

Gambling for Recovery? Exploring the Riskiness of European Insurers' Assets during the Covid-19 Crisis 2020

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Abstract

In crisis times, insurance companies might feel the pressure to present an investment portfolio performance that is superior to the market, since investment portfolios back the claims of policyholders and serve as a signal for the claims' safety. I investigate how a stock market crisis as experienced over the course of the Covid-19 pandemic influences insurance firms' decisions on the allocation of their corporate bond portfolio. I find that insurers shift their portfolio holdings towards lower credit risk assets as financial market conditions tighten. This tendency seems to be restricted by the liquidity risk of high-yield assets, and the credit risk of lower-rated investment grade assets. Both effects lead to an increase in the fraction of less liquid assets during the crash and the recovery.

Keywords: Insurance; Covid-19; Financial Stability

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1 Introduction

Financial institutions show the tendency to invest into riskier assets during non-crisis times to increase portfolio performance. The channels through which such behavior manifests are risk-based capital requirements (Becker and Ivashina (2015)), low market interest rates (Dell'Ariccia et al. (2017), Choi and Kronlund (2017)) or regulatory arbitrage concerns (Acharya and Steffen (2015), Swinkels et al. (2018)). However, these studies also observe that as these institutions face financial constraints or market crises, the tendency towards riskier investments vanishes (Ge and Weisbach (2021)). This observation seems to hold despite the presence of incentives that endorse investing riskier. For the insurance industry, possible sources of such incentives are to maximize investment returns, a high share of guarantee products¹ and the resulting pressure to meet the obligations, or lastly risk-taking incentives fostered by non-risk-based regulatory rules.

This paper asks, whether European insurance companies shift their investments towards higher credit risk assets throughout the Covid-19 induced market crash. While many of the studies cited above find no evidence of such behavior in crisis times, most of them focus on the US market. The US market features detailed transaction reporting requirements, which foster research but at the same time also impose public transparency that could lead to changes in investment behavior. I contribute to the existing literature by (i) examining the European insurance market with far less transparent reporting obligations and (ii) presenting an empirical approach that yields information on the credit-risk portfolio composition of public insurance companies on a daily basis. The first contribution directly arises from the fact that the existing literature focuses mainly on the US market and addresses the point of a possible behavioral change under public scrutiny. The fact that asset-level information on investment portfolio holdings is not publicly available in Europe leads to my second contribution, which is to derive the holdings information from empirically estimated share price sensitivities of European insurers. To show that the estimated sensitivities contain information about the asset composition of the insurers, I relate the sensitivities to the annually reported, aggregate investment information of each insurer and find a positive and significant

¹Koijen and Yogo (2022b) find that insurance products with guarantees lead to higher market risk in life insurers' portfolios.

relation for all estimated coefficients. My results show that the exposure of European insurers towards AAA-rated European government bonds increases while the exposure towards BB-rated (high-yield) corporate bonds decreases. These findings on insurers' increased demand for assets with lower credit risk in times of crisis are consistent with the findings in the US market. I also find that credit risk, manifesting in rating downgrades during the market downturn increases insurers exposure to assets with higher credit risk. The liquidity risk associated with lower-rated assets then seems to limit the insurers' scope of action.

[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 price sensitivity of high-yield corporate bonds 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, as the crisis unfolds, insurers steadily reduce their exposure to high-yield corporate bonds, 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.

My analysis gains new insights through the focus on European insurance companies for three reasons. First, there are no regulatory differences between firms in EEA member states, given the Solvency II regulation. This prevents that a subset of the sample is affected by a regulatory change². Second, US insurance firms face stronger disclosure obligations regarding their investments which require them to publicly report daily investment transactions on a quarterly basis. The European market therefore provides a playing field where granular transaction data is not publicly observable, with potential implications for investment behavior. In addition, the lack of detailed data leads to a lack of research on the European market. Third, the peak in trading activity of high-yield bonds is more pronounced and during a more narrow time window on the European market compared to the US market, both attributes foster the identification of the estimates in my analysis ([Figure 1](#)).

²Section 5 includes non-Solvency II firms to increase the number of observations and test the predictive power of my model beyond Solvency II firms.

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 portfolio³. To shed light on insurance firms' investing I use the daily stock market returns of 34 publicly traded 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 investment assets with a given credit rating, I aim to uncover the intra-year 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 the approach presented by [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 the authors' approach by adding a rolling regression setup. The main advantage of this approach by [Acharya and Steffen \(2015\)](#) 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 \(2021\)](#); [Kojien and Yogo \(2015\)](#)). I show that European insurers reduce the credit risk of their asset portfolios significantly during the Covid-19 despite the presence of incentives to gamble on the recovery of markets, which is in line with the prevalent finding in the literature that insurance firms tend to invest safer as financial market conditions tighten. [Becker and Ivashina \(2015\)](#) for instance report that the "reaching for yield" of US insurance companies is not observable during the global financial crisis 2008.

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

³I discuss the valuation concerns, including the role of the liabilities, in greater detail in section 3.1.

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 of [Becker and Ivashina \(2015\)](#) and consistent with the pattern I observe during the Covid-19 market crash.

