Gambling for Recovery?
Exploring the Credit Risk of European Insurers' Bond Portfolios during the Covid-19 Market Crash

ICIR Working Paper No. 46/2023

Edited by Helmut Gründl, Alexander Ludwig, and Manfred Wandt

Marcel Beyer[*,†]

This version: December 2024
Click Here for the most recent version.

Abstract

Using daily stock market data for European insurers, I investigate how a stock market contraction, as experienced during the Covid-19 pandemic, affects insurers' credit risk allocation of their corporate bond portfolio. I find that insurers shift their portfolio holdings pro-cyclically towards lower credit risk assets in the first month of the market contraction. As the crisis progresses, I find evidence for counter-cyclical investment behavior by European insurers, which can neither be explained by credit rating downgrades of held bonds nor by hedging with CDS derivatives. This counter-cyclical investment behavior cannot be observed for US firms, which provides evidence for a difference in investment behavior between US and European insurers. The observed counter-cyclical investment behavior of insurers could be beneficial for the financial system in attenuating price declines though insurance liquidity provision, but excessive risk-taking by insurance companies over longer periods can also reinforce stress in the system.

Keywords: Insurance; Financial Crisis; Financial Stability

JEL Classification: G01, G11, G22, G32

[*]Goethe-Universität Frankfurt, Theodor-W.-Adorno-Platz 3, 60323 Frankfurt am Main, Germany beyer@finance.uni-frankfurt.de

[†]I am grateful for the continuous advice and feedback of Helmut Gründl. I would further like to thank Tobias Berg, Patricia Born, Johan Hombert, Christian Kubitza, Nicolaus Grochola, Alexander Ludwig, Selim Mankai, Christian Schlag as well as the participants of the ARIA annual meeting 2022, the annual meeting of the German Association for Insurance Research 2023, and the EGRIE annual meeting 2023 for comments and suggestions.

1 Introduction

Financial institutions show under certain conditions the tendency to invest into riskier assets to increase portfolio performance. The channels through which such behavior is induced, include risk-based capital requirements[1], low market interest rates[2] or regulatory arbitrage concerns[3]. For insurance firms specifically incentives that endorse riskier investments, are a high share of guarantee products[4] with the resulting pressure to meet the obligations, or risk-taking incentives fostered by non-risk-based regulatory rules. Many studies find that the tendency towards riskier investments vanishes as insurance companies face financial constraints or market crises[5].

However, these studies focus on the US market, which has detailed security-level transaction reporting requirements that are subject to public scrutiny and could therefore influence insurers' investment decisions. The European insurance market adds a new perspective because security-level asset information is reported only to supervisors, resulting in the absence of public scrutiny. In addition to the absence of public scrutiny, Timmer (2018) finds that European insurance firms and pension funds invest in riskier assets during crises. This is consistent with the observation of counter-cyclical investments in lower-rated corporate bonds by German insurers in the first quarter of 2020.[6]. The act of investing counter-cyclically, that is in riskier assets during a market downturn, contrasts with the dominant view based on US data that insurance companies invest more safely during crises. In addition, the European Systemic Risk Board (2023) uses security-level data instead of aggregated sector-level data and finds pro-cyclical behavior for corporate bond investments, which contradicts the findings of Timmer (2018) despite using the same approach.

The mixed evidence in the literature on how European insurance companies invest during crisis times and the evidence that the US findings may not hold for European insurers motivate my research question. I seek to provide insight into the credit risk allocation in the corporate bond

[1] Becker and Ivashina (2015)

[2] Dell'Ariccia et al. (2017), Choi and Kronlund (2017)

[3] Acharya and Steffen (2015), Swinkels et al. (2018)

[4] Koijen and Yogo (2022b) find that insurance products with guarantees lead to higher market risk in life insurers' portfolios.

[5] Becker and Ivashina (2015),Ge and Weisbach (2021), Kirti (2024)

[6] Bundesbank (2020), p. 29.

portfolios of European insurance firms during crises at daily frequency. As transaction information is not publicly available, I exploit the asset pass-through effect, as documented by Chodorow-Reich et al. (2020), using the Covid-19-induced market crash as a laboratory.

My contribution to the existing literature is threefold. First, investigating the European insurance market without publicly observable portfolio holdings information. The difference in public scrutiny opens the possibility of finding behavioral differences between European and US insurers. In doing so, I also address the ambiguity of the results on the investment behavior of European insurers. Thus, I add to the strand of literature on the European market.

Second, given that security-level holdings information is not publicly observable in the European market, I derive changes in the credit risk portfolio composition from empirically estimated share price sensitivities of European insurers, without having access to insurers' security-level holding information. This enables me to inspect daily data, that is more granular than the quarterly data applied in previous research.

Third, to test the robustness of my empirical approach, I also use US data where the transactions are observable, thus presenting a comparison between the crisis investment behavior of US and European insurance firms that, to the best of my knowledge, has not been done before.

My results show that European insurance companies increase investments in AAA-rated European government bonds and, to a minor extent, in A-rated European corporate bonds in response to the crisis. These findings on insurers' increased demand for assets with lower credit risk in crisis times are consistent with the findings in the US market. However, the new information from the daily data shows that insurers already started investing more in high-yield corporate bonds, even before the market recovery began, an observation that does not exist for US data. Additionally, the the flight to safety at the onset of the crisis is most pronounced among firms with lower Solvency Ratios, that are capital requirements divided by own funds, while the firms with the highest Solvency Ratios barely invest safer, but rather exhibit a strong increase in lower rated investment grade bonds (BBB-rated). Finally, I find that credit risk, manifesting in rating downgrades during the market downturn, increases insurers' exposure to assets with higher credit risk (BBB- and BB-rated).

Economically, the results suggest that while both US and European insurers are subject to risk-based regulation, they differ in their overall risk appetite during crises. Public scrutiny through financial reporting may be one explanation for this difference. Moreover, my observations are consistent with the findings of Timmer (2018) and strengthen the hypothesis that European insurers contribute to price stabilization through their counter-cyclical investment behavior, thereby generating positive investment returns when the market recovers. Lastly, I provide evidence that in times of crisis, insurance companies pursue active trading strategies rather than being passive investors waiting for the markets to recover, which is consistent with the observations made at the security level by the European Systemic Risk Board (2023).

These findings have important implications for understanding the behavior of insurance companies in future crises. Insurers with lower Solvency Ratios are acting pro-cyclically by buying safe government bonds and selling assets with high credit risk ratings, thereby releasing regulatory capital. Insurers with higher Solvency Ratios are able to act counter-cyclically, by investing in riskier bonds. Irrespective of the Solvency Ratios, all insurers in the sample buy the lowest rated assets during the crisis. This indicates that the European insurance sector is providing liquidity to markets during contractions.

It is a strong assumption that publicly unobservable transaction information is reflected in daily stock prices. Possible mechanisms through which such information might be incorporated in share prices are difficult to identify. The investment strategies of portfolio managers might be anticipated by other institutional investors, based on the information from analyst calls, quarterly reports or expert conferences. In addition, market participants might derive information from trade volumes or mutual fund redemptions.

To show that the estimated sensitivities from my empirical analysis contain information about the asset composition of the insurers, I relate the estimated sensitivities to annually reported, aggregate portfolio information for each insurer and find a significant relation for all estimated coefficients, following the approach of Acharya and Steffen (2015). The skeptical reader may suspect that confounding factors underlying stock prices might drive changes in the coefficients, rather than publicly unobservable changes in asset exposure. I address these concerns with a series of robustness checks.

First, I validate my methodology using US data, where transaction data is available. This allows me not only to test the validity of the approach, but also to compare the investment behavior of European and US insurers.

Second, I apply the falsification tests suggested by Acharya and Steffen (2015). I compare the estimated insurance coefficients with the estimated coefficients of a set of industry and regional indices. If the coefficients were driven by some confounding factor between equity and corporate bond prices, one would expect significant coefficients for these industries or regions.

For the comparison, I chose the Stoxx Europe 600 - Banks and the Stoxx Euro 600 - Financial Service Providers excluding insurance companies, to compare coefficients within the European financial industry. The MSCI World, S&P 500 and FTSE 100 indices serve to test the findings between regions.

Third, to address multicollinearity issues between the individual corporate bond returns, I use a principal components specification. Hence, by construction the individual factors are orthogonal, but suffer from the need for interpretation. To mitigate this issue, I apply an orthogonalization in my main specification between the two most correlated corporate bond returns.

Shleifer and Vishny (1992) discuss the issue of fire sales, which is the pressure to sell assets at disadvantageous prices. Such a pressure might for example arise given rating downgrades on corporate bonds in combination with downgrade-induced regulatory capital charges (Becker et al. (2021)).

While I observe a sharp decline in the share price sensitivity of high-yield corporate bond returns in response to the market crash in March 2020, I find no clear evidence that insurers "fire-sell" their assets during the market turmoil. Rather, European insurers begin to reinvest in high-yield corporate bonds during the market downturn, even after the wave of credit downgrades in April 2020. This observation helps to show that the combination of risk-based capital requirements and rating downgrades does not necessarily induce fire sales.

Analyzing the European insurance market offers two advantages over the US market. First, there are no regulatory differences between firms in EU member states, given the Solvency II regulation. This prevents that a subset of the sample is affected by a regulatory change[7]. Second, the peak of trading activity in high-yield bonds is more pronounced and during a more narrow time window in the European market compared to the US market, both attributes foster the identification

[7] Section 5 includes non-Solvency II firms to increase the number of observations and test the predictive power of my model beyond Solvency II firms.

of the sensitivity estimates in my analysis (Figure 1). Additionally, I provide a comparison between the US market and the European market in subsection 6.3.

Share prices should reflect the market value of the firm's assets and liabilities, which implies that insurers' share prices relate to the performance of the assets within their investment portfolio[8]. To analyze the investment decisions of European insurers on a daily basis, I use daily stock returns of 34 listed insurance companies that are subject to Solvency II regulation. By estimating the exposure of each insurer's share price to the returns of proxy portfolios that resemble corporate bond assets with a given credit rating, I aim to uncover the intra-quarter investment decisions of European insurers. I then relate the estimated share price exposures for each rating to the aggregate holdings reported in the companies' annual reports to establish a relationship between the estimates and the actual asset composition. This approach follows Acharya and Steffen (2015), who estimate the exposures of European banks' stock market returns to a set of government bond portfolios to infer statements about the investment behavior of those banks. I extend their approach by adding a rolling regression setup. The main advantage of the combination of the Acharya and Steffen (2015) approach with the rolling regression is the ability to gain additional observations through the daily availability of stock market data, while the rolling regression setup allows to track the share price exposures on a daily basis throughout the year.

This paper relates to the literature on exploring the risk-taking of financial firms (Dell'Ariccia et al. (2017); Choi and Kronlund (2017)) and insurance companies in particular (Becker and Ivashina (2015); Ge and Weisbach (2021); Koijen and Yogo (2015)). I contribute an approach that estimates daily changes in insurers' asset holdings without access to security-level holdings data. I further add to the research on the behavior of financial intermediaries during financial crises (He and Krishnamurthy (2011); He and Krishnamurthy (2018)). The authors build a theoretical model that captures frictions between households and financial intermediaries and show that shocks to asset values lead intermediaries to shift their clients' portfolios towards being less risky. I estimate changes in the portfolio composition of insurance companies and thereby track insurance firms' investment behavior and risk appetite. Ge and Weisbach (2021) examine the investment behavior of P&C and life insurers as subject to their financial condition and find that an increase in operating losses induces insurers to invest safer, which is consistent to the pro-cyclicality finding

[8]I discuss the valuation concerns, including the role of the liabilities, in greater detail in subsection 3.1.

of Becker and Ivashina (2015) and consistent with the pattern I observe as the immediate reaction to the Covid-19 market crash.

Kirti (2024) investigates whether life insurance firms in the US took on additional risk in their asset portfolio during the global financial crisis 2008 to recover for potential losses and finds that, while theory suggests a "gamble for recovery" motive[9], in practice, insurers affected more by the crisis shift their investments stronger towards being less risky compared to less affected firms. Kriti's research question is close to mine, but my study provides an additional insight by focusing on a friction in the European market, namely that transaction or holdings data for insurance companies are not publicly available. I compare my findings with European data to the same approach with US data and find that the US sample indeed shows properties that are in line with Kirti's observations, yet the European firms do show a different pattern. Second, by inspecting the market crash associated with the Covid-19 pandemic that concerns income and claim expectations (Coibion et al. (2020); Gormsen and Koijen (2020)), compared to the global financial crisis that unraveled as a credit crisis (Eling and Schmeiser (2010); Baluch et al. (2011)), I provide further evidence regarding crisis types.

Ellul et al. (2022) empirically examine the effects of variable annuities on the investment behavior of US life insurers during the global financial crisis and the Covid-19 market crash. Their results on the asset allocation are consistent with my observations. Additionally, Ellul et al. (2022) observe significant differences in the net trades of liquid and illiquid bonds between insurers with low and high exposure to variable annuity guarantees. Koijen and Yogo (2021) and Koijen and Yogo (2022a) discuss that variable annuities resemble market risk insurance, exposing the underwriting insurers to equity and interest rate risk mismatches. The authors show that insurers with more guarantee business face larger equity drawdowns during the Covid-19 crisis. I follow the proposed identification of guarantee business under Solvency II and incorporate the guarantee business as a control variable in my model.

Ellul et al. (2015) present evidence that historical cost accounting may lead to gains trading by life insurance firms during financial crises. Acharya and Steffen (2015) find that Eurozone banks in the period of 2007-2013 systematically increased their exposure to southern European bonds while

[9] Jensen and Meckling (1976) introduce the term, describing the incentive that a firm acts riskier when facing financial distress.

short-selling German government bonds, which can be associated with risk-shifting and regulatory arbitrage motives. Methodologically, I follow their approach of estimating the exposure of companies' share prices to a range of bond yields, but I extend the model to the business of insurance companies and modify it to better track corporate bonds by accounting for hedging and rating downgrades.

The rest of this article is structured as follows. Section 2 presents the market situation during the Covid-19 market crash. Section 3 discusses valuation considerations and the data. In section 4, I present the regression model and the methodology. To show that these estimations carry information on the investment decisions of insurers, I relate the portfolio holding estimates to reported holdings from annual reports in section 5. In subsection 6.1 and subsection 6.2, I present the results on the estimated portfolio changes and discuss the role of the downgrade wave of April 2020. subsection 6.3 compares the European results to the same approach but with US data, and subsection 6.4 presents two important robustness exercises. Section 7 concludes.

2 The Market Situation in 2020

The Covid-19 induced stock market crash of early 2020 presents an unexpected and sudden change in the market environment. Due to rising infection counts and governments preparing to issue unprecedented restrictions on social life and the economy, the uncertainty about future implications of the spreading pandemic led to a capital market crisis. In March 2020 the European stock market index Euro-Stoxx 50 declined by more than 30 percent over the course of two weeks. This is the biggest fall in global equity markets since the 2008 global financial crisis. At the insurer level, the uncertainty is reflected in falling share prices and decreasing prices of corporate debt investments independent of their rating. Further, the increasing demand for government bonds as a "safe haven", results in higher prices and lower yields on government bonds. Such market developments impose significant challenges to insurers, whose asset and liability values are stressed contemporaneously. The liabilities become less certain and future claims might increase given the health and mortality concerns coming associated with Covid-19. In terms of assets, insurance companies account for 20% of euro area investments in sovereign debt, 20% of non-financial corporate debt and 10% of financial firms' debt in 2022[10].

The EIOPA Insurance Statistics Report (EIOPA (2020)) aggregates the holdings of over 1.800 EU insurance firms and presents that corporate and government bonds represent the largest group of assets on insurers' balance sheets. In the last quarter of 2019, government and corporate bonds account for 32% and 27% of total investments, excluding the investments for unit- and index-linked contracts. For comparison, the third largest investment category is collective investment undertakings with 20%, direct stock investments only account for three percent. EIOPA (2020) further presents that during the first quarter of 2020 the aggregate value of equity holdings of insurance companies decreased by over 24%, and the value of corporate bonds decreased by roughly 4%, both represent the largest quarterly movements in the past five years. At the same time the values of technical provisions for non-life and life business grew by 2% and 3.3%, respectively.

