.02
	(0.41)	(0.45)	(0.39)	(0.60)	(0.54)	(0.57)
GOVINV	0.25	0.25	0.26	0.26	0.24	0.26
	(1.51)	(1.48)	(1.53)	(1.58)	(1.51)	(1.53)
STKINV	-0.62**	-0.63**	-0.63**	-0.63**	-0.63**	-0.63**
	(-2.09)	(-2.11)	(-2.10)	(-2.55)	(-2.49)	(-2.40)
NONSTK	0.24	0.26	0.23	0.25	0.25	0.26
	(1.47)	(1.35)	(1.38)	(1.42)	(1.32)	(1.26)
NONAFF	-0.11	-0.11	-0.19	-0.12	-0.13	-0.11
	(-1.29)	(-1.27)	(-1.56)	(-1.25)	(-1.27)	(-1.62)
FIRM DUMMIES	Yes	Yes	Yes	Yes	Yes	Yes
YEAR DUMMIES	Yes	Yes	Yes	Yes	Yes	Yes
N	9,154	9,023	9,154	9,154	9,023	9,154
Adj.R^2	0.67	0.64	0.68	0.67	0.64	0.68

Panel B: Measuring Credit Risk using Average Credit Spreads of Bond Portfolios

	UIVOL			UCVOL		
INTERCEPT	2.38***	2.32***	2.29***	2.27***	2.22***	2.21***
	(6.48)	(6.93)	(6.81)	(6.45)	(6.26)	(6.56)
BG	-0..69*	-0.82*	-0.63*	-0.53*	-0.44	-0.45*
	(-1.75)	(-1.81)	(-1.76)	(-2.09)	(-1.57)	(-1.72)
BG*LGSIZE	-0.91**			-0.62**		
	(-2.09)			(-2.13)		
BG*NONSTK		-0.34			-0.65	
		(-0.22)			(-0.92)	
BG*NONAFF			-1.05*			-1.18*
			(-1.71)			(-1.89)
LOGSIZE	-0.04	-0.04	-0.03	-0.03	-0.02	-0.02
	(-0.99)	(-0.95)	(-0.82)	(-0.56)	(-0.53)	(-0.56)
LOGAGE	0.15*	0.14*	0.13*	0.13*	0.14*	0.13*
	(1.72)	(1.82)	(1.76)	(1.74)	(1.80)	(1.79)
PROFIT	0.02	0.01	0.01	0.01	0.01	0.01
	(0.61)	(0.32)	(0.29)	(0.37)	(0.35)	(0.32)
DURATION	0.05**	0.05**	0.05**	0.05**	0.05**	0.05**
	(2.55)	(2.57)	(2.40)	(2.34)	(2.32)	(2.34)
BETA	0.01	0.01	0.01	0.01	0.01	0.01
	(0.12)	(0.15)	(0.24)	(0.24)	(0.24)	(0.23)
GOVINV	0.01	0	0	-0.01	-0.01	-0.01
	(0.07)	(0.04)	(0.02)	(-0.05)	(-0.07)	(-0.07)
STKINV	0.85**	0.83**	0.83**	0.84**	0.83**	0.83**
	(2.38)	(2.45)	(2.45)	(2.37)	(2.47)	(2.45)
NONSTK	-0.24	-0.24	-0.23*	-0.23*	-0.23*	-0.23*
	(-1.47)	(-1.47)	(-1.79)	(-1.79)	(-1.75)	(-1.78)
NONAFF	0.05	0.06	0.05	0.03	0.04	0.05
	(0.82)	(1.08)	(1.09)	(0.90)	(1.16)	(1.10)
FIRM DUMMIES	Yes	Yes	Yes	Yes	Yes	Yes
YEAR DUMMIES	Yes	Yes	Yes	Yes	Yes	Yes
N	9154	9,023	9,154	9154	9,023	9,154
Adj.R^2	0.55	0.53	0.55	0.55	0.53	0.55

Table 6: Regressions of Bond Portfolio Credit Risk on Other Background Risk Proxies

This table reports the coefficients from panel regressions of bond portfolio credit risk measures on other background risk measures. The model specification is the same as in Table 4. We use four measures for background risk: LEVERAGE, LONGTAIL, HERFL, and HERFS. The t-statistics (adjusted for two-way clustering) reported in the parentheses. The sample period is from 1996 to 2008. Note: *** p<0.01, ** p<0.05, * p<0.10.