[Kirti \(2017\)](#) 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” motive⁴, in practice insurers affected more by the crisis shift their investments stronger towards being less risky compared to less affected firms. Kirti’s research question is close to mine, yet my study differs on the one hand by inspecting the market crash associated with the Covid-19 pandemic that concerns income and claim expectations ([Coibion et al. \(2020\)](#); [Gormsen and Kojen \(2020\)](#)) compared to the global financial crisis that unraveled as a credit crisis ([Eling and Schmeiser \(2010\)](#); [Baluch et al. \(2011\)](#)). On the other hand, European insurers report their asset holdings directly to the regulator, with no public access to this information. Thus, I cannot rely on the securities reporting data as [Kirti \(2017\)](#), or [Ge and Weisbach \(2021\)](#) do, yet my findings are consistent with both studies.

[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. The results on the asset allocation are consistent to 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. [Kojen and Yogo \(2021\)](#) and [Kojen and Yogo \(2022a\)](#) discuss that variable annuities resemble market risk insurance that may expose 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 identification of guarantee business as SFCR template S.12.01.02 entry “insurance with profit participation” proposed by [Kojen and Yogo \(2022b\)](#) and incorporate the guarantee business as a control variable in my model.

[Ellul et al. \(2015\)](#) presents evidence that historical cost accounting may lead to gains trading by life insurance firms during the financial crisis, which I do not observe in my sample. [Acharya and Steffen \(2015\)](#) find that Eurozone banks in the period of 2007-2013 systematically increased

⁴[Jensen and Meckling \(1976\)](#) introduce the term, describing the incentive that a firm acts riskier when facing financial distress.

their exposure to southern European bonds while short-selling German government bonds, which can be associated with risk-shifting and regulatory arbitrage motives. Methodologically, I follow their approach to estimate the exposure of the firms' stock prices to a set of bond returns, but extending the model to suit the business of insurance companies.

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 concerns and the data. In section 4, I show my 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 section 6 I present the results on the estimated portfolio changes and discuss the role of the downgrade wave of April 2020.

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 represents the largest stock market depreciation around the world since the global financial crisis of 2008. 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 becomes 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 2022⁵.

The EIOPA Insurance Statistics Report ([EIOPA \(2020\)](#)) aggregates the holdings of over 1.800 EU insurance firms and presents that corporate and government bonds on represent the largest

⁵According to [European Central Bank \(2022\)](#), excluding indirect investments through investment funds

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 are 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 UK. The figure shows that in March 2020 the total numbers of trades of corporate, and high yield bonds present an all time high. During 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 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 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.

3 Valuation Concerns and Data

3.1 Valuation Concerns

Share prices should reflect the market value of the firm's assets and liabilities. If the European stock market features at least a semi-strong market efficiency regime⁶, share prices comprise all publicly available information on the structure of the firm's assets. This implies that insurers' share prices relate to the performance 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. 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.

⁶[Lim and Brooks \(2011\)](#) provides an overview on the adequacy of this hypothesis. In section 5, I test the asset composition information incorporated in the stock prices and find a significant, positive relationship between estimates and reported values.

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 an 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 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 domicile in EU member states, with the

remainder split between 14 firms domiciled in the United Kingdom 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 15 individual firm observations from the sample, resulting in a number of 41 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 sector⁷.

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

Finally, the ECB Data Warehouse provides macroeconomic variables⁸. These are the monthly percentage change in the consumer price index, the euro exchange rates and the yield on an aggre-

⁷Measured in gross written premiums; market size includes non-publicly traded firms

⁸For 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.

gated 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 percentiles⁹.

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 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 Euribor varied within a range of 15 bps, with an average of -47.77 bps. The nominal effective exchange rate of the Euro against the EER-19 group of trading partners, as reported by the ECB, fluctuated between 95.49 and 102.29 points, with an average of 99.13. For comparison, the mean of the Euribor in the previous year was -37.49 with a maximum variation of 4 bps,

⁹To mitigate single firm events. This is in line with previous research on crises and financial distress by [Ge and Weisbach \(2021\)](#) and [Ellul et al. \(2015\)](#).

and the indexed Euro exchange rate fluctuates between 95.49 and 101.67 points, with an average of 98.2 points. The index value of the CPI increased monotonically by on average 0.8 % per month during my sample period.

Panel 3 shows 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 premium¹⁰ 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. 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 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.

¹⁰Written premiums net of reinsurance

4 Methodology

To analyse 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:

$$R_{i,d} = \beta_{Gov} HPR_{1day}(Y_{Gov,d}) + \beta_{CorpA} R_{CorpA,d} + \beta_{CorpBBB} E_{CorpBBB,d} + \beta_{CorpBB} R_{CorpBB,d} + \gamma' M_m + \delta'_{LoB} LoB_{i,y} + \eta' Firm_{i,y} + \alpha + \epsilon_{i,d} \quad (1)$$

This analysis builds 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 this sample has different frequencies of data, I use the indices d for daily, m for monthly and y for yearly. For government bonds, the model uses holding period returns (HPR) constructed using yield curve spot rates. The corporate bonds are implemented as index returns. I model the exposure of the stock return R_{id} to the yield of an aggregated Euro area AAA-rated government bond portfolio with one year maturity $Y_{Gov,d}$ by constructing the one-day HPR of the respective yields. This is the hypothetical return of buying a zero bond with the yield $Y_{Gov,d-1}$ and selling it after one day.

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 category¹¹ show large correlations, both before

¹¹Investment grade refers to ratings between AAA and BBB-, high-yield bonds are rated BB+ and below.