In addition, to the aggregate trends in equity markets and insurers' balance sheets, the trading activity on secondary corporate bond markets spikes heavily in March 2020. Panel 1 of Figure 1 presents the monthly total trades as reported under the MiFid II post-trade reporting obligation on EU trading venues, including the UK. The figure shows that in March 2020 the total numbers of trades of corporate, and high-yield bonds present an all time high. In March 2020, monthly trading activity for corporate bonds rises by 42% compared to the previous month and by 84.51% compared to March 2019, the trading activity of high-yield bonds increases by 78.86% and 99%, respectively. In contrast, the trading activity of government bonds in March 2020 is almost at the level of March 2019. Panel 2 of Figure 1 presents the data on US markets obtained from the TRACE trading repository and draws a similar picture with the main difference, that the increase in corporate and high-yield bond trading is more persistent in the months following March 2020. Additionally, the largest group of traded bonds are corporate bonds, whereas on European secondary markets government bonds prevail. Because the statistic aggregates total transactions, it does not explain whether insurers act as buyers or sellers given the market circumstances. This raises the question of whether insurers felt the incentive or the pressure to gamble on the market's recovery and thereby increase their return on investment. Unfortunately, European insurers are not required to disclose their transactions or to provide a list of securities held to the public. The

[10] According to European Central Bank (2022), excluding indirect investments, through investment funds

only publicly available, standardized reporting of asset composition is the aggregated information in annual reports, which provides little insight into the investment decisions throughout the year. The capital market circumstances combined with the unavailability of holdings information provide a laboratory to exploit the asset pass-through documented by Chodorow-Reich et al. (2020) to estimate corporate bond holdings from stock prices, as discussed in the next section.

3 Valuation Concerns and Data

3.1 Valuation Concerns

Equity prices should reflect the market value of the firm's assets and liabilities. Thus, insurers' share prices contain information on the composition of the assets within their investment portfolio. As the value of the asset portfolio increases (decreases), ceteris paribus, the share price should rise (decline) by a fraction ρ of that change The fraction ρ also depends on the leverage ratio of the insurer. See subsection A.1 for a discussion of this problem within my empirical setup. Thus, in an arbitrage-free market a short-term price deviation in the asset values would directly translate into a corresponding change in the equity value, given the liabilities remain unchanged. The fraction ρ would then equal one. Chodorow-Reich et al. (2020) study how changes in asset values impact the market equity value of life insurers in the US. The authors' interpret the fraction ρ as a pass-through and estimate that during non-crisis times it is approximately 0.1. They conclude that insurance firms act as asset insulators by holding long-run assets to maturity. If during non-crisis times the price of a held asset suffers temporary dislocations, the pass-through of the dislocation is less than 1, because the long term value is barely affected. However, the authors also show that the asset insulation decreases during crises as insurance firms' financial health worsens and they might have to liquidate their holdings at market prices. The more likely a liquidation becomes, the closer ρ approaches 1. My approach highly benefits from the findings of Chodorow-Reich et al. (2020) because a higher coefficient of the pass-through during crises also means that changes in the asset values become more apparent in stock prices, making it easier to infer statements on the composition of the asset portfolio. The increased pass-through manifests as a jump in the R^2 in my results during the crisis. Given the market perceives the Covid-19 crisis as a signal about rising expected claims, the jump in the explanatory power (R^2) can be interpreted as the fact that the markets take insurers' asset structure stronger into pricing considerations, which then also empowers the hypothesis that the market has sufficient information on the portfolio structure of insurers.

However, insurers' share prices depend not only on the market value of their assets, but also on the market value of their liabilities. This is especially important for insurance companies as the reservation for insurance claims on the liability side reflects the lines of business in which an insurer operates. In the short-run of the market crash in March 2020, the liabilities affect the share price in two ways. First, the expected profitability of certain lines of business changes. Uncertainties about, for instance health care costs, mortality rates, or business continuity could increase the expected severity, frequency, or both of policyholder claims in associated lines of business and thus lead through changes in the reserves to share prices adjustments. Given that market expectations of the impact of Covid-19 on the profitability of insurance lines are the same for all European insurers, the influential parameter on share price movements is the extent to which an individual insurer is exposed to lines of business that are associated with adjustments in expected claims. I control for these market expectations of claims using the share of net written premiums of a certain business line in the total net written premiums of that firm with data from the "Line of Business" segment of Solvency Financial Conditions Reports (SFCRs). Unfortunately, those reports are issued annually, thus the annual SFCR data is more static than the daily stock market data. However, in the short run, liabilities are more difficult to adapt than assets, mitigating the shortfall of the data on liabilities being updated less frequently in the model. Second, the macroeconomic financial determinants of liability valuation, such as interest rates, inflation, or exchange rates, might fluctuate during the economic downturn and thus affect the market value of liabilities. I control for possible discrepancies between insurers' exposure to those factors by imposing a set of macroeconomic control variables. Thus, the line of business variables incorporate the composition of liability into the analysis and the combination of line of business and firm size, as well as the macroeconomic variables control for the value of liabilities.

3.2 Data

I retrieve daily stock prices, market capitalizations, and equity and CDS index data from January 1, 2016 until December 31, 2020 from Refinitiv: Eikon. The cross-section of the sample consists of 56 insurance firms from 24 countries. Of these firms, 37 domiciled in EU member states, with the remainder split between 14 firms domiciled in the UK, and 6 firms in Switzerland. To adjust the dataset for stale prices, I apply a truncation that excludes a company if the 25th percentile of its absolute returns is zero, that is all firms that show no price movements in at least 25 percent of the trading days. The truncation removes 14 individual firm observations from the sample, resulting in a number of 42 firms. The results of the analysis are robust to changing the truncation threshold to the 10th percentile or the median. Insurers that do not issue SFCR reports are excluded whenever SFCR-related data is applied. Those are all 6 Swiss firms and one UK firm, reducing the sample size to 34 companies in this case. At the end of 2020, the final sample of firms represents a total of 37 percent of the market share of the European insurance sector[11].

SNL Financial provides company-specific financial information, such as balance sheet and income statement items. The SNL Financial database contains data from (semi-)annual regulatory filings which I collect for all issue dates throughout my sample period. All firms in the sample have the same end of period date, December 31. The SFCR reports are also issued on this date. I track the liquidity of the sample firms, by retrieving quarterly reported cash and cash equivalents. Figure 2 shows the share of cash and cash equivalents in total assets. One can see that the crisis year 2020 not only presents the highest liquidity share over the last five years, but is also the only occasion in the sample period when the share of cash and cash equivalents increases between the second and third quarters. This observation is most likely due to the uncertainty during the Covid-19 crisis and the desire of insurers to maintain liquidity. To consider this information in my model, I include a control variable for the share of cash and equivalents.

Bloomberg offers fixed income data from January 2016 to December 2020, including prices and maturities of a set of European corporate bond indices, aggregated by rating. The returns on these portfolios will serve as a proxy to measure the degree of credit risk exposure of European corporate bonds in the investment portfolios of European insurers. Bloomberg further provides data on the

[11] Measured in gross written premiums; market size includes non-publicly traded firms

Vstoxx volatility index, which I use to account for the stock market volatility in the European market.

Finally, the ECB Data Warehouse provides macroeconomic variables[12]. These are the monthly percentage change in the consumer price index, the euro exchange rates and the yield on an aggregated euro area portfolio of AAA-rated government bonds with a maturity of one year. Also, the level of the one-month Euribor rate and the ten-year benchmark yield on European government bonds, which I use to construct a measure for the term structure of interest rates. My analysis considers trading days only, thus removing from all datasets all day observations on which less than half of the insurers were traded on the stock markets. I winsorize all returns at the 0.5th and 99.5th percentiles[13].

The main analysis in this paper uses data between August 2019 and December 2020. The descriptive statistics of the final sample are shown in Table 1. Panel 1 shows the summary statistics over the time series of portfolio returns. The average daily stock return of the firms in my sample is 0.028 %, with a standard deviation of 1.7 %. The large standard deviation and the extreme minimum and maximum values indicate that the stock prices of the 42 firms in my sample are highly volatile, fluctuating around an average return close to zero, a feature that also applies to the returns of the European corporate bond indices. During the observation period investment-grade and high-yield bonds show an average return close to zero, with negative daily returns of up to − 2.5 % and − 3.8 %, respectively. The maturities of the corporate bond portfolios are on average 4.7 and 6.7 years with very little variation over the observation period. This is intuitive, as the maturity of the bond portfolios should not decrease by more than one year over the course of a year of observation, unless the portfolios are rebalanced towards shorter maturities.

Panel 2 presents the time series properties of the macroeconomic control variables of the regression model. The summaries are consistent with the observations on the portfolios in panel 1. I observe large volatility with an average daily return of 0.028 % in the market portfolio for which I use the Euro Stoxx 50 index. The large volatility during the Covid-19 crash also materializes in

[12] For the selection of macroeconomic control variables, I partially follow Acharya and Steffen (2015), as they incorporate the economic key factors that influence the financial business sector.

[13] To mitigate errors in the dataset and single firm events. This is in line with previous research on crises and financial distress by Ge and Weisbach (2021) and Ellul et al. (2015).

the Vstoxx index, which has an average daily return of 0.45 % with a standard deviation of 8.6 % and a maximum daily return of 43.83 %. The base interest rate was negative during the sample period. The nominal effective exchange rate of the Euro against the EER-19 group of trading partners, as reported by the ECB, fluctuated between 89.03 and 102.36 points with an average of 97.14 points, compared to the previous year with a range of 95.49 to 101.67 points and an average of 98.2 points. The mid spread return on Markit's 5-year CDX indices for North American High-Yield (CDXHY5Y) and Investment-Grade (CDXIG5Y) show mean daily returns of 0.04% and 0.197%, respectively. Both indices are positively skewed, although the skew is more pronounced for the investment-grade index. The spreads of the aggregate European counterpart, the iTraxx European Main Index (ITEEU5Y), average 0.108 % daily growth with a median of − 0.141 %, indicating a similar right-skewness as the North American Investment-Grade Index spread returns. The standard deviations of all indices are at the same level. As the statistical properties of all the CSD indices are quite similar, I will use Markit's rating aggregated CDX indices in my analysis, as they are can be better mapped to the respective rating aggregated bond indices.

Panel 3 shows the macroeconomic variables. The Euribor at monthly frequency fluctuated between − 56 bps and − 40.96 bps, with an average of − 47.77 bps. For comparison, the mean of the Euribor in the previous year was − 37.49 with a maximum variation of 4 bps. The index value of the CPI increased monotonically by an average of 0.8 % per month during the sample period.

Panel 4 displays the cross-sectional characteristics of the insurers in my sample. The lines of business HEALTH, BC, CREDIT, LIFE, and GUARANTEE represent the share of the respective line's net written premium[14] in their total net written premium according to the SFCR reports issued at the end of 2019. BC represents premiums related to business continuity and miscellaneous financial loss. GUARANTEE is obtained from SFCR template S.12.01.02 entry "insurance with profit participation" as proposed by Koijen and Yogo (2022b). The largest business line of individual insurers in my sample is life insurance, with an average of 50.88 % of net written premiums. 13.5 % of the net written premiums stem from guarantee products, followed by health with an average of 6.52 % and a maximum of 58.05 %. Credit and financial loss insurance premiums account for the smallest share; one insurer in the sample solely offers credit insurance, which inflates the average. The lowest asset value in the sample is 221 million € for Deutsche Familienversicherung AG, while

[14] Written premiums net of reinsurance

the largest firm, Allianz SE, has assets worth over 1 trillion €. The average insurer in the sample has total assets worth 169 billion €. The median is 60 billion €, indicating that the distribution of the sample firms' total assets is positively skewed. A fact that is further illustrated given that 24 firms have total assets below the sample average. To account for the wide range of insurers' asset values, I use the logged value of total assets as a control variable for size in the regression model. The average share of cash, and cash equivalents in total assets of my sample is 3.6 %, the minimum share is 0.4 % and the maximum is 12.6 %. The difference between the minimum and the maximum is 12.2 percentage points and shows why I control for company liquidity. The share index- and unit-linked investments in total assets is on average 19 %. The discrepancy between the minimum value of 0 and the maximum value of 78.2 % arises due to the fact that my sample includes both life and non-life insurers and underlines the importance of controlling for index-linked and unit-linked contracts, since the market risks associated with the assets held for these contracts are not borne by the insurers but by the policyholders.

4 Methodology

To analyze the changes in the portfolio composition of European insurance companies during the Covid-19 crisis, I estimate the exposures of individual insurers' stock returns to the returns of diversified portfolios, representing government and corporate bonds aggregated by credit rating. To control for the influence of macroeconomic interdependencies, I apply a set of macroeconomic control variables, following the research on bank's asset allocation by Acharya and Steffen (2015). Further, I include net written premiums to account for the influences of each insurers' business mix on its asset price, as well as size and liquidity considerations. This leads to the following regression model:

$$\begin{aligned} R_{i,d} =& \beta_{Gov} HPR_{1day}\left(Y_{Gov,d}\right) + \beta_{CorpA} R_{CorpA,d} + \beta_{CorpBBB} E_{CorpBBB,d} + \beta_{CorpBB} R_{CorpBB,d} \\ &+ \lambda_{CorpA} R_{CorpA,d} \cdot R^{CDS}_{IG,d} + \lambda_{CorpBBB} E_{CorpBBB,d} \cdot R^{CDS}_{IG,d} + \lambda_{CorpBB} R_{CorpBB,d} \cdot R^{CDS}_{HY,d} \\ &+ \gamma' Market_d + \delta' Macro_m + \eta'_{LoB} LoB_{i,y} + \zeta' Firm_{i,y} + \alpha + \epsilon_{i,d} \end{aligned} \quad (1)$$

The analysis is based on a pooled OLS regression. The dependent variable is a panel consisting of the cross-section i and the daily time series d of each sample firm's daily stock return R_{id}. Since the variables have different frequencies of data, I use the indices d for daily, m for monthly and y for yearly. For government bonds, the model uses one-day holding period returns (HPR), constructed using yield curve spot rates. This is the hypothetical return of buying a zero bond with the yield $Y_{Gov,d-1}$ and selling it after one day. The corporate bonds are implemented as index returns.

I include corporate bond holdings by using the returns of the "Bloomberg Pan-European Aggregate Corporate Bonds Indices" which aggregate European corporate bonds by credit rating. Inspecting index data instead of individual bond returns ensures that the return reflects the risk premium associated with the referenced credit rating of the asset rather than default expectations of single firms.

Table 2 suggests that multicollinearity might cause problems with this setup, because the corporate bond indices within the investment-grade category[15] show large correlations, both before and during the market downturn. Since variance inflation factors further encourage collinearity issues between A-rated and BBB-rated coefficients, I decide to orthogonalize the returns of the BBB-rated corporate bond portfolio to explain only the variation that is not already explained by $R_{CorpA,d}$. The orthogonalized return is called $E_{CorpBBB,d}$. In addition, due to multicollinearity concerns[16] and given that most of the variation within investment-grade is already captured by considering A and BBB ratings, I do not include proxies for AA- and AAA-rated corporate bonds in the regression.[17]

The second line of formula (1) presents the controls for hedging through CDS. Aside buying or selling, insurance companies can also change their exposure to corporate bonds by buying CDS contracts, which provide credit protection at the cost of a regular spread payment. I use the mid spread returns of Markit's North American High-Yield and Investment-Grade CDX indices to control for hedging effects across credit rating categories. The CDS controls are implemented as interaction terms rather than through linear addition because of collinearity issues between CDS spreads and bond prices. The interaction terms do a good job of cleaning the β coefficients from the effects of CDS holdings without signs of multicollinearity. Figure A.2 compares the model

[15] Investment grade refers to ratings between AAA and BBB-, high-yield bonds are rated BB+ and below.