	Bond Rating as Dependent Variable					Credit Spread as Dependent Variable				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
INTERCEPT	21.60***	21.61***	21.54***	21.62***	21.93***	2.26***	2.23***	2.20***	2.30***	2.21***
	(37.86)	(35.60)	(37.38)	(37.72)	(32.96)	(5.77)	(5.37)	(5.27)	(5.79)	(5.30)
LEVERAGE	0.45***				0.36**	-0.25**				-0.22*
	(2.65)				(2.41)	(-2.11)				(-1.93)
LONG		0.35*			0.17*		-0.16*			-0.14*
		(1.89)			(1.79)		(-1.82)			(-1.77)
HERFL			0.33**		0.20*			-0.22**		-0.14
			(2.17)		(1.92)			(-2.21)		(-1.50)
HERFS				0.03	0.05				0.01	0.02
				(0.15)	(0.36)				(0.16)	(0.40)
LOGSIZE	0.05	0.06	0.06	0.06	0.05	0	-0.02	-0.02	-0.01	-0.02
	(1.03)	(0.91)	(1.01)	(0.94)	(0.82)	(-0.04)	(-0.79)	(-0.74)	(-0.59)	(-0.96)
LOGAGE	0.13	0.12	0.13	0.12	0.12	0.13*	0.12*	0.12	0.13	0.12*
	(0.97)	(0.91)	(0.95)	(0.92)	(0.75)	(1.77)	(1.83)	(1.61)	(1.43)	(1.78)
PROFIT	-0.03	-0.04	-0.03	-0.04	-0.06	0.01	0.02	0.02	-0.02	0.02
	(-0.69)	(-1.01)	(-0.62)	(-1.02)	(-1.34)	-0.2	-0.68	-0.54	-0.58	-0.57
DURATION	-0.04**	-0.04**	-0.04**	-0.04**	-0.04**	0.05**	0.06**	0.05**	0.06**	0.05**
	(-2.03)	(-1.99)	(-2.00)	(-2.00)	(-2.07)	-2.13	-2.19	-2.18	-2.23	-2.18
BETA	0.02	0.02	0.02	0.02	0.03	0	0	0	0	0
	(0.54)	(0.49)	(0.48)	(0.50)	(0.32)	(0.09)	(0.13)	(0.21)	(0.07)	(0.31)
GOVINV	0.27*	0.26	0.26	0.27	0.27	-0.01	-0.01	-0.01	-0.01	-0.01
	(1.66)	(1.64)	(1.59)	(1.64)	(1.59)	(-0.15)	(-0.11)	(-0.16)	(-0.13)	(-0.09)
STKINV	-0.55*	-0.65**	-0.75**	-0.65**	-0.63**	0.81**	0.65**	0.66**	0.85**	0.80**
	(-1.84)	(-2.13)	(-2.33)	(-2.12)	(-2.05)	-2.33	-2.25	-2.26	-2.29	-2.27
NONSTK	0.16	0.19	0.32	0.18	0.2	-0.22*	-0.20**	-0.24**	-0.24**	-0.22**
	(1.05)	(1.19)	(1.30)	(1.13)	(1.09)	(-1.75)	(-2.06)	(-2.23)	(-2.34)	(-2.28)
NONAFF	-0.14*	-0.13	-0.13*	-0.13	-0.12	0.04	0.04	0.04	0.03	0.04
	(-1.77)	(-1.62)	(-1.66)	(-1.62)	(-1.33)	-1.22	-1.08	-0.94	-0.79	-1.06
FIRM DUMMIES	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YEAR DUMMIES	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	9,154	9,154	9,154	9,154	9,154	9,154	10,379	10,379	10,720	10,378
Adj.R^2	0.64	0.64	0.64	0.64	0.66	0.55	0.54	0.53	0.53	0.55

Table 7: Intertemporal Smoothing and Alternative Background Risk Effect

This table reports the coefficients from panel regressions of bond portfolio credit risk on other background risk and the intertemporal smoothing ability. The model specification is the same as in Table 4. We use four measures for background risk: LEVERAVE, LONGTAIL, HERFL, and HERFST. The sample period is from 1996 to 2008. Note: **** p<0.01, ** p<0.05, * p<0.10.