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 concerns¹² 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.

M_t represents the macroeconomic variables at time t . I control for market co-variation and market volatility by using the return on the Euro Stoxx 50 index and the return on the Vstox index, respectively. 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. 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 continuous specification for robustness. The binary variables equal one if the fraction of net written premiums associated with

¹²[Table 2](#) provides the correlations of all corporate bond portfolio returns

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.

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 the insurers or rather are driven by a change in the market assessment of the share price sensitivities. To show that changes in the estimates relate to changes in the asset allocation of insurers, 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 holdings 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 indicators of changes in the asset allocation. A useful property 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. As the share price only reflects publicly available information, 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 is published.

I use year-end data from 42 firms in the sample over the period 2016 to 2019. The data include the 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 the data points in [Figure 3](#) according to their affiliation to the life insurance ("LIFE") business line according to a median split. The blue dots reflect 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. The holdings data from the annual reports (on the x-axis) are compared with the estimated share price sensitivities of the respective ratings (on the y-axis) for all ratings in the four panels. Furthermore, the figure depicts 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 categories¹³, which explains the higher significance of these two panels compared to AAA-rated government and BB-rated corporate bond holdings.

¹³See [European Systemic Risk Board \(2020b\)](#) p.4.

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 unequal 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 literature¹⁴ 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 exposure 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 1 percentage point change in the return on the respective bond portfolio leads to an average change in the aggregate insurers share price by y

¹⁴See for example [Becker and Ivashina \(2015\)](#) and [Ge and Weisbach \(2021\)](#).

percentage points¹⁵. 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. The coefficients represent the aggregated share price sensitivity of the insurers given their aggregated asset structure. Altering the structure of investments would no longer result in an all else equal interpretation, which proves useful as the change in the sensitivity over time is supposed to carry information about the asset structure. This property ultimately allows me to track the changes in the asset structure, which is the point of interest in my analysis.

Negative regression coefficients arise from the fact that all price variables are implemented as returns (holding period return for 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, an 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 insurers share prices and investment grade bond returns is consistent with previous research by [Hartley et al. \(2016\)](#) and [Grochola et al. \(2022\)](#). Beyond 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 dependency between corporate bond prices and counterparty 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. The sign of the coefficients indicates the direction of the sensitivity of the effect of the variables on returns, while the coefficient determines

¹⁵All else equal; y is the value on the y-axis in panel 1 of [Figure 4](#).

the magnitude. Therefore, I focus in my interpretation on the magnitude of the coefficients rather than their sign.

The magnitude depends on the extent to which price movements in the bond portfolios affect the equity value of insurers, and thus translate into the level of exposure of a firm to the respective investment. [Figure 4](#) shows in panel 1 that the average exposure of firms to AAA-rated government bonds as well as A- and BBB-rated corporate bonds is significant and small, going into the crisis. As the crisis unravels, the exposure to AAA-rated government bonds more than quadruples, while remaining significant. The increase in the coefficient indicates that insurers are actively increasing their exposure to AAA-rated government bonds. When the economy recovers after the crash in March 2020, the exposure to safer government assets remains large, though decreasing. During the crisis the sensitivities of A-rated and BBB-rated corporate bonds switch their sign, which indicates that the effect of credit default considerations overrules the need for new assets. While A-rated corporate bonds change sign only for a short period immediately after the crash, BBB-rated assets remain positive until the stock and investment grade bond markets have fully recovered.

After the spike at the beginning of the market crash, the coefficients on A-rated corporate bonds are at their pre-crisis level and insignificant at the 5 per cent level. The lower test statistics arise from the orthogonalization as the A-rated coefficient only includes information that is not already explained by BBB-rated bonds. BBB-rated corporate bonds, which represent the lowest rating in the investment grade, show a significant and increasing pattern (in absolute terms) before March 2020, with a decline prior to the market crash. During the crisis period, the BBB coefficient increases compared to the pre-crisis level and remains constant and largely significant until mid-August 2020. Regarding the assets below investment grade, insurers display an increasing exposure to bonds with a rating of BB going into the crisis, which immediately drops as the market crashes and quickly recovers afterwards, slightly decreasing throughout the summer of 2020.

The evidence suggests that insurers, on aggregate, increased their exposure to AAA-rated government bonds during the market crash in March 2020. The decreasing pattern for BB-rated corporate bonds and the constant pattern for BBB- and A-rated corporate bonds suggest that insurers did not increase their holdings in the respective asset-types throughout the crisis. The absence of increasing exposures of lower credit rating assets after the initial spike is consistent with the literature on insurance firms' investment behavior during crisis times ([Becker and Ivashina](#)

(2015) and Kirti (2017)) and financial distress (Ge and Weisbach (2021)). Further, the persistent exposures of lower credit risk assets after the stock market recovery is consistent with European Central Bank (2020)¹⁶ and might either be driven by the inability to liquidate these assets or by the fact that insurance firms were waiting for further developments of the Covid-19 situation. Evidence for the inability to liquidate the low credit rating assets is provided by European Systemic Risk Board (2020a). The ESRB reports that BB-rated and B-rated corporate bonds experience a larger peak in bid-ask spreads during the Covid-19 market crash than during the global financial crisis 2008. The higher bid-ask spreads help to explain why insurers may have been unwilling to unwind their positions. Higher transaction costs and lower prices may also explain a possible reluctance to sell BBB-rated corporate bonds. The sharp initial decline in the coefficient for BB-rated corporate bonds suggests that insurance companies are keen to sell these assets quickly. However, after the coefficient rebounds, the decline in the BB-rated coefficients is much slower, which may be due the large decline in liquidity of high-yield corporate bonds.