[16] Table 2 provides the correlations of all corporate bond portfolio returns

[17] For further robustness to multicollinearity, I present the results of a principal components regression in subsection 6.4 and in Table 6. The results are robust to the orthogonalization specification.

specifications with CDS, without CDS and with both CDS and downgrade controls (subsection 6.2).

In the daily frequency variable $Market_d$, I control for market co-variation, and market volatility by using the return on the Euro Stoxx 50 index, and the return on the Vstoxx index, respectively. Additionally, I use the level of the indexed exchange rate change of the Euro as reported by the ECB to control for the relative attractiveness of the Euro.

M_m represents the macroeconomic variables at monthly frequency m. Short-term interest rates are captured by the Euribor. I do not include controls for the industrial production, the term structure of interest rates and the Economic Sentiment Index proposed by Acharya and Steffen (2015) due to high correlations during the crisis period with other macroeconomic variables during the crisis period.

The variable $Firm_{i,y}$ includes the firm-specific control variables liquidity, size, and unit-linked business as the share of cash and cash equivalents $CashEq_{i,y}$ in total assets and the investments held for index- and unit-linked contracts as a fraction of all assets $Unit\_Share_{i,y}$, respectively. Further, I include the business line shares ($LoB_{i,y}$), which are the net written premiums in a line of business divided by the total net written premiums per insurer, to account for the business mix. In terms of business lines, I consider life, guarantee, health, credit and business continuity. In addition, I use the logarithm of firms' total assets in the regression formula to control for firm size. The results are robust to the addition of further factors from Fama and French (2015), such as value and profitability, while investment strategy should be captured by the corporate bond proxies and is therefore not included.

Because a continuous implementation of a variable that is bound between zero and one can lead to limitations in the interpretability (see Bertrand and Morse (2011) and Frydman and Wang (2019)), I include a median split into dummy variables to test the robustness of the continuous specification and the results remain unchanged. The binary variables equal one if the fraction of net written premiums associated with line of business LoB in total net written premiums of firm i is above the sample median, and zero otherwise.

I apply a rolling regression throughout the observation period with a window length of 100 days, which equals roughly five months of trading days. The rolling approach allows me to show daily developments of the regression coefficients while keeping the number of observations per regression constant. Apart from tracking daily developments another advantage of the rolling regression method is, that it does not require the definition of treatment and control groups. The rolling windows feature a right-sided alignment, which means that each coefficient is calculated using the last 100 data points, leading to $T = 345$ estimations in the output. I track the regression coefficients, standard errors, and adjusted R^2 for each point in time t. The standard errors are heteroscedasticity robust and clustered across individuals. The resulting autocorrelation between subsequent, individually estimated beta coefficients is not problematic because I do not construct standard errors across coefficients and does not affect the interpretation of the coefficients.

With respect to window length, the trade-off between smaller estimation windows with more recent data and thus higher explained variation, and larger estimation windows with more data points and thus lower standard errors. However, the problem with long estimation windows is that more weight is put on older, outdated information, which might override recent effects, leading to a slower response. Therefore, I choose to use 100 days of observations in the baseline analysis. The results are robust to the use of 75, 125, and 150.

5 Share Price Exposures and Investment Holdings

Before inspecting the results of the model, an important question is whether the estimated share price sensitivities are related to the actual portfolio holdings of insurers or rather driven by a change in the market's assessment of share price sensitivities. To show that changes in the estimates relate to changes in insurers' asset allocation, I follow the approach presented by Acharya and Steffen (2015). I estimate the regression coefficients at the end of the financial period for each insurer in the sample individually and relate them to the asset information published in the respective insurers' annual reports. If the estimates are informative about the reported asset allocation, I can interpret the intra-year aggregate regression coefficients as introduced in section 4 as indicative of the asset allocation. A useful feature is that the financial reports are published with a delay of two to three months after the reporting date. This means that the additional information on the portfolio structure in the annual reports is not publicly available during the estimation window. Thus, I am able to compare the pre-publication market expectation in the estimates at the year-end to the publicly reported holdings after the publication of the annual report.

I use year-end data from 42 firms in the sample over the period 2016 to 2019. The data include firms that are not subject to Solvency II regulation, which provides the benefit of additional observations. However, I am not able to control for cross-sectional differences between insurers in this setup because I use a non-panel OLS approach to produce results for each firm individually. As a result, the model loses the controls for firm-specific variables presented in panel 3 of Table 1, which includes the controls for insurance business lines and is the main drawback of this approach. To mitigate this issue, I color-code the data points in Figure 3 according to their affiliation to the life insurance ("LIFE") business line using a median split. The blue dots represent insurers whose share of net written premiums in that line of business is above the sample median, while the red dots represent insurers below the median. Since this categorization relies on data from SFCR reports, non-Solvency II firms cannot be assigned this ratio and are colored gray. Finally, the year-end dates do not coincide with any crisis period. On the one hand, this means that the analysis cannot profit from the increased pass-through effect during crisis periods, as reported in Chodorow-Reich et al. (2020). On the other hand, I do not face the disadvantage of increased correlation among A and BBB rated corporate bond indices, as reported in Table 2. Thus, it is not necessary to orthogonalize the corporate bond index returns for this analysis.

Figure 3 presents the results for all insurers, and the color scheme visualizes the life insurance activity. For all ratings in the four panels, the holdings information from the annual reports (on the x-axis) are plotted against the estimated share price sensitivities of the respective ratings (on the y-axis). The figure also shows a fitted line to illustrate the average relationship. The upper left corner of each panel shows the R^2 and p-value of the fitted line. Each panel presents a significant and positive relation between the reported bond holdings and the point estimates. The significant and positive relation establishes the interpretation that the regression coefficients include information on the insurers' portfolio composition, and can thus help to answer the question of how European insurance companies changed their portfolio composition during the Covid-19 market crisis. Note that the reported data include not only European corporate or government bonds, but all assets that are assigned the respective rating. The resulting dilution is less pronounced for A-rated and BBB-rated corporate bonds, as these bonds represent the largest amount of insurance companies' investments in the respective categories[18], which explains the higher significance of these two panels

[18] See European Systemic Risk Board (2020b) p.4.

compared to AAA-rated government and BB-rated corporate bond holdings.

In terms of life insurance business, a clear distinction is visible in the holdings of A-rated assets. Insurers associated with life insurance business appear to be less engaged in A-rated assets, compared to non-life firms. In panel 2 of Figure 3, all insurers above 40 % A-rated Assets in total Assets bearing credit risk are non-life insurers. The uneven distribution between life and non-life business lines signals that life insurance companies do not concentrate their asset holdings in A-rated European corporate bonds, but rather diversify their credit risk exposure. This observation is supported by the fact that the majority of life insurers invest between 0 and 40 % in each of the presented corporate bond categories. Previous literature[19] suggests that in non-crisis periods life insurers favor riskier BBB-rated assets to increase the yield of their investment portfolio. I cannot confirm this observation in my dataset.

Although I show that the exposure coefficients help to assess movements of insurers' corporate bond portfolios, I am not able to translate the coefficients into an asset structure measured in monetary units. There is no evidence to assume a constant conversion rate from the share price exposure into actual holdings, particularly between the pre-crisis and crisis period. Furthermore, the absence of comprehensive data on portfolio holdings makes it impossible to calibrate a meaningful conversion from the regression coefficients into the holdings composition.

6 Results

6.1 The Impact of the Crisis on Bond Holdings

Panel 1 of Figure 4 shows the daily development of the rolling regressions over time. The vertical red lines represent the dates of the first day of the market crash, the day of the lowest point (the reversal) and the day the reversal trend ended. The orange, green, cyan, and purple lines represent the regression coefficients β_{Gov}, $\beta_{CorpBBB}$, β_{CorpA}, and β_{CorpBB}, respectively. Thus, each point reflects the average sensitivity of the sample firms to the respective returns over the past 100 days. A dot indicates that the coefficient is significant at the 5 percent level. The interpretation of a coefficient at time t is that a 1 percentage point change in the return on the

[19] See for example Becker and Ivashina (2015) and Ge and Weisbach (2021).

respective bond portfolio leads to an average change in the aggregate insurers share price by y percentage points[20]. Correspondingly, a positive coefficient on, for instance, BB-rated bonds does not mean that investing more in BB-rated assets has a positive impact on the share price of insurers. Neither does it mean that insurers with more investment-grade assets perform worse if the coefficient is negative. It it important to keep that in mind that the beta coefficients represent the aggregate share price sensitivity of the insurers given their current asset structure. Changing the asset structure would no longer lead to an all else equal interpretation, which is useful because the change in sensitivity over time thus carries information about the current state of the asset structure. This property ultimately allows me to track changes in the asset structure, which is the point of interest in my analysis.

In interpreting my results, I focus on the absolute value of the coefficients rather than their sign. The sign of the betas indicates the direction of the effect on returns, while the level of the betas determines the size of the effect. Thus, the size determines the extent to which price movements in bond portfolios affect insurer stock prices. If betas are predictive of asset holdings, the pass-through of asset prices should affect the magnitude rather than the direction. However, before analyzing the Figure 4, I would like to provide some intuition about the direction of the effects.

Negative regression coefficients arise from the fact that all price variables are implemented as returns (holding period return for yield variables on government bonds). An increase in the return resembles a higher price and a lower yield. As a consequence, asset-liability management becomes more expensive for insurers. Thus, one interpretation of negative coefficients can be that the effect of higher purchase prices outweighs the increase in the value of owned assets, leading to a negative effect on share prices. The observation of a negative relationship between insurer share prices and investment-grade bond returns is consistent with previous research by Hartley et al. (2016) and Grochola et al. (2022). In addition to the effect of higher purchase prices, rising bond prices may also indicate a reduction in the probability of counterparty default, which helps to explain why the coefficients on high-yield bonds are positive. The fraction of the counterparty default risk component in the price of high-yield bonds is higher than for investment-grade bonds. Therefore, the perceived gain in safety associated with a price increase has a positive effect on the stock price. Haddad et al. (2021) examine the relationship between corporate bond prices and counterparty

[20] All else equal; y is the value on the y-axis in panel 1 of Figure 4.

default considerations as represented by CDS spreads. The authors observe that the CDS spreads of lower-rated bonds and high-yield bonds increased during the market crash, which translates into higher expected counterparty default probabilities for these instruments. The observation of higher expected counterparty default probabilities is consistent with my explanation for the change in the regression coefficient. Haddad et al. (2021) also find significant price dislocations for higher-rated investment-grade bonds that were not reflected in their CDS spreads, suggesting that the expected counterparty default of the safer bonds barely changed.

Figure 4 shows in panel 1 that in the pre-crisis period the regression coefficients of AAA-rated government bonds and BBB-rated corporate bonds in absolute terms range between 0.5 to 1, being statistically significant. Toward the end of 2019, AAA-rated government bond betas approach 0 and become insignificant, while the BB-rated betas gain in size ans significance. As the crisis unfolds, the exposure to AAA-rated government bonds more than triples, although it is temporarily insignificant around the time of the stock market crash. The increase in the coefficient indicates that insurers actively increase their investments in AAA-rated government bonds. During the recovery period the exposure to AAA-rated government bonds decreases but remains higher than before the market crash. The increased exposure to safer assets is also reflected in the path of the A-rated corporates. The coefficients, depicted in green, depart from zero after the market crash. The coefficient for A-rated companies does not reach a sustained, significant level during the crisis and most of the recovery, although it is slightly higher than before the crisis.

BBB-rated corporate bonds represent the lowest rating in the investment-grade category. Prior to March 2020, their coefficient, shown in violet, shows a significant and increasing pattern in absolute terms, with a decline before the market crash. The BBB-beta increases during the crisis period and becomes insignificant approaching zero during recovery, indicating that the exposure reduces. Note that when the CDS correction terms are not included in the regression, the coefficients on BBB-rated corporate bonds are larger and significant[21]. This suggests that investments in BBB-rated corporate bonds were hedged rather than sold.

Looking at the assets below investment-grade, insurers display an increasing exposure to BB-rated bonds going into the crisis, which immediately decreases as the market crashes and quickly recovers, while prices are still falling.

[21] See Appendix Figure A.2

The evidence suggests that on aggregate, insurers increased their investments in AAA-rated government and corporate bonds of all ratings during period of market turmoil in March 2020. Moreover, insurers sold their high-yield corporate bonds in the immediate aftermath of the market crash and appear to have taken on new exposures in the middle of the market crash. The increasing investments in higher credit rating assets during the market crash is consistent with the literature on insurance firms' investment behavior during crisis times (Becker and Ivashina (2015) and Kirti (2024)) and financial distress (Ge and Weisbach (2021)). The sharp initial decline in the coefficient for BB-rated corporate bonds suggests that insurers are keen to sell these assets quickly. However, the rapid recovery also suggests that falling prices and a more developed crisis situation could make high-yield bonds attractive to some insurers, leading to a reversal of the overall trend. Timmer (2018) documents counter-cyclical behavior of European insurance companies during crises. However, rating downgrades could provide an alternative explanation for the rebound in the coefficient for BB-rated bonds, which would also help to explain the increase in the coefficient for BBB-rated bonds in the first month of the market crash. After being downgraded, previously A- and BBB-rated bonds lead to increases in the coefficients of the respective ratings below. I test the hypothesis that the rebound relates to credit rating downgrades in subsection 6.2.

The persistent exposures of high-yield assets after the stock market recovery is consistent with European Central Bank (2020)[22] and might either be driven by the inability to liquidate these assets at reasonable price or by the fact that insurance firms were waiting for further developments of the Covid-19 situation. Evidence of a possible inability to liquidate the high-yield assets is provided by the European Systemic Risk Board (2020a). The ESRB reports that BB- and B-rated corporate bonds experienced a larger peak in bid-ask spreads during the Covid-19 market crash than during the 2008 global financial crisis.

Finally, the path of adjusted R^2 over time is shown in panel 2 of Figure 4. The share of explained variation in the total variation of the firms' returns rises sharply during the Covid-19 crisis. The increase in explained variation suggests that the model does a better job of explaining the insurers' returns during the crisis. On the one hand, this result could be driven by an increase in trading activities to adjust the portfolio. On the other hand, a higher general market volatility induces more variation in otherwise less active variables, which can therefore relate more strongly to the

[22] Chart 4.2

other variables in the model. Most importantly, the jump of the R^2 relates to Chodorow-Reich et al. (2020) who find that the impact of changes in the value of portfolio assets on insurers' share prices is strongest during market downturns.

Table 3 reports the regression results for the entire observation period from mid-2019 to December 2020, with binary interaction terms for the crisis, recovery, and post-recovery periods of the Covid-19 market crash in March 2020. These starting dates of each period are represented by each vertical red line in Figure 4 and correspond to the dates February 14, April 16, and June 15, respectively. In addition, I also include binary interaction terms for the insurers with the highest Solvency Ratio, that is, regulatory capital requirements divided by own funds, to test whether regulatory capital constraints help explain the observed patterns from Figure 4. I refer to the high Solvency Ratio firms as 'unconstrained' for the analysis of my results. Column (1) reports the main specification according to formula (1), and column (2) replaces firm-specific control variables with firm fixed effects, which by definition should include firm-specific characteristics such as the insurance business mix. Since I do not need firm-specific SFCR data, the fixed effects specification has more observations by including non-Solvency II insurers and thus provides further robustness.