Panel A: Measuring Credit Risk using Average Ratings of Bond Portfolios

	LEVERAGE			LONGTAIL			HERFS		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
INTERCEPT	21.92***	21.57***	21.60***	22.28***	22.32***	22.35***	22.51***	22.21***	22.17***
	(36.42)	(37.82)	(37.82)	(36.92)	(37.73)	(36.34)	(36.62)	(36.41)	(36.39)
BG	0.35**	0.39**	0.43**	0.32*	0.30**	0.25*	0.31*	0.26*	0.30*
	(2.31)	(2.12)	(2.52)	(1.80)	(2.31)	(1.93)	(1.89)	(1.82)	(1.87)
BG*LGSIZE	0.50**			0.31*			0.40**		
	(2.36)			(1.93)			(2.14)		
BG*NONSTK		0.2			0.32			0.08	
		(1.09)			(1.33)			(0.21)	
BG*NONAFF			0.60*			0.54			0.61**
			(1.87)			(1.63)			(2.25)
LOGSIZE	0.04	0.05	0.05	0.03	0.02	0.03	0.05	0.06	0.06
	(0.77)	(1.17)	(1.04)	(0.46)	(0.43)	(0.45)	(1.35)	(1.54)	(1.48)
LOGAGE	0.11	0.13	0.13	0.13	0.12	0.12	0.14	0.12	0.12
	(0.91)	(0.99)	(0.98)	(0.91)	(0.63)	(0.85)	(1.05)	(1.06)	(1.08)
PROFIT	-0.04	-0.03	-0.03	-0.04	-0.05	-0.04	-0.03	-0.02	-0.02
	(-0.95)	(-0.75)	(-0.67)	(-0.92)	(-1.14)	(-0.96)	(-0.61)	(-0.51)	(-0.53)
DURATION	-0.04**	-0.04**	-0.04**	-0.04**	-0.05**	-0.04**	-0.04**	-0.04**	-0.04**
	(-2.10)	(-2.02)	(-2.04)	(-2.17)	(-2.14)	(-2.11)	(-2.07)	(-2.05)	(-2.05)
BETA	0.02	0.02	0.02	0.02	0.02	0.02	0.03	0.02	0.02
	(0.46)	(0.49)	(0.55)	(0.39)	(0.43)	(0.39)	(0.52)	(0.40)	(0.48)
GOVINV	0.25*	0.27*	0.27*	0.27*	0.25*	0.25*	0.27*	0.26*	0.26*
	(1.86)	(1.69)	(1.66)	(1.66)	(1.70)	(1.73)	(1.78)	(1.74)	(1.82)
STKINV	-0.56*	-0.56*	-0.55*	-0.68**	-0.65**	-0.65**	-0.69**	-0.75***	-0.72**
	(-1.72)	(-1.91)	(-1.85)	(-2.53)	(-2.61)	(-2.54)	(-2.40)	(-2.64)	(-2.52)
NONSTK	0.17	0.18	0.16	0.16	0.21	0.2	0.33	0.32	0.33
	(1.06)	(1.03)	(1.06)	(0.97)	(1.05)	(1.00)	(1.48)	(1.30)	(1.48)
NONAFF	-0.1	-0.14*	-0.1	-0.13	-0.11	-0.12	-0.13	-0.11	-0.12*
	(-1.56)	(-1.76)	(-1.54)	(-1.49)	(-1.56)	(-1.58)	(-1.66)	(-1.51)	(-1.88)
FIRM DUMMIES	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YEAR DUMMIES	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	9,154	9,023	9,154	9154	9,023	9,154	9154	9,023	9,154
Adj.R^2	0.65	0.65	0.65	0.64	0.64	0.64	0.64	0.64	0.64