The rebound in the coefficient for BB-rated bonds after the initial fall, and the increase in the coefficient for BBB-rated bonds from 0.4 to almost 1 in absolute terms after the market crash, disturb the picture of insurers trying to reduce the credit risk in their portfolios. A possible explanation for both patterns is that rating downgrades of formerly 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 section 6.2.

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 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.

¹⁶Chart 4.2

Table 3 reports the regression results for particular dates defined to represent pre-crash, post-crash and recovered phases of the Covid-19 market crash in March 2020. These dates are also represented by the vertical red lines in Figure 4 and correspond to the dates 14 February, 16 April and 15 June, respectively. Columns (1) to (3) report the unorthogonalized results. In columns (4) to (6) I present the orthogonalized data, which is the specification I use to generate the output in Figure 4. The orthogonalization replaces the returns on the European BBB-rated corporate bond index with the residuals of a regression of the BBB-rated corporate bonds returns on the A-rated corporate bond returns. The specification in columns (7) to (9) replaces the insurer specific variables with firm fixed effects, which by definition should include firm specific properties such as the insurance business mix. Since I do not need to incorporate SFCR data, the fixed effects specification has more observations, by including non-Solvency II insurers.

I observe that the stock market exposure ("Market") of the sample firms is significant and positive in all specifications. The market coefficients are increasing, which indicates that the market co-variation of the sample rises during the crash and the recovery. The coefficient on BB-rated government bonds is significant and decreasing in all specifications, indicating that the exposure to this asset type decreases relative to the pre-crash level.

In the specification without orthogonalization I observe a strong significant increase in the absolute values of the A-rated coefficients, suggesting that the exposure to A-rated bonds increases. When controlling for the variation that is already explained by BBB-rated corporate bonds, that is in the orthogonalized specification in columns (4) to (6), the pre-crash estimate is significant and negative, while the post-crash and recovered estimates become less significant and smaller in magnitude. Both observations are robust to the specification with firm fixed-effects in columns (7) to (9), where I find a significant impact of the A-rated corporate bond index on the insurers' share prices before and no significance thereafter. The BBB-rated coefficients in the pre- and post-crisis regressions are significant and increasing in absolute terms. By construction, the BBB-rated coefficients remain unchanged by the orthogonalization. The fact that the coefficients on A-rated bonds are less significant and smaller when $E_{corpBBB}$ is used suggests that A-rated and BBB-rated bonds have a joint effect that reduces the explanatory power of both variables. Table 2 shows that the correlations of all investment grade corporate bond returns are large. The correlations suggest that some of the explanatory power of all ratings above BBB may be driven by their classification

as investment grade. Moreover, this covariation is particularly high during crisis times, leading to higher variance inflation factors of both coefficients, which is the main reason why I apply the orthogonalization.

The AAA-rated government bond exposure is significant and increases in the post-crash period. In the recovery period, the coefficient is smaller in magnitude but still significant. The decline between post-crash and the recovery suggests that insurers bought safe government bonds when the markets crashed and sold the instruments during the recovery, an observation that is robust in all specifications.

In terms of lines of business, I find no significant effects for either the credit, business continuity or health insurance lines. A larger share of life insurance business is weakly associated with a superior performance pre-crisis. The positive effect of life insurers is negated for larger shares of guarantee business within the life insurance portfolios. An increase in the Euribor and an appreciation of the Euro are associated with a weaker performance in the post-crash and recovery periods, which is consistent across all specifications. The negative Euribor effect is most likely due to higher financing costs during the economic downturn. In addition, larger insurers show a significant negative impact on stock returns during the market crash period.

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 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 terms¹⁷ 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](#), both the impact and the reversal of the BB-rated coefficients during the crisis are less pronounced when controlling for downgrades. While the minimum value of the impact and the maximum value of the reversal range from 0.6 to almost 2 in [Figure 4](#), the same range is 0.9 and 1.6 in [Figure 6](#). This observation indicates that insurers did not actively invest in high-yield assets during the crisis, but rather were exposed to rating downgrades. It further suggests that a significant fraction of bonds within the BBB-rated corporate bond portfolio are prone to rating downgrades, which is

¹⁷Given 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.

consistent with the findings of [Becker and Ivashina \(2015\)](#) that US insurers show disproportionately high investments in assets that are vulnerable to rating downgrades. The insignificant, close to zero coefficients of the BBB-rated bonds in March 2020 when considering downgrades, strengthen the hypothesis that a significant fraction of BBB-rated securities were downgraded to BB rating. The path of the coefficients in the recovery period remains similar, although less significant. The coefficients for A-rated bonds are mainly insignificant in [Figure 4](#). Taking into account the downgrades, the coefficients become significant and slightly increasing, indicating an increase in the holdings of corporate bonds rated A or higher.

The results of the downgrade analysis are in line with the observations from the [European Systemic Risk Board \(2020b\)](#), that conducts a stress test of a mass bond downgrade scenario for European financial institutions and finds that insurance companies face the largest investment value loss. 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 given risk-based capital charges, which also makes in insurers' assets more vulnerable to rating downgrades.