The AAA-rated government betas are negative and significant in both specifications. During the crisis and recovery, AAA-rated government betas increase in absolute terms, consistent with the observation in Figure 4, but the interaction terms of these periods with unconstrained firms are insignificant. This suggests that the increase in AAA-rated government bonds is common to all insurers. The significant recovery period for unconstrained insurers indicates divestment after the shock. A-rated corporate bonds show insignificant exposure before the market turmoil. During the crisis and recovery, I observe an increase in the level for constrained insurers, which is consistent with the observation of safer investment behavior of constrained firms for AAA-rated government bonds. If the picture is painted that constrained insurers invest safer, the counterpart, that unconstrained insurers invest riskier, can be observed in the betas of BBB-rated firms. Here, the crisis interaction for constrained firms offsets the effect, leading to a constant pre-crisis exposure but with a change in sign. This is in contrast to unconstrained insurers, whose exposure increases sharply during the crisis. For BA-rated corporate bonds, I observe an increase during the crisis that is common to all insurers, while the direction of the effect is reversed for unconstrained insurers. The fact that the crisis interactions are significant for all asset types has implications for the liquidity provision of insurance companies during crises. While the majority of insurance companies buy safer assets, they do not limit themselves to super-safe government assets, thus helping to mitigate price declines in investment grade and below corporates.

In terms of lines of business, I find no significant effects for any insurance line. A lower exchange rate of the Euro is associated with a weaker performance. In addition, the unconstrained insurers show a significant positive effect on stock returns.

6.2 The Effect of Credit Rating Downgrades

I test the hypothesis that credit rating downgrades partly drove credit risk exposures during the Covid-19 crisis by examining global long-term credit rating data, obtained from Bloomberg. Figure 5 shows the total number of rating downgrades over time. The outer area, in white, shows the total number of rating notches that issuers were downgraded on that day. The inner, blue curve shows the total number of full rating downgrades, that are downgrades resulting in a new rating, for example from AA− to A+. The red vertical lines represent the pre-crash, post-crash, and recovered dates as presented in Table 3. I observe a sharp increase in issuer downgrades following the Covid-19 market crash in late March and throughout April 2020, for both notches and full rating downgrades. In Europe, 18 Western European corporate bond issuers fell below investment-grade in the first two quarters of 2020, the highest number of fallen angels since the European sovereign debt crisis in 2012. There have been 94 downgrades within the investment-grade category, which is higher than in previous years but far lower than in 2012, when 346 issuers were downgraded. The US constitutes 27 fallen angels and 183 downgrades within investment-grade category between January and June 2020.

I incorporate credit rating downgrades into the analysis by adding the following interaction terms[23] to formula (1):

$$
\begin{aligned}
R_{i,d}^{DG} = \; & R'_{i,d} + \theta_{total} * TotalDG_d \\
& + \theta_{A.AA} R_{CorpA,d} DG_{AA,d} + \theta_{A.A} R_{CorpA,d} DG_{A,d} \\
& + \theta_{BBB.A} E_{CorpBBB,d} DG_{A,d} + \theta_{BBB.BBB} E_{CorpBBB,d} DG_{BBB,d} \\
& + \theta_{BB.BBB} R_{CorpBB,d} DG_{BBB,d} + \theta_{BB.BB} R_{CorpBB,d} DG_{BB,d}
\end{aligned}
\tag{2}
$$

Where $R'_{i,d}$ represents formula (1). $TotalDG_d$ measures the total rating downgrades as the sum of all downgraded notches for corporate debt issuers, as shown on the left axis of Figure 5. $TotalDG_d$ controls for the overall impact of rating downgrades on the stock prices. $R_{CorpA,d}DG_{AA,d}$ interacts the return of the A-rated corporate bond portfolio, as presented in formula (1), with the number of full rating downgrades from AA to A. Similarly, $R_{CorpA,d}DG_{A,d}$ captures the interaction of the return of the A-rated portfolio with the number of full rating downgrades from A to BBB. Thus, the $\theta_{x.y}$ coefficients read as the effect on the stock price sensitivity of x, given the number of full rating downgrades in category y. Or more clearly, $\theta_{A.AA}$ measures the change in the regression coefficient of the A-rated portfolio return, depending on the number of from AA rating to A rating and following the same logic further down the rating scale. Finally, the coefficient β_{CorpA} reflects the overall exposure of the stock price to A-rated corporate bonds, while $\theta_{A.AA}$ and $\theta_{A.A}$ capture the change in the exposure coefficient β_{CorpA} depending on the number of rating downgrades from categories AA to A and A to BBB, respectively.

Figure 6 shows the results when controlling for credit rating downgrades. Compared to Figure 4, the reversal of the BB-rated coefficients during the crisis is less pronounced when controlling for downgrades. While the BB-rated beta in Figure 4 is roughly 1.3 before the crisis and 1.9 at the end of the crisis, the same range is 1.3 and 1.5 in Figure 6. This observation indicates that part of the increase in the BB-rated coefficient can be attributed to rating downgrades. The same observation holds true for the coefficient spikes during the crises for A-rated and BBB-rated coefficients.

After controlling for the April 2020 downgrade wave, the increase in the BB-rated coefficient remains persistent. This supports the interpretation that insurance firms began to reinvest in high-yield corporate bonds during the market crash, and is consistent with the finding of anti-cyclical

[23]Given that all ratings in this formula address corporate bonds and for the sake of clarity, I drop the "corp" notation in the subscript of the downgrade observation and the regression coefficients.

investment behavior by Timmer (2018). It further indicates inflows into the BB-rated holdings from downgrades, implying that a fraction of bonds within the BBB-rated corporate bond portfolio of insurers are vulnerable to rating downgrades. This is consistent with the findings of Becker and Ivashina (2015) that US insurers show disproportionately high investments in investment-grade assets, that are vulnerable to rating downgrades. The coefficients for A-rated bonds continue to increase after the crash period, in contrast to the results presented in Figure 4. This suggests that A-rated holdings are also affected by rating downgrades, with downgraded assets leading to a reduction in overall exposure to A-rated corporate bonds. The lower level of the coefficient for BBB-rated bonds after April 2020, taking into account downgrades, supports the hypothesis that a proportion of A-rated bonds were downgraded to BBB.

The results of the downgrade analysis are consistent with the observations of the European Systemic Risk Board (2020b), which conducts a stress test of a mass bond downgrade scenario for European financial institutions and finds that insurance companies face the largest loss in investment value. Additionally, Becker and Ivashina (2015) observe that insurers tend to "reach-for-yield", which describes the tendency to buy bonds with higher yields within a rating category to maximize the return under risk-based capital charges, which also makes in insurers' assets more vulnerable to rating downgrades.

6.3 US Comparison

The goal of the following section is to test the methodology in this paper in the US context, where insurer transactions are observable. This serves to strengthen the empirical validity of the approach I present.

I use security level data on insurance companies' trades from their NAIC reports in Schedule D. The data is provided by S&P Global. S&P Global also delivers balance sheet and P&L items for the firms in the sample. I aggregate insurers' trades on the smallest publicly listed parent company to build the connection between transactions and share prices. Additionally, I obtain security ratings and share prices from Datastream. I excluded all parent firms that are not insurance firms from the analysis. This leaves me with a final sample of 43 US insurers.

Following the methodology presented in section section 4, I estimate the aggregate corporate bond sensitivities of the sample. The results are shown in panel 1 of Figure 7. Compared to the results for European firms, US insurers do not show an increase in BB-rated betas during or after the crisis. The size coefficients of BBB-rated firms do not rise above pre-crisis levels in absolute terms. Both observations are robust to the prevailing view, based on US data, that US firms do not increase their risk exposure during crises. Further evidence is provided by the path of A-rated and AAA-rated betas, both of which rise above pre-crisis levels in absolute terms, suggesting a focus on safer assets. The jump in the adjusted R^2 of the regression is robust to the European specification.

Figure 8 shows the absolute values of the coefficient paths from Figure 7. As mentioned in section 4, I interpret the size of the coefficient rather than their sign, thus I inspect the absolute values of the betas in this plot. The transactions are aggregated by rating and asset type and indexed at 100 at September 2019. The black line depicts the percentage change in asset holdings to the index.

The panels on AAA-rated government bonds and BB-rated corporate bonds are intuitive to interpret. Rising coefficients are good estimates of increasing asset holdings, while coefficients close to zero signal divestment. The BBB-rated corporate bonds show decreasing betas at the beginning of the observation period. The high start of the coefficients for BBB corporates may be due to transactions before the observation period in this figure. In any case, during the period of decreasing coefficients, the holdings barely increase by roughly 0.1 percent, which is does not contradict the assumption of correlation with increases in holdings. Starting in November 2019, when the coefficients begin to rise, transactions also increase by about 0.3 percent during the crisis, and the increase accelerates during the recovery in April 2020. This is consistent with my interpretation of the coefficients. Lastly, A-rated corporate bonds. Here, the coefficients overestimate the increase in assets, but they do not fail to capture the increase. Halfway through the market recovery, the coefficients on A-rated bonds fall to near zero and are disconnected from the increase in holdings until July 2020, when the coefficients begin to rise again. This is most consistent with the overestimation of wealth pass-through at the beginning of the market crash. In summary, all coefficients help explain the increase in their respective asset holdings, with the exception of A-rated corporate bonds in the period between April and July 2020. I therefore conclude that the methodology I use is capable of estimating transaction information from stock prices.

6.4 Robustness Analyses

Acharya and Steffen (2015) suggest a comparison between the estimated insurance coefficients and the estimated coefficients of a set of industry and regional indices. In the event that the coefficients are driven by some confounding factor between equity and corporate bond prices, it would be expected that significant coefficients would not be unique for the insurance industry. For the comparison, I chose the Stoxx Europe 600 - Banks and the Stoxx Euro 600 - Financial Service Providers excluding insurance companies, to compare coefficients within the European financial industry. The MSCI World, S&P 500 and FTSE 100 indices serve as region tests. Table 4 presents the results of this analysis. Most indices show no significant interaction with the crisis period, the only exceptions being the MSCI World for BA-rated corporate bonds and European banks for AAA-rated government bonds. The remaining indices mostly show significant interactions during the recovery, which is not surprising as the market recovery is associated with rising prices and thus increasing investments.

For further robustness, I apply a principal components regression. The weights of the principal components analysis are represented in Table 5. I choose the first 4 components out of 11 available. Each additional component would add less than one percent of the marginal explained variance. I interpret the first component PCA_10Y_IG as long term, low credit risk. The second component PCA_HY has a negative weight on high yield bond returns and a positive weight on long term low credit risk bonds. I interpret this as high-yield related and expect an effect of opposite sign compared to β_{corpBB} due to the negative weight. The third component loads positively on BBB-rated corporates and negatively on all other ratings, so I identify it as representing BBB-rated corporates. Finally, the fourth component loads positively on long-term high-yield bond yields and negatively on shorter maturities and higher ratings. I interpret this spread as a liquidity premium.

Table 6 shows the regression results. For AAA-rated bonds, the crisis interaction is no longer significant in the no fixed effects specification, but remains significant in the fixed effects specification. The coefficients on long-term safe assets show a significant absolute increase during the crisis and the recovery, which is consistent with the previous results. The increase in the coefficient on the liquidity premium component is consistent with my interpretation that insurance companies bought riskier assets during the crisis, which inherently carry higher liquidity risk. The coefficients for BBB- and BB-rated assets are consistent with the previous results, with the betas for BB having the opposite sign as expected.

7 Conclusion

Using publicly available data on European insurers' stock prices, corporate bond price indices and government bond yields, I propose a regression model that estimates the corporate bond composition of insurance firms' investment portfolios. The estimated exposures are positively related to the holdings information reported by the sample insurers in their annual reports, which suggests that the interpretation of the regression coefficients as indicators for the asset compositions is justified. None of the presented robustness checks, including an application to US data with available transaction data, justifies that the relationship between coefficients and holdings does not hold. Figure 6 shows the effect after controlling for rating downgrades and CDS hedging. The results suggest that insurers shifted their portfolio holdings towards higher credit quality as an immediate response to the crisis, thereby releasing own funds bound in risk-based capital requirements. As the crisis progressed, but before market prices started to recover, insurers began to increase their holdings of riskier bonds, while still investing in safe government instruments. As markets were recovering, I observe a reduction in the government bond holdings, and a steady slightly decreasing exposure to high-yield corporate bonds. The latter may be partly due to the pro-cyclical liquidity risk associated with high-yield investments, where financially unconstrained institutional investors could have waited for transaction costs to fall or, alternatively, investors could have waited for prices to recover further, regardless of liquidity concerns. The fact that high-yield corporate bond funds experience redemptions of up to 10 % in April 2020[24] supports this interpretation, because investors can redeem the fund at its net asset value at any time, which indicates investor behavior without market frictions.

In the sub-investment-grade, the exposure to BB-rated bonds drops sharply, and recovers quickly during the market crash, and is constant in the recovery period. As possible reasons for the trend reversal in the BB-rated coefficient, I suggest an exogenous shock to credit rating quality in the

[24] European Systemic Risk Board (2020a)

form of rating downgrades of formerly higher-rated bonds and a shift in the investment behavior in high-yield corporate bonds as the crisis progresses. Interacting rating aggregated bond index returns with the number of full rating downgrades suggests that some of the rapid recovery of the BB-rated coefficient during the crisis is indeed due to rating downgrades, yet a significant part of the increase remains unexplained by downgrades.

In theory, risk-based capital charges may create an incentive to sell lower quality assets during crises, thereby creating the risk of fire-sales, [25]. While this thread seems to be justified in the first month of the crisis, the trend reversal in the BB-rated coefficient suggests that insurers are instead acting counter-cyclically.

In addition, I observe a large increase in the explanatory power of the bond portfolio returns on the share prices during the Covid-19 crisis in 2020, which is consistent with the finding of Chodorow-Reich et al. (2020) that the influence of investment assets on insurers' share prices increases during crisis periods. The finding that insurance companies proactively shift their assets towards safer investments when the financial conditions tighten, strengthens the prevailing view in the literature that in times of crisis, insurers favor safety over return.

At the start of the market crash, insurers acted pro-cyclically by buying safe government bonds and selling their assets with the highest credit risk. This releases own funds bound in regulatory capital charges. As the crisis unfolded and prices declined, insurers began to reinvest in high-yield assets, acting counter-cyclically. In addition, the results suggest that insurance companies are active in trading during crises rather than passive investors, an observation that is consistent with the security level observations of the European Systemic Risk Board (2023). These findings help to understand the behavior of European insurers in future crises. While the counter-cyclical behavior might help to stabilize prices, by providing liquidity to the markets, and offers attractive return opportunities, it also puts insurers' solvency under strain during a period of economic contraction of unknown duration. Both effects need to be taken into account when designing regulatory capital charges and when assessing the stability of the financial system in Europe, given the importance of the insurance firms. A possible extension of my research would be to see how the results of this paper are affected by insurers' geographical exposure to differences in country-specific life expectancy or income, as well as Covid-19 containment measures, although these measures largely

[25]Especially if portfolios are similar between firms. Girardi et al. (2021) provide evidence for this hypothesis.

overlap across European countries.

8 Tables and Figures

Table 1: Descriptive Statistics

This table shows the descriptive statistics of the financial variables used in the analysis. The variables are grouped into daily portfolio or index returns (panel 1), daily market variables (panel 2), monthly macroeconomic control variables (panel 3) or time-invariant firm-specific data (panel 4). Company-specific data is averaged across all the reports during the sample period. The sample covers all European insurers that were publicly traded and active from August 2019 to December 2020. EU.corp.IG and EU.corp.HY represent the returns of an European corporate bond index aggregated by investment-grade and high-yield classification, respectively. EU.gov.AAA is the return of an aggregated euro area portfolio of AAA-rated government bonds with a maturity of one year. CDXHY5Y, CDXIG5Y, and ITEEU5Y are the mid spread returns on Markit's North American High-Yield and Investment-Grade CDX, and the iTraxx European Main 5 year CDS indices, respectively. HEALTH, BC, CREDIT, LIFE and GUARANTEE represent the share of net written premiums of the respective line of business, where BC stands for Business Continuity.