Panel B: Measuring Credit Risk using Average Credit Spreads of Bond Portfolios

	LEVERAGE			LONGTAIL			HERFS		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
INTERCEPT	2.98***	2.84***	2.18***	2.71***	2.85***	2.87***	2.60***	2.72***	2.73***
	(5.31)	(5.53)	(5.93)	(5.77)	(5.42)	(5.21)	(5.31)	(5.95)	(5.66)
BG	-0.22*	-0.21*	-0.23*	-0.15*	-0.19*	-0.17*	-0.22*	-0.21-	-0.22*
	(-1.82)	(-1.79)	(-1.73)	(-1.73)	(-1.77)	(-1.74)	(-1.90)	(-1.83)	(-1.86)
BG*LGSIZE	-0.27**			-0.24*			-0.25*		
	(-2.20)			(-1.89)			(-1.91)		
BG*NONSTK		-0.04			-0.12			-0.08	
		(-0.60)			(-1.26)			(-1.18)	
BG*NONAFF			-0.1			-0.13			-0.12
			(-0.33)			(-1.17)			(-1.64)
LOGSIZE	-0.02	-0.02	0	0.04	0.02	0.02	0.04	0.01	0.01
	(-0.40)	(-0.12)	(-0.07)	(1.56)	(0.76)	(0.74)	(1.38)	(0.59)	(0.56)
LOGAGE	0.14*	0.14*	0.14*	0.15*	0.14*	0.14*	0.14*	0.12	0.12
	(1.66)	(1.82)	(1.79)	(1.76)	(1.67)	(1.75)	(1.74)	(1.50)	(1.54)
PROFIT	-0.05	-0.05	0.01	-0.06	-0.06	-0.06	-0.04	-0.04	-0.04
	(-0.83)	(-0.78)	-0.21	(-0.79)	(-0.81)	(-0.78)	(-0.61)	(-0.58)	(-0.58)
DURATION	0.05**	0.05**	0.05**	0.06**	0.05**	0.06**	0.05**	0.05**	0.05**
	(2.01)	(2.03)	(2.49)	(2.21)	(2.19)	(2.21)	(2.00)	(2.01)	(2.01)
BETA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.05)	(0.05)	(0.09)	(0.10)	(0.15)	(0.09)	(0.15)	(0.15)	(0.13)
GOVINV	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(-0.08)	(-0.08)	(-0.02)	(-0.14)	(-0.15)	(-0.12)	(-0.18)	(-0.26)	(-0.22)
STKINV	0.80**	0.80**	0.81**	0.65**	0.66**	0.65**	0.62**	0.65**	0.64**
	(2.20)	(2.14)	(2.28)	(2.26)	(2.33)	(2.30)	(2.17)	(2.30)	(2.29)
NONSTK	-0.23*	-0.24*	-0.21*	-0.22**	-0.21**	-0.22**	-0.23**	-0.28**	-0.24**
	(-1.74)	(-1.71)	(-1.75)	(-2.06)	(-2.44)	(-2.16)	(-2.29)	(-2.53)	(-2.34)
NONAFF	0.03	0.04	0.12	0.04	0.03	0.06	0.02	0.02	-0.05
	(0.99)	(0.85)	(0.62)	(1.09)	(1.03)	(0.69)	(0.51)	(0.75)	(-0.90)
FIRM DUMMIES	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YEAR DUMMIES	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	9,154	9,023	9,154	9,154	9,023	9,154	9,154	9,023	9,154
Adj.R^2	0.55	0.55	0.55	0.54	0.54	0.54	0.53	0.53	0.53

Table 8: Regression of Investment Performance on Background Risk Measures

This table reports the coefficients of panel regressions of investment performance on insurer background risk measures and control variables. The specific model is a fixed firm effect assuming cross-sectional and time-series correlations in the residual terms (Petersen, 2006). The dependent variable is realized capital gains(loss) scaled by invested assets. NONCRISIS is a dummy variable that equals to zero for 2007 and 2008 and one for other sample years. All the control variables are defined in the same way as Table 4. The t-statistics (adjusting for two-way clustering) are reported in the parentheses. The sample period is from 2001 to 2009. Note: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

	(1)	(2)	(3)	(4)
Intercept	2.85***	2.94***	3.00***	3.01***
	(7.49)	(7.62)	(7.15)	(7.16)
NONCRISIS	0.84***	1.05***	0.79***	0.80***
	(10.98)	(14.62)	(18.78)	(21.47)
UIVOL	2.98***			
	(3.29)			
UIVOL*NONCRISIS	-2.70***			
	(-3.39)			
UCVOL		1.90***		
		(3.60)		
UCVOL*NONCRISIS		-3.20***		
		(-3.54)		
$\beta_{i,t}^{UI}$*UIVOL			3.18***	
			(4.12)	
$\beta_{i,t}^{UI}$*UIVOL*NONCRISIS			-3.72***	
			(-3.09)	
$\beta_{i,t}^{UI}$*UCVOL				2.01***
				(2.68)
$\beta_{i,t}^{UI}$*UCVOL*NONCRISIS				-2.58***
				(-3.20)
LOGSIZE	0.14***	0.14***	0.15***	0.16***
	(3.33)	(3.26)	(3.43)	(3.48)
LOGAGE	-0.92***	-0.97***	-1.06***	-1.06***
	(-8.06)	(-8.43)	(-8.37)	(-8.40)
NONAFF	-0.27**	-0.27***	-0.27**	-0.27**
	(-2.54)	(-2.61)	(-2.39)	(-2.37)
NONSTK	0.62	0.66	0.66	0.65
	(1.49)	(1.44)	(1.52)	(1.51)
FIRM DUMMIES	Yes	Yes	Yes	Yes
Number of observations	13,244	13,244	12,383	12,383
Adjusted R2	0.211	0.202	0.232	0.233

Figure 1: Percentage Holding of Corporate Bonds with Ratings Below A

The figure shows the average percentage holding of corporate bonds below A rated by S&P during the sample period. In each calendar year from 1996 to 2008, insurers are ranked into decile portfolios based on the proportional holding of corporate bonds below A rating. We first compute the average proportional holding of corporate bonds below A rating in each year and then average the numbers over the sample period.