In combination, the effect of the rating downgrades and the increase in bid-ask spreads as reported by the [European Systemic Risk Board \(2020a\)](#) suggest that even though insurers try to shift their portfolio holdings towards higher credit quality assets, their ability to do so may be constrained by the procyclical liquidity risk associated with high yield investments. The fact that high-yield corporate bond funds experience redemptions of up to 10 % in March 2020¹⁸ supports this interpretation, because investors can redeem the fund at its net asset value at any time, which indicates investor behavior without market frictions.

7 Conclusion

Using publicly available data on European insurers' stock prices, corporate bond price indices and government bond yields, I propose a regression model whose estimates relate to the asset 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

¹⁸[European Systemic Risk Board \(2020a\)](#)

suggests that the interpretation of the regression coefficients as indicators for the asset compositions is justified. The analysis provides evidence that European insurance companies reduced their exposure to higher credit risk assets and increased their exposure to assets with lower credit risk throughout the Covid-19 induced market crash in March 2020 and the subsequent recovery period. This contradicts the hypothesis that insurers gamble on the recovery of the bond market to generate a superior return on assets. In the sub-investment grade, the exposure to BB-rated bonds drops sharply, and recovers quickly during the market crash and slightly decreases after March 2020. As a possible reason I suggest rating downgrades of formerly higher-rated bonds and the escalating illiquidity of high-yield corporate bonds. Interacting the rating aggregated bond index returns with the number of full rating downgrades suggests that a significant fraction of the BB-rated coefficient's quick recovery during the crisis is indeed due to rating downgrades. European insurers shift their portfolio holdings towards higher credit-rating assets, trying to free capital bound in risk-based capital charges, but are constrained by the credit and liquidity risk they assume during non-crisis times. An exogenous shock to credit rating quality increases insurers' exposure to lower-rated and less liquid assets. Risk-based capital charges incentivize selling these assets, thereby creating the threat of fire-sales, if portfolios are similar between firms¹⁹. Yet, the slow but steady decline in the BB-rated exposure suggests that insurers adapt their stressed positions patiently trying to avoid high transaction costs.

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.

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 overlap across European countries. As this paper focuses on corporate bonds, it provides a foundation for further research on insurers' fixed-income investment decisions during crises. For example, the absence of a gamble for recovery

¹⁹[Girardi et al. \(2021\)](#) provide evidence for this hypothesis.

with respect to corporate bonds during the Covid-19 crisis might not hold for European government bonds, given the fact that the Solvency II regulation imposes the same capital requirements on government bonds of all EEA member states regardless of the issuer's rating²⁰. Thus, one could rule out considerations about capital charges as a motive for portfolio reallocation during the Covid-19 crisis.

²⁰For example [Swinkels et al. \(2018\)](#) express their concerns about increased risk-taking by insurance companies as a consequence of the absence of risk-based capital charges.

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 categorised into daily portfolio or index return (Panel 1), macroeconomic control variable (Panel 2), or company-specific (Panel 3) groups. 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 or high yield classification, respectively. EU.gov.AAA is the yield of an aggregated euro area portfolio of AAA-rated government bonds with a maturity of one year. HEALTH, BC, CREDIT, LIFE, and GUARANTEE represent the share of the respective line's net written premium, where BC abbreviates 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: Macroeconomic Variables							
Market	%	338	0.028	1.790	- 12.401	0.060	9.236
Vstox	%	338	0.448	8.662	- 18.467	- 1.311	43.830
FX Index	Level	16	99.127	1.816	95.490	98.837	102.293
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 3: 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_EU_”Rating”), the holding period return of the AAA-rated government bond (Gov_EU_AAA), and the return of the Euro Stoxx 50 index (”Market”). The data ranges from March 2019 until August 2019 in Panel 1 and March 2020 until August 2020 in Panel 2. The diagonal of the matrix is left out for brevity and redundancy. Variables used in the regression model are in bold.

Panel 1: Pre-Crisis

	Gov_EU_AAA	corp_EU_AAA	corp_EU_AA	corp_EU_A	corp_EU_BBB	corp_EU_BB
corp_EU_AAA	0.59					
corp_EU_AA	0.53	0.95				
corp_EU_A	0.51	0.89	0.91			
corp_EU_BBB	0.25	0.58	0.65	0.76		
corp_EU_BB	0	-0.11	-0.07	0.12	0.33	
Market	-0.13	-0.23	-0.18	-0.05	0.17	0.54

Panel 2: Crisis

	Gov_EU_AAA	corp_EU_AAA	corp_EU_AA	corp_EU_A	corp_EU_BBB	corp_EU_BB
corp_EU_AAA	0.49					
corp_EU_AA	0.37	0.89				
corp_EU_A	0.17	0.6	0.72			
corp_EU_BBB	-0.11	0.27	0.43	0.83		
corp_EU_BB	-0.1	-0.02	0.07	0.44	0.55	
Market	-0.3	-0.29	-0.2	0.14	0.38	0.54

Table 3: Regression Coefficients

This table presents the regression coefficients of the main model at points in time representing pre-crash, reversal and recovered throughout the Covid-19 turmoil. Each regression covers the 100 days prior to the presented date. The time points resemble the dates 14 February, 15 April, and 15 June. The rows present the regression coefficients given the three specifications: unorthogonalized, orthogonalized, and business lines as binary variables. The 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 parenthesis. Insignificant controls on CPI, share of CashEq, share of index- and unit- linked business, Line of Business Health and Business Continuity, and the regression constant are dropped for brevity.