Statistic	Unit	Obs	Mean	St. Dev.	Min	Median	Max
Panel 1: Portfolio Returns							
Avg.Stock.Return	%	338	0.028	1.709	− 10.783	0.062	7.771
EU.corp.IG	%	338	− 0.001	0.272	− 2.490	0.012	0.981
EU.corp.HY	%	338	0.0002	0.518	− 3.785	0.023	2.105
EU.corp.IG.Maturity	Years	338	6.694	0.052	6.401	6.700	6.798
EU.corp.HY.Maturity	Years	338	4.772	0.096	4.611	4.783	4.951
EU.gov.AAA	bps	338	− 0.036	1.532	− 8.966	0.050	9.289
Panel 2: Market Variables							
Stock_Market	%	338	0.028	1.790	− 12.401	0.060	9.236
Vstoxx	%	338	0.448	8.662	− 18.467	− 1.311	43.830
FX Index	Level	338	97.142	2.998	89.030	97.798	102.363
CDXHY5Y	%	338	0.040	3.530	− 9.366	− 0.063	11.411
CDXIG5Y	%	338	0.197	3.874	− 8.730	0.011	13.966
ITEEU5Y	%	338	0.108	3.852	− 9.627	− 0.141	14.836
Panel 3: Macroeconomic Variables							
Euribor	bps	16	− 47.774	4.461	− 56.068	− 45.548	− 40.959
CPI Growth	%	16	0.889	0.404	0.300	0.900	1.400
Panel 4: Firm-Specific Variables							
HEALTH	%	34	6.519	7.487	0.00	3.710	58.05
BC	%	34	0.705	1.065	0.00	0.283	10.86
CREDIT	%	34	3.316	14.88	0.00	0.004	100
LIFE	%	34	50.878	34.07	0.00	55.312	100
GUARANTEE	%	34	13.495	14.881	0.00	6.963	48.45
Assets	Mn €	42	169,532	249,501	221	60,272	1,035,598
Liquid Share	%	42	3.6	2.7	0.4	2.9	12.6
Unit Share	%	42	19	23.1	0	12.7	78.2

Table 2: Corporate Bond Index Correlations

This table presents the correlations of the European corporate bond returns aggregated by credit rating (corp_"Rating"), the holding period return of the AAA-rated government bond (Gov_AAA), and the return of the Euro Stoxx 50 index ("Stock_Market"). The data ranges from March 2019 to August 2019 in panel 1 and March 2020 to August 2020 in panel 2. The diagonal of the matrix is omitted for brevity and due to redundancy. Variables used in the regression model are shown in bold.

Panel 1: Pre-Crisis

	Gov_AAA	corp_AAA	corp_AA	**corp_A**	**corp_BBB**	**corp_BB**
corp_AAA	0.59					
corp_AA	0.53	0.95				
corp_A	0.51	0.89	0.91			
corp_BBB	0.25	0.58	0.65	**0.76**		
corp_BB	0	-0.11	-0.07	0.12	0.33	
Stock_Market	-0.13	-0.23	-0.18	-0.05	0.17	0.54

Panel 2: Crisis

	Gov_AAA	corp_AAA	corp_AA	**corp_A**	**corp_BBB**	**corp_BB**
corp_AAA	0.49					
corp_AA	0.37	0.89				
corp_A	0.17	0.6	0.72			
corp_BBB	-0.11	0.27	0.43	**0.83**		
corp_BB	-0.1	-0.02	0.07	0.44	0.55	
Stock_Market	-0.3	-0.29	-0.2	0.14	0.38	0.54

Table 3: Regression Coefficients

This table reports the regression coefficients of the sample firms' stock prices on a series of rating-aggregated corporate bond index returns. To complement the rolling regression results from Figure 4, the results in this table are estimated over the full observation period from October 2019 to December 2020, with binary crisis, recovery, and post-recovery period interaction terms. *SR.dummy* is a binary variable that is 1 if the Solvency Ratio of an insurer is within the 90% quantile in the cross-section. Corporate bond returns and market returns are measured in percent; government bond holding period returns are measured in 10 basis points. Robust standard errors are clustered by firm and reported in parentheses. Insignificant Controls, CDS interaction terms, insignificant coefficients and the regression constant are omitted for brevity.

	Dependent variable:	
	$R_{i,d}$, measured in percent	
	(1)	(2)
corp_EU_A_P	−0.012	−0.108
	(0.101)	(0.108)
corp_A ×*dummy.crisis*	−0.858**	−0.681*
	(0.385)	(0.397)
corp_A ×*dummy.recovery*	−0.645*	−0.580
	(0.366)	(0.376)
corp_A ×*dummy.recovery* × *SR.dummy*	2.635***	2.624***
	(0.981)	(1.015)
corp_BB	0.674***	0.705***
	(0.159)	(0.174)
corp_BB ×*dummy.crisis*	0.581**	0.491**
	(0.238)	(0.248)
corp_BB ×*dummy.recovery* ×*SR.dummy*	−2.354***	−2.349***
	(0.782)	(0.814)
gov_AAA	−0.535***	−0.394**
	(0.163)	(0.177)
gov_AAA ×*dummy.crisis*	−0.851*	−1.403***
	(0.501)	(0.529)
gov_AAA ×*dummy.recovery*	−0.936*	−1.078*
	(0.561)	(0.562)
corp_BBB	−0.746***	−0.706***
	(0.133)	(0.142)
corp_BBB ×*dummy.crisis*	1.416***	1.313**
	(0.484)	(0.516)
corp_BBB ×*dummy.post*	−0.895*	−0.695
	(0.492)	(0.517)
corp_BBB ×*dummy.crisis* × *SR.dummy*	−3.161**	−3.147**
	(1.335)	(1.405)
Orthorgonalized	Yes	Yes
CDS Interaction	Yes	Yes
Firm FE	No	Yes
Observations	15,096	15,984
Adjusted R^2	0.328	0.295
F Statistic	105.285*** (df = 49; 15046)	114.345*** (df = 40; 15908)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 4: Falsification Tests

This table reproduces the falsification test proposed by Acharya and Steffen (2015). The regression coefficients of the main model from Table 3 are compared with the Stoxx Europe 600 - Banks and the Stoxx Euro 600 - Financial Service Providers excluding Insurance to compare the coefficients within the European financial sector and with the MSCI World, S&P 500 and FTSE 100 indices for regional comparison. If there is a confounding factor between equity and corporate bond prices, one would expect to observe significant coefficients for these industries or regions. Robust standard errors are clustered across firms and reported in parentheses. Controls, CDS interaction terms, insignificant coefficients and the regression constant are omitted for brevity.

	Dependent variable: $R_{i,d}$, in precent					
	Insurance	EstxBanks	EstxFSP	MSCIWorld	SP500	FTSE100
	(1)	(2)	(3)	(4)	(5)	(6)
corp_EU_A	−0.012	−0.120	0.019	−0.376	−0.510	0.053
	(0.102)	(1.234)	(0.399)	(0.284)	(0.351)	(0.433)
corp_A ×*dummy.crisis*	−0.816**	1.119	−1.268	−1.705	−2.382	−2.327
	(0.374)	(3.403)	(2.086)	(2.370)	(2.977)	(1.765)
corp_A ×*dummy.recovery*	−0.335	−0.352	−2.235**	−1.657	−1.874	−2.988***
	(0.356)	(2.771)	(0.975)	(1.313)	(1.748)	(0.899)
corp_A ×*dummy.post*	−0.006	−0.140	−0.558	1.209**	1.483*	−0.097
	(0.356)	(1.926)	(0.698)	(0.568)	(0.759)	(0.763)
corp_BB	0.675***	−3.553	0.645	−0.249	−0.723	0.118
	(0.159)	(2.687)	(0.975)	(0.801)	(1.034)	(0.877)
corp_BB ×*dummy.crisis*	0.545**	3.433	1.792	2.380*	2.744	1.664
	(0.232)	(3.095)	(1.442)	(1.410)	(1.776)	(1.225)
corp_BB ×*dummy.recovery*	−0.261	3.939	2.385*	3.360***	3.977**	3.256***
	(0.299)	(3.424)	(1.223)	(1.269)	(1.636)	(1.012)
corp_BB ×*dummy.post*	−0.302	3.896	1.278	1.142	1.103	1.494
	(0.268)	(2.838)	(0.972)	(0.795)	(1.028)	(0.991)
gov_AAA	− 0.535***	−2.018	−0.474	−0.490	−0.390	−0.564
	(0.164)	(2.883)	(0.666)	(0.369)	(0.504)	(0.647)
gov_AAA ×*dummy.crisis*	−1.036**	7.523*	−0.429	−0.848	−1.406	−0.203
	(0.492)	(4.286)	(2.070)	(2.585)	(3.304)	(1.915)
gov_AAA ×*dummy.recovery*	−1.048*	4.598	1.667	2.422*	3.346*	2.089
	(0.543)	(4.994)	(1.743)	(1.252)	(1.735)	(1.508)
gov_AAA ×*dummy.post*	0.470	8.549*	1.616	0.122	0.210	−0.604
	(0.475)	(4.462)	(1.394)	(1.102)	(1.463)	(1.221)
corp_BBB	−0.746***	−2.326	0.112	−0.120	−0.237	0.434
	(0.134)	(2.291)	(0.587)	(0.392)	(0.496)	(0.612)
corp_BBB ×*dummy.crisis*	1.044**	3.130	4.013	0.638	0.173	2.359
	(0.479)	(4.903)	(2.608)	(3.309)	(4.105)	(2.344)
corp_BBB ×*dummy.post*	−0.553	7.145*	1.797	1.647	1.512	1.133
	(0.506)	(4.257)	(1.410)	(1.375)	(1.818)	(1.567)
Orthogonalized	Yes	Yes	Yes	Yes	Yes	Yes
CDS Interaction	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,096	337	337	337	337	337
Adjusted R^2	0.325	0.030	0.736	0.528	0.397	0.654

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5: PCA Rotation Matrix

This table shows the rotation matrix, that is the matrix of eigenvalues that represent the loadings of each variable in each principal component. The principal components are ordered by their variance contribution, which is depicted below the table. The cells of the tables are colored blue for the variables that contribute most positively to each component and red for the variables that contribute most negatively. The column names represent the interpretation of the components. Robust standard errors are clustered across firms and reported in parentheses. Controls, CDS interaction terms, insignificant coefficients and the regression constant are omitted for brevity.

	PCA_10Y_IG	PCA_HY	PCA_BBB	PCA_LiqPrem
corp_AAA	0.255	0.126	-0.218	-0.397
corp_AA	0.417	0.157	-0.251	0.094
corp_A	0.238	-0.096	-0.049	-0.405
corp_BAA	0.239	-0.336	0.829	-0.119
corp_IG	0.213	−0.162	−0.289	−0.350
corp_BA	0.043	-0.582	-0.199	0.118
corp_HY	0.030	-0.668	-0.264	0.210
corp_1Y	0.030	-0.029	0.032	-0.171
corp_5_7Y	0.186	-0.087	0.055	-0.483
corp_10Y	0.751	0.135	0.055	0.460
RF	0.0001	0.001	0.0005	0.0001
Importance of Components				
Standard Deviation	0.6748	0.3127	0.15614	0.09086
Proportion of Variance	0.7624	0.1637	0.04082	0.01382
Cumulative Proportion	0.7624	0.9261	0.96690	0.98073

Table 6: PCA Regression

This table reports the regression coefficients of the sample firms' stock prices on the first 4 principal components of the rating-aggregated corporate bond index returns. These 4 components explain over 98 percent of the variation in the corporate bond indices. The assignment of the principal components to their interpretation is shown in Table 5 in the Appendix. Robust standard errors are clustered across firms and reported in parentheses. Controls, CDS interaction terms, insignificant coefficients and the regression constant are omitted for brevity.

	Dependent variable: $R_{i,d}$, measured in percent	
	(1)	(2)
gov_AAA	-0.517^{***}	-0.303^{*}
	(0.173)	(0.165)
gov_AAA ×*dummy.crisis*	-0.472	-0.776^{*}
	(0.497)	(0.462)
gov_AAA ×*dummy.recovery*	-0.877	-1.371^{***}
	(0.591)	(0.529)
PCA_10Y_IG	0.007	-0.021
	(0.029)	(0.027)
PCA_10Y_IG ×*dummy.crisis*	-0.276^{***}	-0.217^{**}
	(0.097)	(0.088)
PCA_10Y_IG ×*dummy.recovery*	-0.297^{**}	-0.247^{**}
	(0.127)	(0.116)
PCA_LiqPrem	-0.578^{***}	-0.509^{**}
	(0.211)	(0.202)
PCA_LiqPrem ×*dummy.crisis*	2.506^{***}	2.439^{***}
	(0.573)	(0.530)
PCA_BBB	-0.758^{***}	-0.734^{***}
	(0.136)	(0.128)
PCA_BBB ×*dummy.crisis*	0.773^{*}	0.852^{**}
	(0.405)	(0.372)
PCA_HY	-0.380^{***}	-0.373^{***}
	(0.099)	(0.093)
PCA_HY ×*dummy.crisis*	-0.362^{**}	-0.406^{***}
	(0.150)	(0.143)
PCA_HY ×*dummy.recovery*	0.456^{**}	0.395^{**}
	(0.179)	(0.167)
PCA_HY ×*dummy.post*	0.389^{**}	0.335^{**}
	(0.158)	(0.145)
CDS Interaction	Yes	Yes
Firm FE	No	Yes
Observations	15,096	18,648
Adjusted R^2	0.327	0.317
F Statistic	117.664^{***} (df = 44; 15051)	164.373^{***} (df = 36; 18570)
Note:		*p<0.1; **p<0.05; ***p<0.01

Figure 1: MiFiD II Post-Trade Bond Reporting

The graph in panel 1 shows the monthly aggregated trades of bonds on EU secondary markets, including the UK. Observations range from January 2018 to December 2020. The y-axis represents the number of reported trades per month. The colored lines represent the different types of bonds. Panel 2 presents the monthly trades from the TRACE bond trade repository of the US secondary markets.

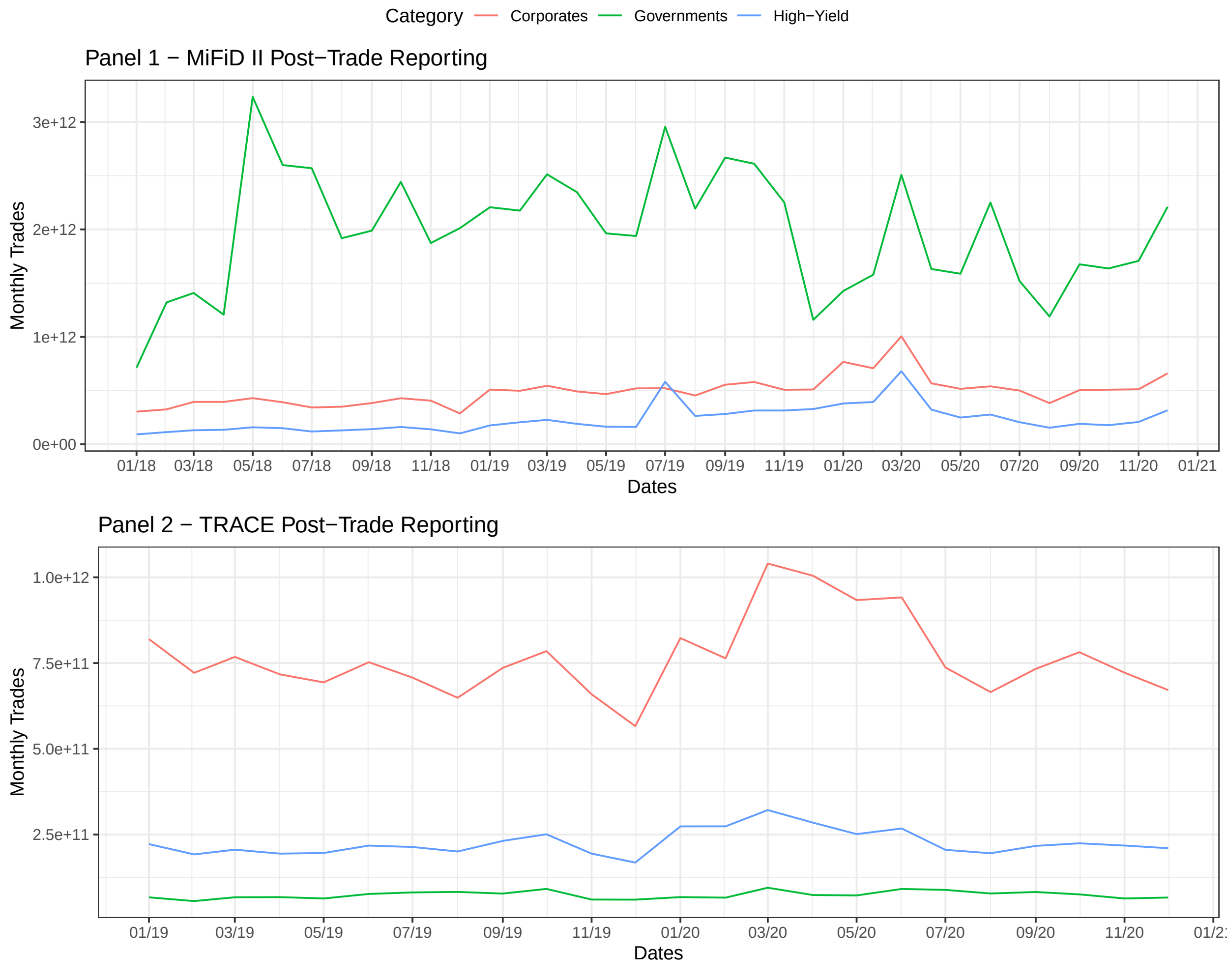


Figure 2: Average Share of Cash and Cash of Liquid Assets

This figure shows the average share of cash and cash equivalents in the total assets of the 42 insurance companies in the sample in each quarter over the years 2015 to 2020. The data are presented for each quarter of each year in order to identify possible seasonal effects.