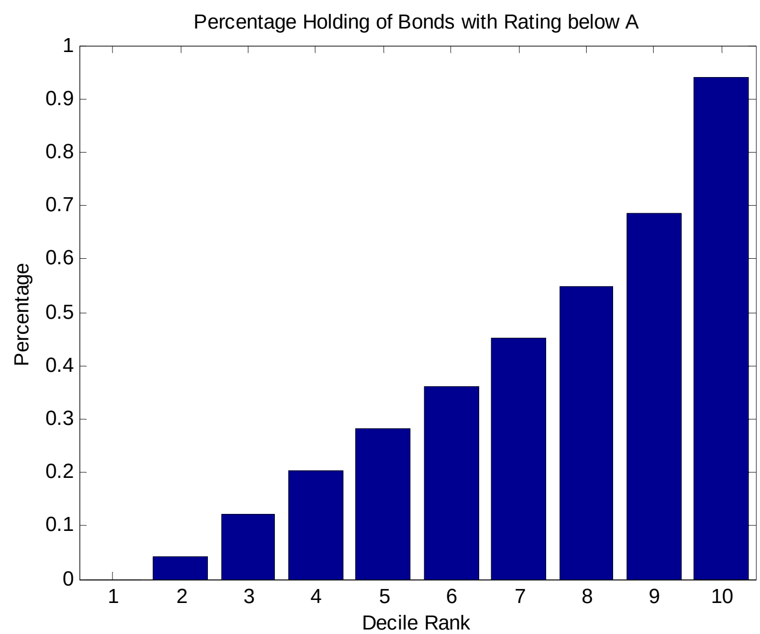

Figure 2: D10 and D1 Difference in Credit Risk Measure over Time

The figure shows the spreads between D10 and D1 portfolios sorted by background risk measures over time. The first two panels are for the differences between rating spreads across D10 and D1 portfolios. The later two panels are for the differences of credit spreads across D10 and D1 portfolios. Variables are defined in the same way as those in Table 3.

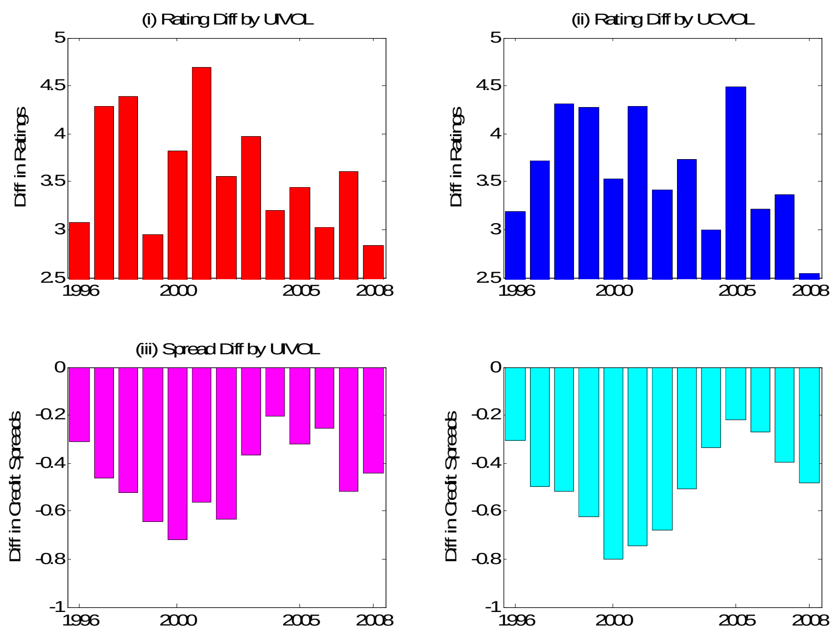

Figure 3: Time Series of Average Investment Performance

The figure shows the average of insurers' annual investment performance from 2001 to 2009. Investment performance of an insurer is measured by the insurer's annual realized capital gains scaled by year beginning invested assets. We calculate the equal-weighted average of investment performance in each year.