	<i>Dependent variable:</i>								
	<i>R_{i,d}</i> , measured in percent								
	Unorthogonalized			Orthogonalized BBB-Rated			Fixed-Effects		
	pre-crash (1)	post-crash (2)	recovered (3)	pre-crash (4)	post-crash (5)	recovered (6)	pre-crash (7)	post-crash (8)	recovered (9)
Gov_EU_AAA	- 0.407 (0.297)	- 2.112*** (0.342)	- 1.641*** (0.335)	- 0.407 (0.297)	- 2.112*** (0.342)	- 1.641*** (0.335)	- 0.223 (0.269)	- 2.193*** (0.311)	- 1.801*** (0.304)
corp_EU_A	0.202 (0.274)	- 1.265*** (0.354)	- 1.142*** (0.347)	- 0.316** (0.149)	- 0.392* (0.233)	- 0.409* (0.227)	- 0.543*** (0.141)	- 0.320 (0.213)	- 0.332 (0.206)
corp_EU_BBB	- 0.620** (0.268)	0.838*** (0.310)	0.695** (0.276)						
<i>E_{corpBBB}</i>				- 0.620** (0.268)	0.838*** (0.310)	0.695** (0.276)	- 0.600** (0.243)	0.893*** (0.290)	0.656** (0.258)
corp_EU_BB	2.222*** (0.376)	1.852*** (0.198)	1.573*** (0.187)	2.222*** (0.376)	1.852*** (0.198)	1.573*** (0.187)	2.428*** (0.343)	1.806*** (0.182)	1.533*** (0.169)
Market	0.644*** (0.082)	0.677*** (0.062)	0.724*** (0.045)	0.644*** (0.082)	0.677*** (0.062)	0.724*** (0.045)	0.644*** (0.074)	0.678*** (0.058)	0.736*** (0.041)
Vstoxx_growth	0.007 (0.008)	0.017*** (0.006)	0.018*** (0.005)	0.007 (0.008)	0.017*** (0.006)	0.018*** (0.005)	0.008 (0.007)	0.017*** (0.005)	0.017*** (0.005)
FX	- 0.028 (0.053)	- 0.092* (0.052)	- 0.104*** (0.031)	- 0.028 (0.053)	- 0.092* (0.052)	- 0.104*** (0.031)	- 0.023 (0.047)	- 0.088* (0.047)	- 0.107*** (0.029)
Euribor	0.002 (0.026)	- 0.260*** (0.092)	- 0.041* (0.022)	0.002 (0.026)	- 0.260*** (0.092)	- 0.041* (0.022)	0.028 (0.025)	- 0.256*** (0.082)	- 0.043** (0.020)
ln_Assets	0.002 (0.045)	- 0.159*** (0.060)	- 0.055 (0.066)	0.002 (0.045)	- 0.159*** (0.060)	- 0.055 (0.066)			
Life	0.460** (0.227)	0.318 (0.290)	0.159 (0.287)	0.460** (0.227)	0.318 (0.290)	0.159 (0.287)			
Guarantee	- 0.601*** (0.232)	- 0.370 (0.362)	- 0.124 (0.419)	- 0.601*** (0.232)	- 0.370 (0.362)	- 0.124 (0.419)			
Orthogonalized	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No	Yes	Yes	Yes
Observations	3,400	3,400	3,400	3,400	3,400	3,400	4,200	4,200	4,200
Adjusted R ²	0.153	0.406	0.415	0.153	0.406	0.415	0.145	0.396	0.408
F Statistic	41.583***	122.627***	142.687***	41.583***	122.627***	142.687***	94.452***	277.914***	339.368***

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 secondary EU markets including UK. The observations range from January 2018 until December 2020. The y-axis presents 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 secondary US markets.