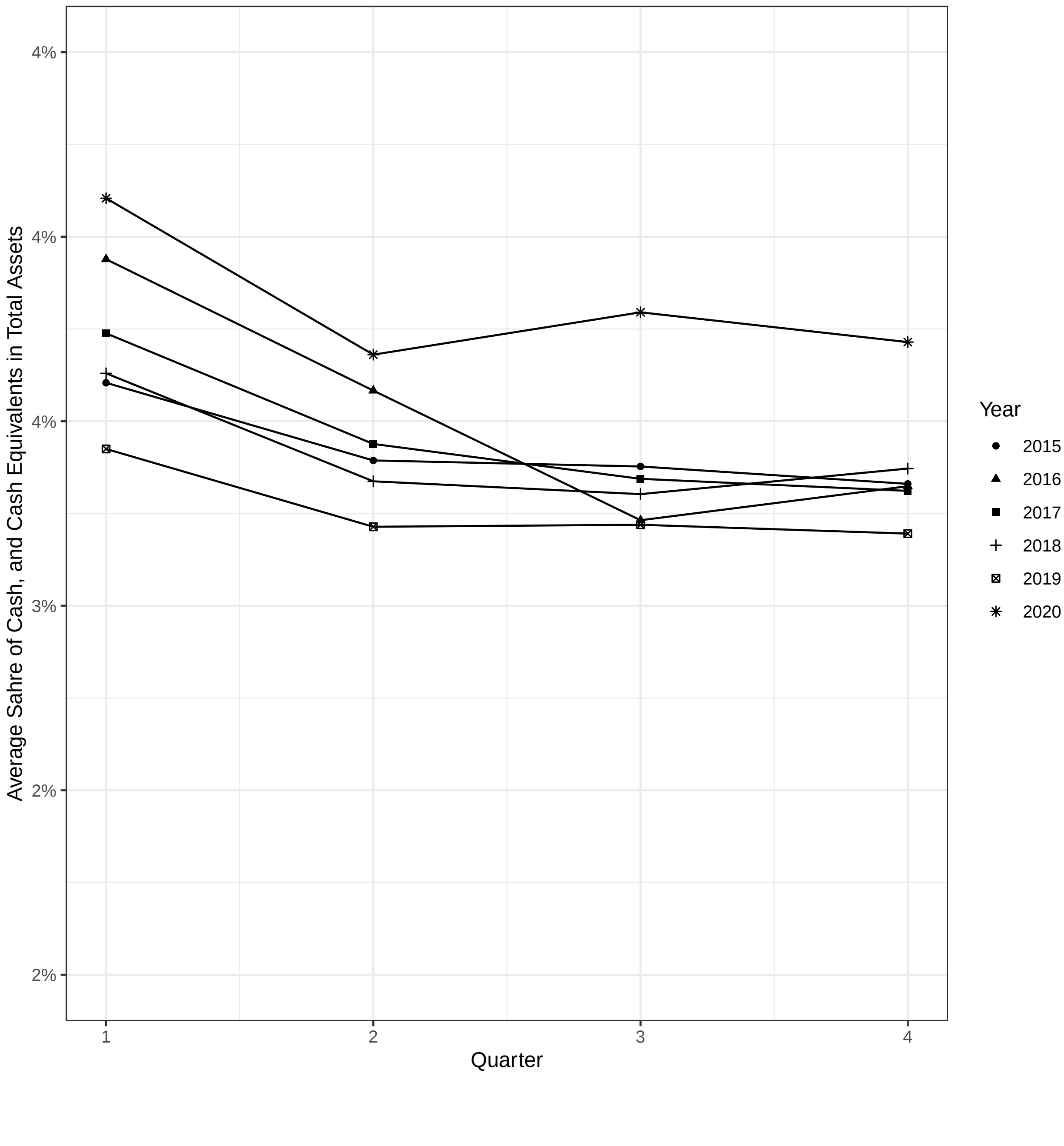


Figure 3: Link Exposures to Holdings

This figure provides evidence for the linkage between the regression coefficients and the portfolio holdings of the sample insurers. The x-axis plots the reported fraction of AAA-, A-, BBB-, and BB-rated assets in all credit risk bearing assets, using data from insurers' annual reports between 2016 and 2019. The y-axis shows the coefficients of the share price regression on the set of credit rating aggregated portfolios. The fitted regression line in blue depicts the relation between the estimated exposures on the y-axis and the reported holdings on the x-axis. The $\mathbf{R^2}$ and p-value of the fitted lines can be found in the top left corner of each panel.

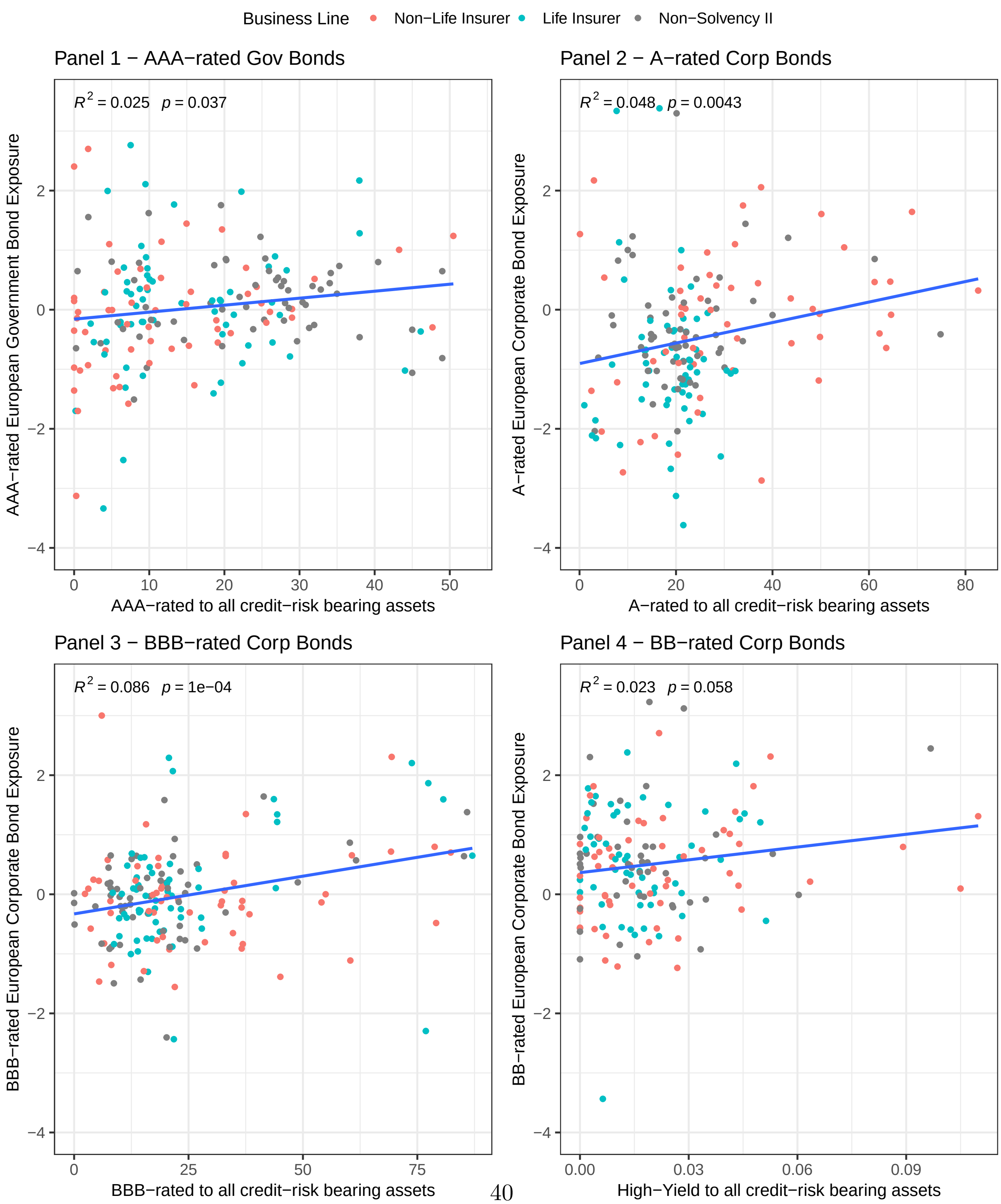


Figure 4: Rolling Regression Results

This figure presents the results of the rolling regression as specified in formula (1). Panel 1 reports the daily development of the rolling regression between September 2019 and December 2020. The orange, green, cyan, and purple lines represent the regression coefficients β_{Gov}, $\beta_{CorpBBB}$, β_{CorpA}, and β_{CorpBB}, respectively. Each point reflects the average exposure of the sample firms to respective returns over the past 100 days. A dot indicates significance at the 5 percent level. Panel 2 presents the path of adjusted R^2 over time. The red lines in both panels represent the dates 14. February, 15. April, and 15. June and resemble the pre-crash, post-crash and recovery columns in Table 3.

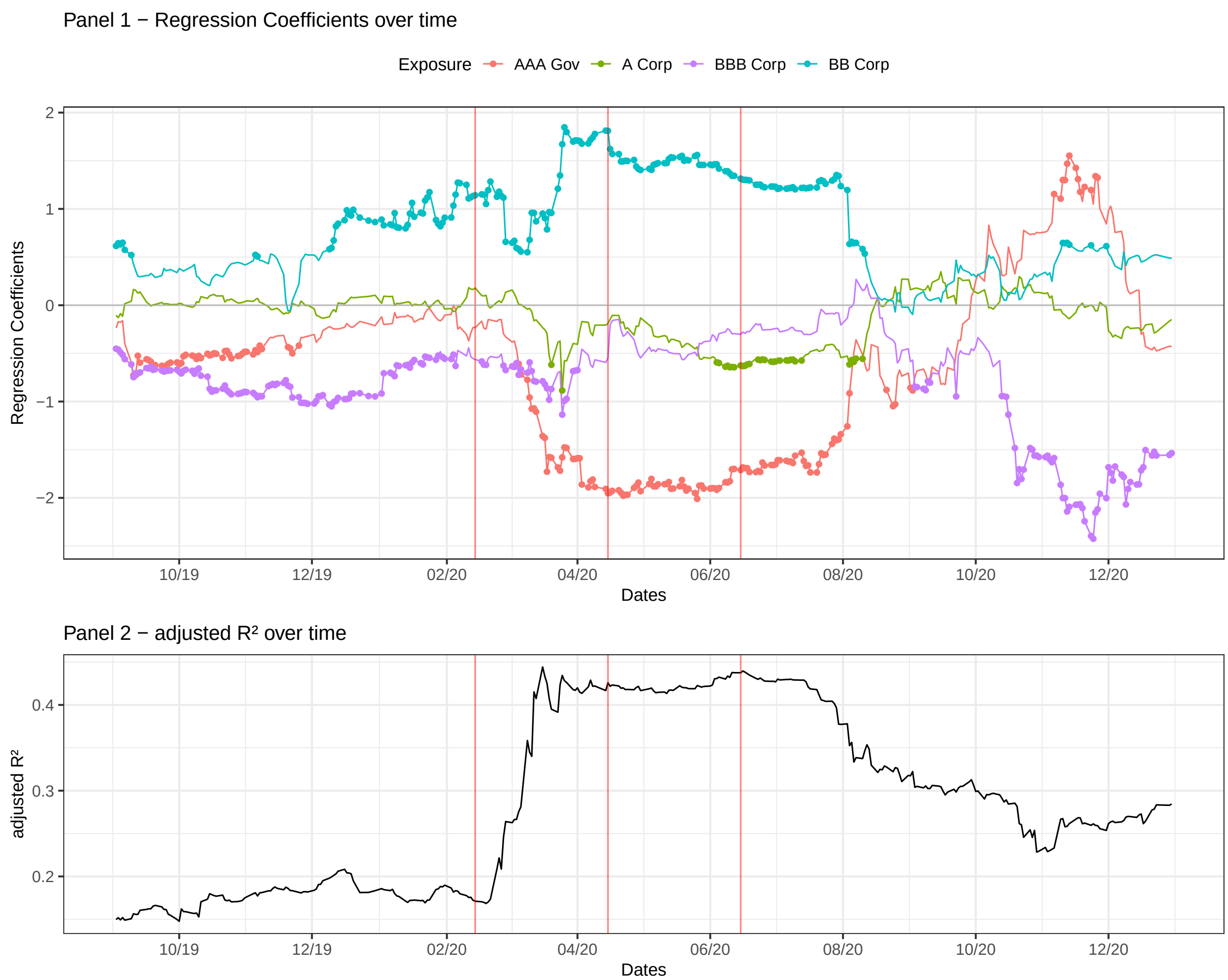


Figure 5: Corporate Debt Issuer Credit Rating Downgrades

This figure shows the overall number of daily rating downgrades between January 2020 and July 2020. The white outer area shows the total number of rating notches that issuers were downgraded on that day. The inner, blue curve illustrates the total number of full rating downgrades, that are downgrades resulting in a new rating. The red lines represent the dates 14. February, 15. April, and 15. June and resemble the pre-crash, post-crash and recovery columns in Table 3.