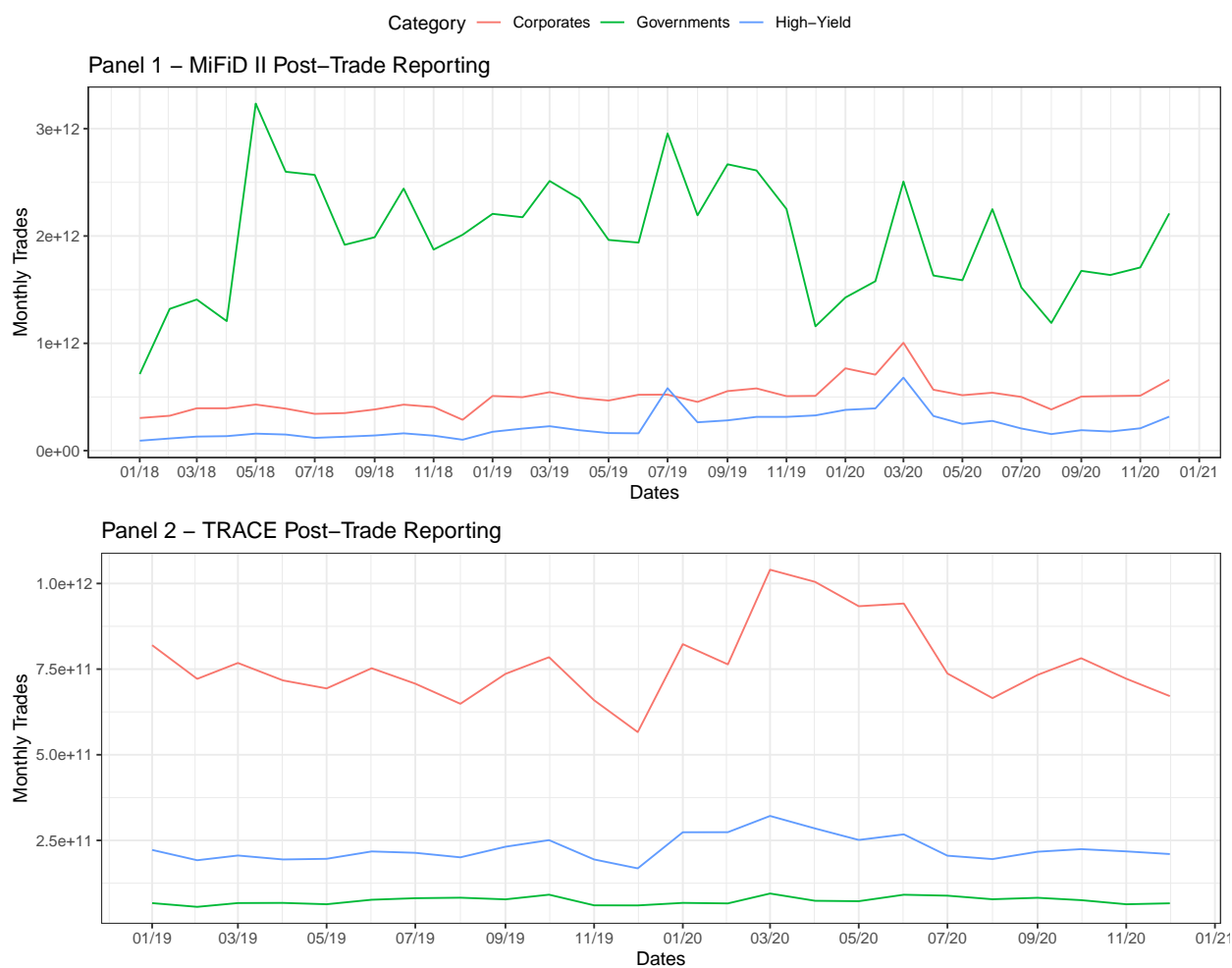


Figure 2: Average Share of Cash and Cash of Liquid Assets

This figure plots the average share of cash, and cash equivalents over each quarter in total assets of the 42 insurance firms in the sample over the years 2015 to 2020. To see possible seasonality effects, the data is presented for each quarter of each year.