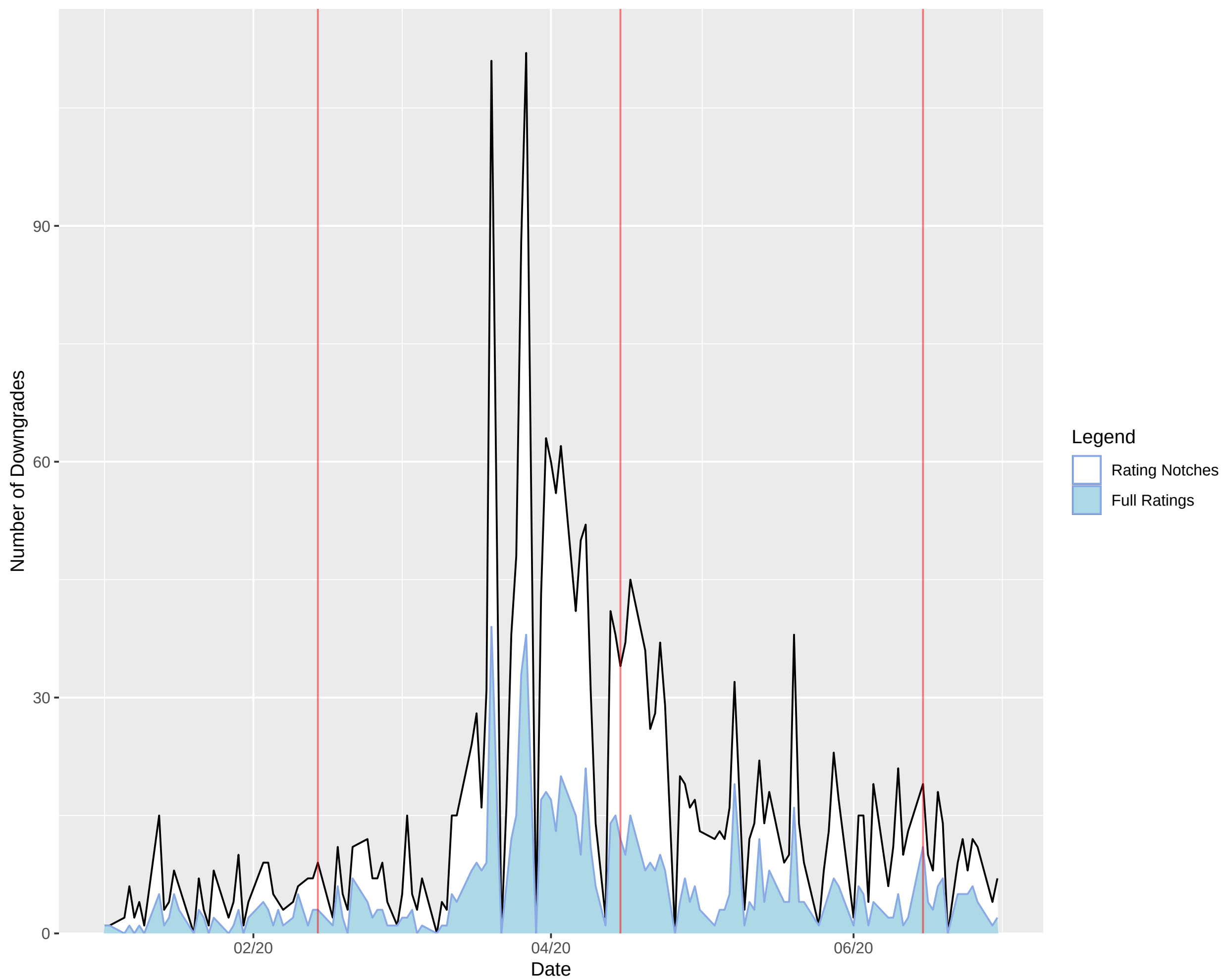


Figure 6: Downgrade Analysis Regression Results
This figure shows the results of the rolling regression when controlling for credit rating downgrades as specified in formula (2), that includes rating downgrade interactions. The daily development of the rolling regression is plotted between September 2019 and December 2020. The orange, green, cyan, and purple lines represent the regression coefficients β_{Gov}, $\beta_{CorpBBB}$, β_{CorpA}, and β_{CorpBB}, respectively. Corporate bond and stock prices are in percent, government bond returns are scaled to 10 basis points for comparison.Each point reflects the average exposure of the sample firms to respective returns over the past 100 days. A dot indicates significance at the 5 percent level. The red lines in both panels represent the dates 14. February, 15. April, and 15. June and resemble the pre-crash, reversal and recovery columns in Table 3.

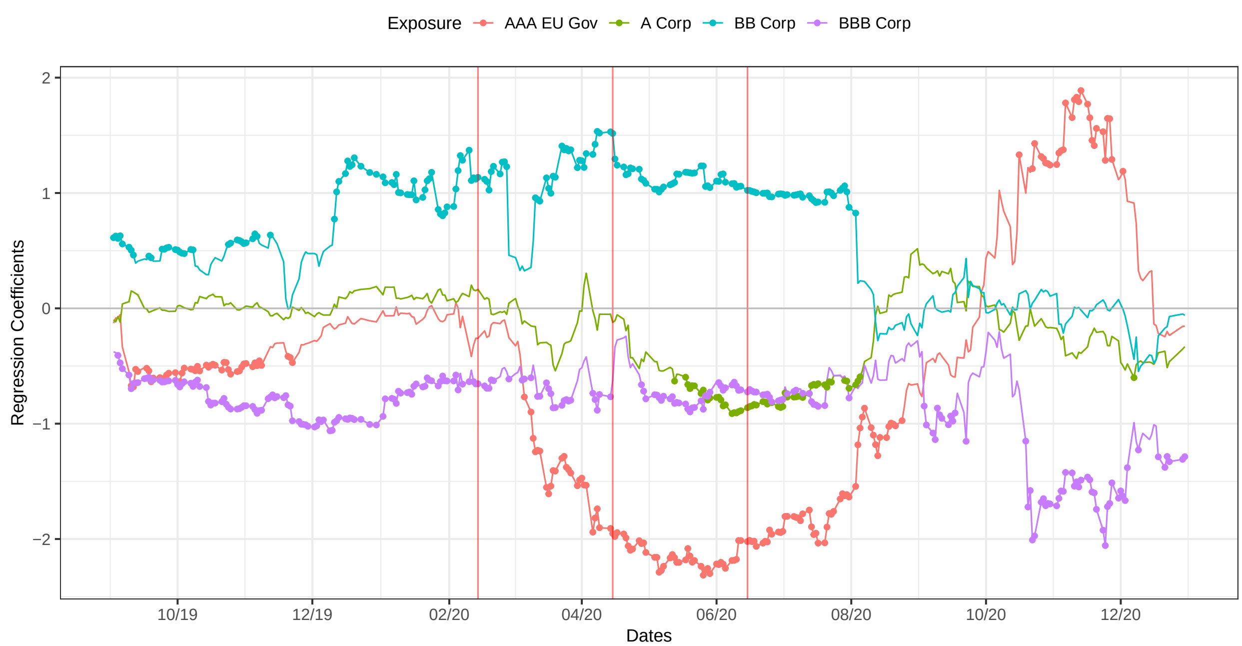


Figure 7: Rolling Regression Results

This figure is a reproduction of Figure 4 with US data. The graph presents the results of the rolling regression as specified in formula (1). Panel 1 reports the daily development of the rolling regression between September 2019 and December 2020. The orange, green, purple, and cyan lines represent the regression coefficients β_{Gov}, β_{CorpA}, $\beta_{CorpBBB}$, and β_{CorpBB}, respectively. Where the coefficients on $\beta_{CorpBBB}$ are orthorgonalized. Each point reflects the average exposure of the sample firms to respective returns over the past 100 days. A dot indicates significance at the 5 percent level. Panel 2 presents the path of adjusted R^2 over time. The red lines in both panels represent the dates 14. February, 15. April, and 15. June and resemble the pre-crash, post-crash and recovery columns in Table 3.

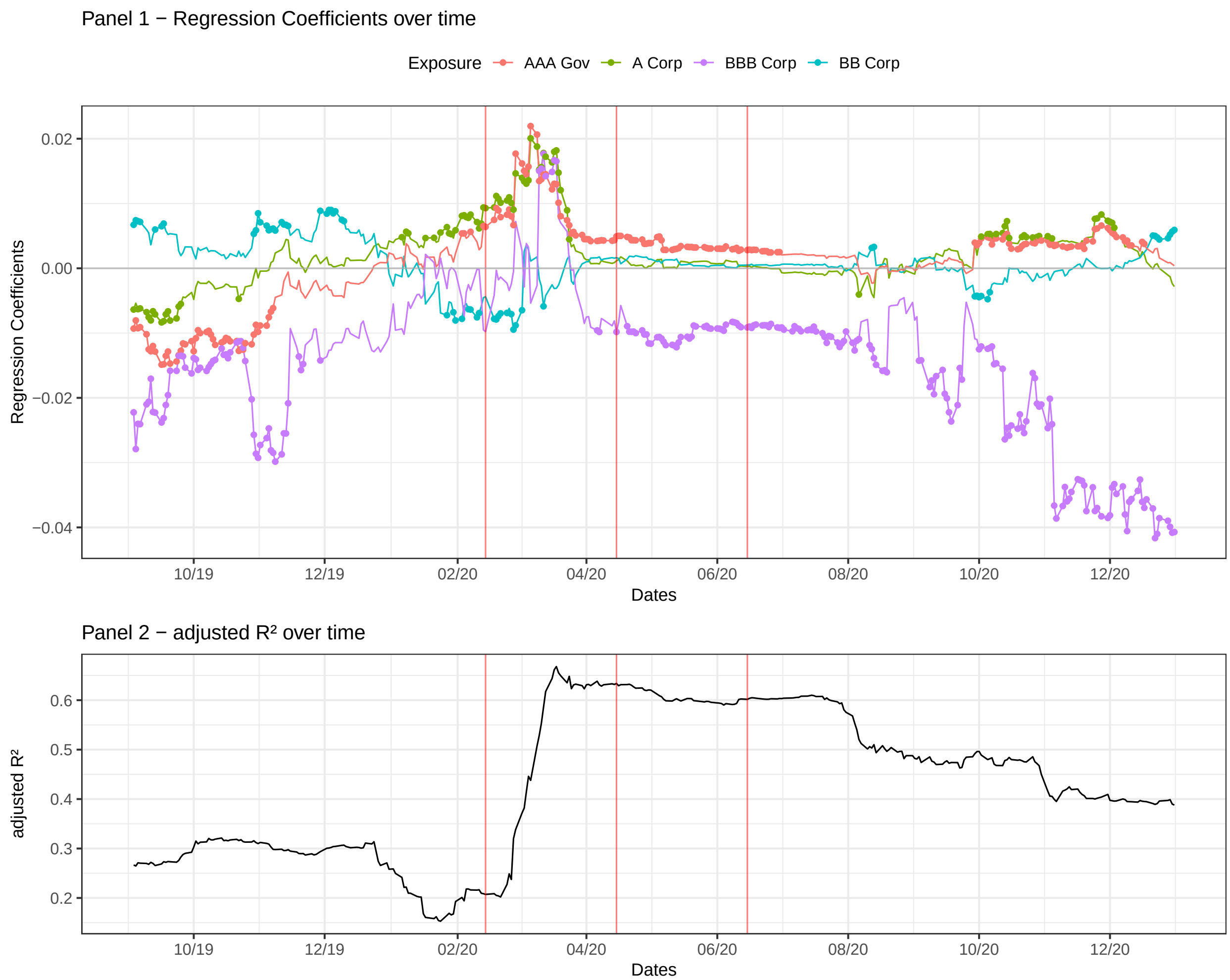
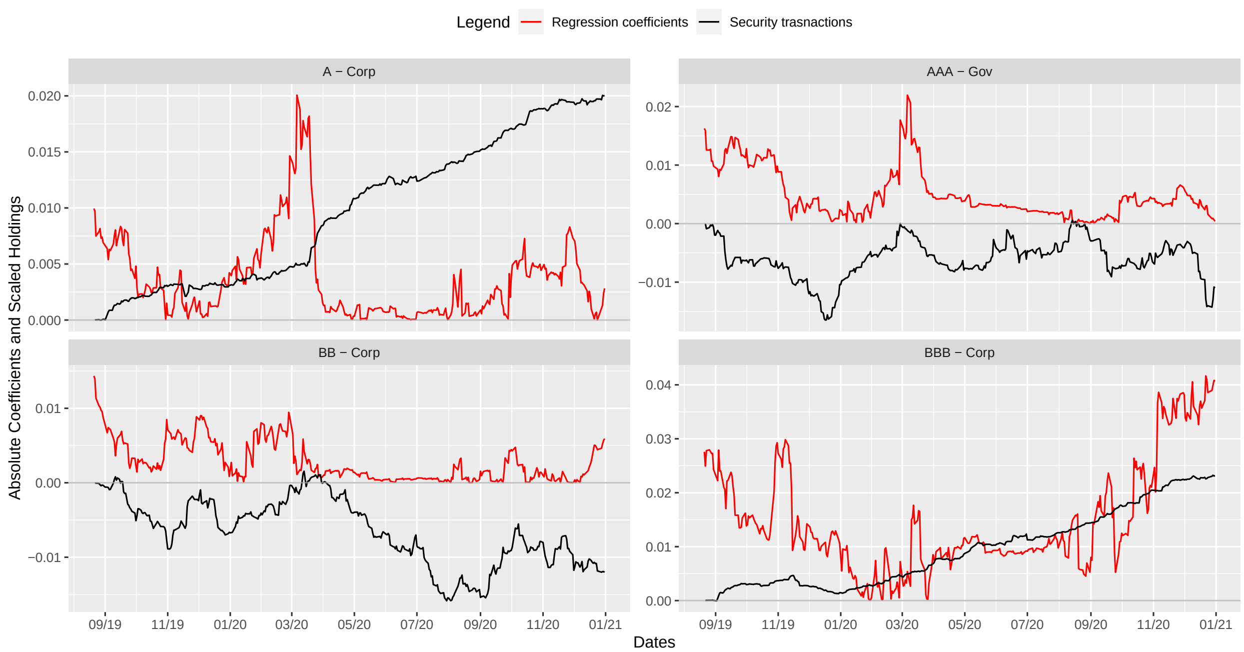


Figure 8: Link Coefficient Paths to Transactions - US Data

This figure shows the coefficient paths from Figure 7. The absolute values of the regression coefficients are shown in red. Transactions as a percentage change from the beginning of the observation period, September 2019, in the respective asset categories are shown in black. Both values share the y-axis. The x-axis shows dates. Transaction data are taken from the NAIC Schedule D report. The plot provides evidence of the relationship between the regression coefficients and the portfolio holdings of the sample of US insurers.



References

Acharya, V. V. and Steffen, S. (2015). The “greatest” carry trade ever? understanding eurozone bank risks. *Journal of Financial Economics*, 115(2):215–236.

Baluch, F., Mutenga, S., and Parsons, C. (2011). Insurance, systemic risk and the financial crisis. *The Geneva Papers on Risk and Insurance - Issues and Practice*, 36(1):126–163.

Becker, B. and Ivashina, V. (2015). Reaching for yield in the bond market. *The Journal of Finance*, 70(5):1863–1902.

Becker, B., Opp, M. M., and Saidi, F. (2021). Regulatory forbearance in the u.s. insurance industry: The effects of removing capital requirements for an asset class. *The Review of Financial Studies*, 35(12):5438–5482.

Bertrand, M. and Morse, A. (2011). Information disclosure, cognitive biases, and payday borrowing. *The Journal of Finance*, 66(6):1865–1893.

Bundesbank (2020). Finanzstabilitätsbericht. page 28f.

Chodorow-Reich, G., Ghent, A., and Haddad, V. (2020). Asset insulators. *The Review of Financial Studies*, 34(3):1509–1539.

Choi, J. and Kronlund, M. (2017). Reaching for yield in corporate bond mutual funds. *The Review of Financial Studies*, 31(5):1930–1965.

Coibion, O., Gorodnichenko, Y., and Weber, M. (2020). The cost of the covid-19 crisis: Lockdowns, macroeconomic expectations, and consumer spending. NBER Working Paper 27141.

Dell'Ariccia, G., Laeven, L., and Suarez, G. A. (2017). Bank leverage and monetary policy's risk-taking channel: Evidence from the united states. *The Journal of Finance*, 72(2):613–654.

EIOPA (2020). Eiopa insurance statistics. Technical report, EIOPA.

Eling, M. and Schmeiser, H. (2010). Insurance and the credit crisis: Impact and ten consequences for risk management and supervision. *The Geneva Papers on Risk and Insurance - Issues and Practice*, 35(1):9–34.

Ellul, A., Jotikasthira, C., Kartasheva, A., Lundblad, C. T., and Wagner, W. (2022). Insurers as asset managers and systemic risk. *The Review of Financial Studies*, 35(12):5483–5534.

Ellul, A., Jotikasthira, C., Lundblad, C. T., and Wang, Y. (2015). Is historical cost accounting a panacea? market stress, incentive distortions, and gains trading. *The Journal of Finance*, 70(6):2489–2538.

European Central Bank (2020). *Financial Stability Review, November 2020.* Publications Office.

European Central Bank (2022). *Financial Stability Review, November 2022.* Publications Office.

European Systemic Risk Board (2020a). *Issues note on liquidity in the corporate bond and commercial paper markets, the procyclical impact of downgrades and implications for asset managers and insurers.* Publications Office.

European Systemic Risk Board (2020b). *A system-wide scenario analysis of large-scale corporate bond downgrades: an ESRB technical note.* Publications Office.

European Systemic Risk Board (2023). Insurers' investment behaviour and the coronavirus (covid-19) pandemic.

Fama, E. F. and French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1):1–22.

Frydman, C. and Wang, B. (2019). The impact of salience on investor behavior: Evidence from a natural experiment. *The Journal of Finance*, 75(1):229–276.

Ge, S. and Weisbach, M. S. (2021). The role of financial conditions in portfolio choices: The case of insurers. *Journal of Financial Economics*, 142(2):803–830.

Girardi, G., Hanley, K. W., Nikolova, S., Pelizzon, L., and Sherman, M. G. (2021). Portfolio similarity and asset liquidation in the insurance industry. *Journal of Financial Economics*, 142(1):69–96.

Gormsen, N. and Koijen, R. (2020). Coronavirus: Impact on stock prices and growth expectations. *SSRN Electronic Journal*.

Grochola, N., Browne, M. J., Gründl, H., and Schlütter, S. (2022). Exploring the market risk profiles of u.s. and european life insurers. ICIR Working Paper Series No. 39/2021.

Haddad, V., Moreira, A., and Muir, T. (2021). When selling becomes viral: Disruptions in debt markets in the COVID-19 crisis and the fed's response. *The Review of Financial Studies*, 34(11):5309–5351.

Hartley, D., Paulson, A., and Rosen, R. J. (2016). *Measuring Intrerest Rate Risk in the Life Insurance Sector: The U.S. and the U.K.* Economics, Regulation, and Systemic Risk of Insurance Markets. Oxford University Press.

He, Z. and Krishnamurthy, A. (2011). A model of capital and crises. *The Review of Economic Studies*, 79(2):735–777.

He, Z. and Krishnamurthy, A. (2018). Intermediary asset pricing and the financial crisis. *Annual Review of Financial Economics*, 10(1):173–197.

Jensen, M. C. and Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, 3(4):305–360.

Kirti, D. (2024). When gambling for resurrection is too risky. *Journal of Banking and Finance*, 162:107–125.

Koijen, R. S. J. and Yogo, M. (2015). The cost of financial frictions for life insurers. *American Economic Review*, 105(1):445–475.

Koijen, R. S. J. and Yogo, M. (2021). The evolution from life insurance to financial engineering. *The Geneva Risk and Insurance Review*, 46(2):89–111.

Koijen, R. S. J. and Yogo, M. (2022a). The fragility of market risk insurance. *The Journal of Finance*, 77(2):815–862.

Koijen, R. S. J. and Yogo, M. (2022b). Global life insurers during a low interest rate environment. *AEA Papers and Proceedings*, 112:503–508.

Shleifer, A. and Vishny, R. W. (1992). Liquidation values and debt capacity: A market equilibrium approach. *The Journal of Finance*, 47(4):1343–1366.

Swinkels, L., Blitz, D., Hallerbach, W., and van Vliet, P. (2018). Equity solvency capital requirements - what institutional regulation can learn from private investor regulation. *The Geneva Papers on Risk and Insurance - Issues and Practice*, 43(4):633–652.

Timmer, Y. (2018). Cyclical investment behavior across financial institutions. *Journal of Financial Economics*, 129(2):268–286.

A Appendix

A.1 Leverage Ratio Dilution

Based on the balance sheet identity, the equity value is the residual of assets minus liabilities:

$$E_t = A_t - L_t \tag{3}$$

where E_t, A_t, and L_t represent the market value of equity, assets and liabilities respectively at time t. Further define $\Delta E_t = E_t - E_{t-1}$ and ΔA_t, ΔL_t analogously. Then the following relationship holds:

$$\Delta E_t = \Delta A_t - \Delta L_t \tag{4}$$

Thus, changes in the asset values directly translate into changes in the equity value, if the value of liabilities remains unchanged.

However, when defining the intertemporal changes as rates of return: $r_{e,t} = \frac{\Delta E_t}{E_{t-1}}$, $r_{A,t}$ and $r_{L,t}$ analogously, the relationship between the asset return and the equity return in t depends on the leverage ratio $\frac{A_{t-1}}{E_{t-1}}$ in $t-1$:

$$r_{e,t} = \frac{\Delta E_t}{E_{t-1}} = \frac{\Delta A_t}{E_{t-1}} - \frac{\Delta L_t}{E_{t-1}} = \frac{A_{t-1}}{E_{t-1}} r_{A,t} - \frac{L_{t-1}}{E_{t-1}} r_{L,t} \tag{5}$$

Now assume that the liability value is fixed, i.e. $L_t = L_{t-1}$.

The linear regression defined in (6) estimates the effect of a change in the asset return on the change in the equity return, and is a condensed version of the model I use in my analysis, where I aim to isolate insurers' exposure to a set of asset types.

$$r_{E,t} = \beta r_{A,t} + \epsilon_t \tag{6}$$

With the fixed liability assumption, equation (5) tells us that β estimates $\frac{A_{t-1}}{E_{t-1}}$ in this scenario. This is a problem because the market value of equity in the previous period E_{t-1} can lead to changes in β even if A_{t-1} remains unchanged, potentially causing my model to capture changes in the leverage ratio whereas I am trying to capture changes in asset values.

Note: In the application in my paper the leverage problem is far less pronounced than in the theoretical derivation presented above for two reasons: (i) I do not use the value of all assets, but proxy returns that represent certain asset categories. (ii) The proxy assets are not necessarily owned by the insurers. (iii) I control for possible sources of changes in the market value of equity that are not induced by changes in the asset value such as market movements or liability valuation.

A.1.1 Solution

To solve the leverage ratio problem, I apply the following regression formula:

$$\Delta E_t = \beta' r_{A,t} + \epsilon_t \tag{7}$$

Still assuming that the liabilities remain unchanged, β' estimates A_{t-1}, because

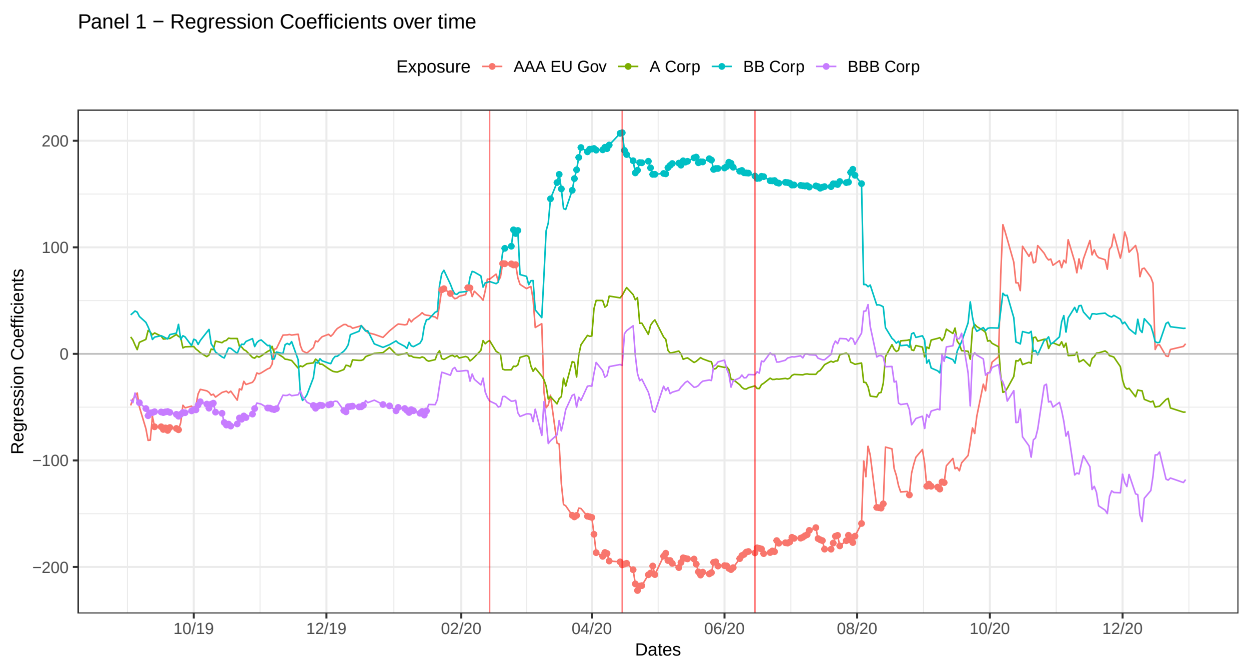
$$\Delta E_t = \Delta A_t = A_{t-1} \frac{\Delta A_t}{A_{t-1}} = A_{t-1} r_{A,t} \tag{8}$$

Figure A.1 presents the results of specification (8), which are robust to the results I report in my paper, where I apply formula (6).

Note: Reasons for not using (8) in the main specification: (i) I want a standardized measure that is comparable across firms, especially given the pooled result. (ii) Price change specification (8) may cause stationarity problems. (iii) Comparability between dependent variable (change in equity value) and independent variables (change in bond prices).

Figure A.1: Rolling Regression Market Capitalization Robustness

This figure presents the results of the rolling regression as specified in formula (8), reporting the daily development of the rolling regression between September 2019 and December 2020. The orange, green, cyan, and violet lines represent the regression coefficients β_{Gov}, $\beta_{CorpBBB}$, β_{CorpA}, and β_{CorpBB}, respectively. Each point reflects the average exposure of the sample firms to respective returns over the past 100 days. A dot indicates significance at the 5 percent level. The red lines represent the dates 14. February, 15. April, and 15. June and resemble the pre-crash, post-crash and recovery. The dependent variable is the change in market capitalization instead of the stock return as in the main specification. The coefficient paths are robust to the paths in Figure 4.



A.2 Lagged Regressors

Table A.1: Lagged Regressors
This table presents the regression coefficients of the main model. The rows present the regression coefficients under four specifications: main model (for reference), lagged dependent variable, lagged bond returns, and lagged dependent variable and bond returns. Corporate bond returns and the market return are measured in percent; government bond holding period returns in 10 basis points. Robust standard errors are clustered across firms and reported in parentheses. Controls, CDS interaction terms, insignificant coefficients and the regression constant are omitted for brevity. The development of all variables of interest is robust to the baseline specification.

	Dependent variable:			
	$R_{i,d}$, measured in percent			
	Base	Lagged Dependent Variable	Lagged Bond Returns	Lagged Dependent Variable and Bond Returns
corp_A	−0.166	−0.154	−0.202*	−0.194*
	(0.116)	(0.116)	(0.114)	(0.114)
corp_A_lag			0.188	0.156
			(0.159)	(0.161)
corp_BA_P	0.844***	0.908***	1.037***	1.047***
	(0.137)	(0.139)	(0.146)	(0.146)
corp_BA_lag			−0.090	−0.028
			(0.119)	(0.125)
Euribor	−0.008**	−0.009***	−0.007**	−0.007**
	(0.003)	(0.003)	(0.003)	(0.003)
gov_AAA	−0.910***	−0.928***	−0.667***	−0.691***
	(0.195)	(0.196)	(0.186)	(0.187)
gov_AAA_lag			−0.208	−0.251
			(0.189)	(0.189)
HML	0.521***	0.525***	0.520***	0.521***
	(0.031)	(0.031)	(0.031)	(0.031)
Market	0.659***	0.654***	0.654***	0.654***
	(0.038)	(0.038)	(0.037)	(0.037)
SMB	0.163***	0.169***	0.205***	0.211***
	(0.060)	(0.060)	(0.059)	(0.058)
corp_BAA	−0.532***	−0.551***	−0.488***	−0.494***
	(0.148)	(0.149)	(0.147)	(0.147)
corp_BAA_lag			−0.577***	−0.555***
			(0.138)	(0.138)
$R_{i,d}$_lag		−0.024**		−0.021*
		(0.012)		(0.012)
Orthorgonalized	Yes	Yes	Yes	Yes
CDS Interaction	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No
Observations	15,096	15,096	15,096	15,096
Adjusted R^2	0.319	0.320	0.322	0.322
F Statistic	216.834*** (df = 21; 15074)	206.438*** (df = 22; 15073)	188.524*** (df = 25; 15070)	181.104*** (df = 26; 15069)
Note:				*p<0.1; **p<0.05; ***p<0.01

A.3 Additional Tables and Graphs

Table A.2: Country and Firm-Year Fixed Effects

This table presents the regression coefficients of the main model. The rows present the regression coefficients under four specifications: main model (for reference), country fixed effects, and firm-year fixed effects. Corporate bond returns and the market return are measured in percent; government bond holding period returns in 10 basis points. Robust standard errors are clustered across firms and reported in parentheses. CDS interaction terms, insignificant coefficients and the regression constant are omitted for brevity. The development of all variables of interest is robust to the baseline specification, except for A-rated crisis interaction, which indicates firm year effects that are in line with the Solvency Ratio observation in table 3.

	Dependent variable:		
	$R_{i,d}$, measured in percent		
	(1)	(2)	(3)
corp_A	−0.007	−0.007	−0.123
	(0.102)	(0.102)	(0.095)
corp_A ×*dummy.crisis*	−0.821**	−0.821**	−0.441
	(0.374)	(0.375)	(0.340)
corp_BB	0.680***	0.681***	0.688***
	(0.160)	(0.160)	(0.154)
corp_BB ×*dummy.crisis*	0.526**	0.526**	0.478**
	(0.231)	(0.231)	(0.213)
gov_AAA	−0.530***	−0.530***	−0.323**
	(0.164)	(0.164)	(0.155)
gov_AAA ×*dummy.crisis*	−0.936*	−0.937*	−1.367***
	(0.497)	(0.498)	(0.456)
gov_AAA ×*dummy.recovery*	−1.104**	−1.104**	−1.618***
	(0.541)	(0.540)	(0.481)
Euribor	−0.012***	−0.012***	−0.011**
	(0.003)	(0.003)	(0.004)
FX	−0.025**	−0.025**	−0.022**
	(0.012)	(0.012)	(0.011)
HML	0.540***	0.540***	0.546***
	(0.031)	(0.031)	(0.029)
Market	0.683***	0.683***	0.680***
	(0.038)	(0.038)	(0.035)
SMB	0.194***	0.193***	0.171***
	(0.059)	(0.059)	(0.056)
corp_BBB	−0.754***	−0.754***	−0.727***
	(0.134)	(0.134)	(0.126)
corp_BBB ×*dummy.crisis*	1.178**	1.176**	1.183***
	(0.470)	(0.470)	(0.437)
Orthogonalized	Yes	Yes	Yes
Fixed Effects	None	Country	Firm-Year
Observations	15,096	15,096	18,648
Adjusted R^2	0.325	0.325	0.315
F Statistic	146.582*** (df = 33; 15062)	101.080*** (df = 48; 15047)	53.734*** (df = 108; 18539)
Note:			*p<0.1; **p<0.05; ***p<0.01

Figure A.2: Rolling Regression Coefficient Path Comparison

This figure presents the results of the rolling regression during the first two quarters of 2020, for the specifications "No CDS" without CDS controls, i.e. formula (1) without the second line, "With CDS", i.e. formula (1), and "With CDS and DG", i.e. formula (2). Panels 1 to 4 present the regression coefficients β_{Gov}, $\beta_{CorpBBB}$, β_{CorpA}, and β_{CorpBB}, respectively. Each point reflects the average exposure of the sample firms to respective returns over the past 100 days. A dot indicates significance at the 5 percent level. Panel 2 presents the path of adjusted R^2 over time. The red lines represent the dates 14. February, 15. April, and 15. June and resemble the pre-crash, post-crash and recovery.