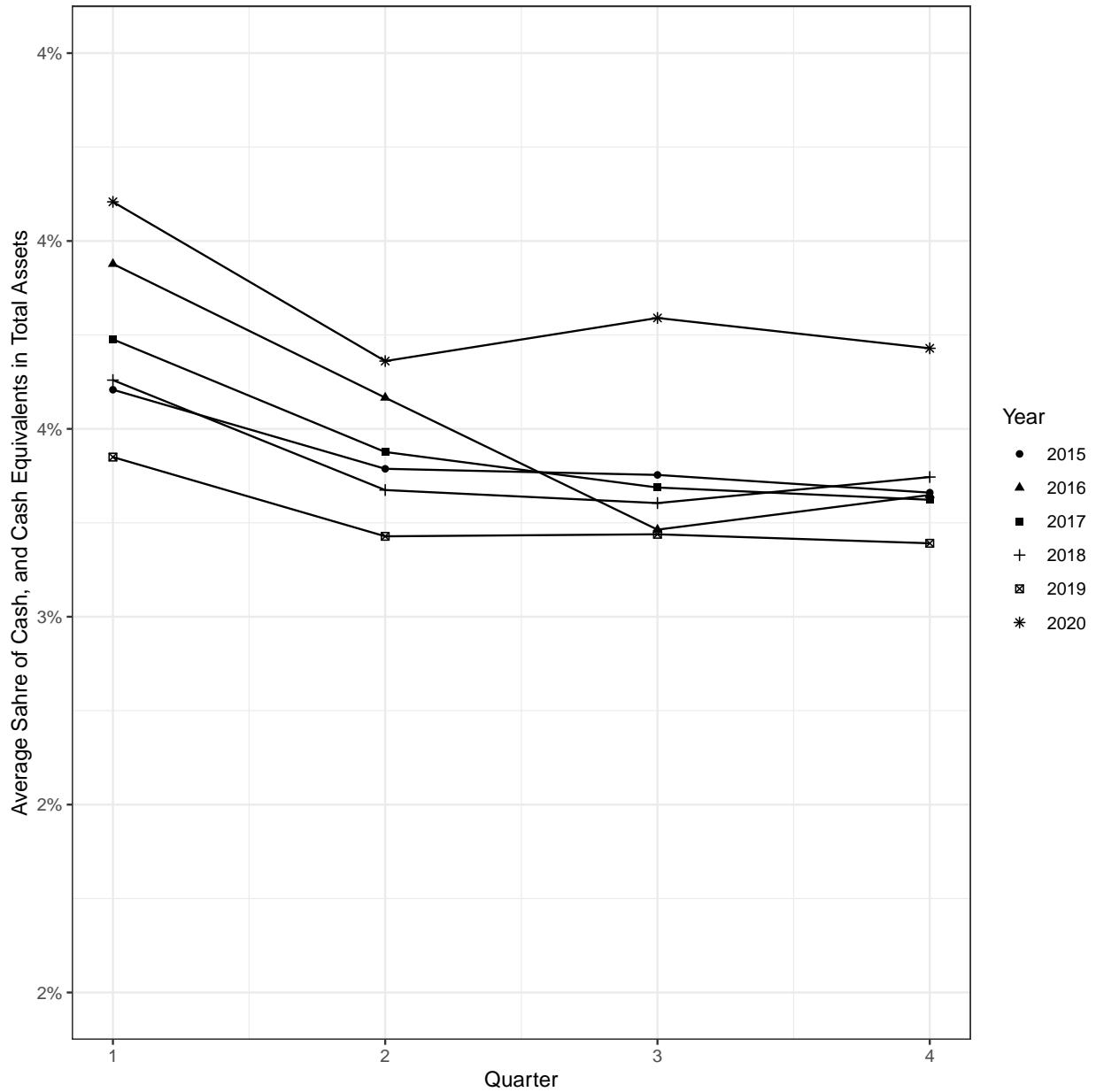


Figure 3: Link Exposures to Holdings

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-rated, A-rated, BBB-rated, and BB-rated assets in all credit risk bearing assets with 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 R^2 and p-value of the fitted lines can be found in the top left corner of each panel.

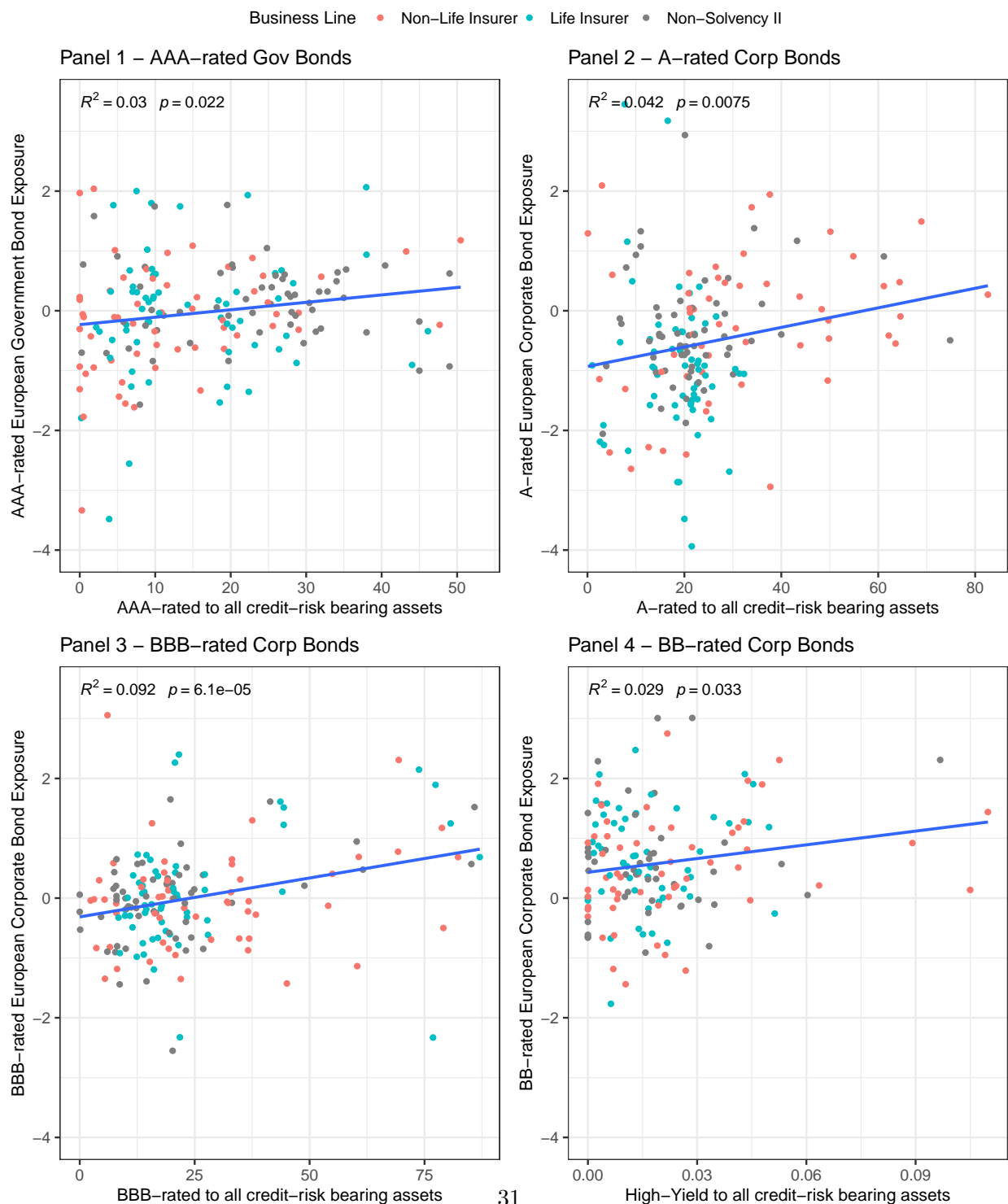
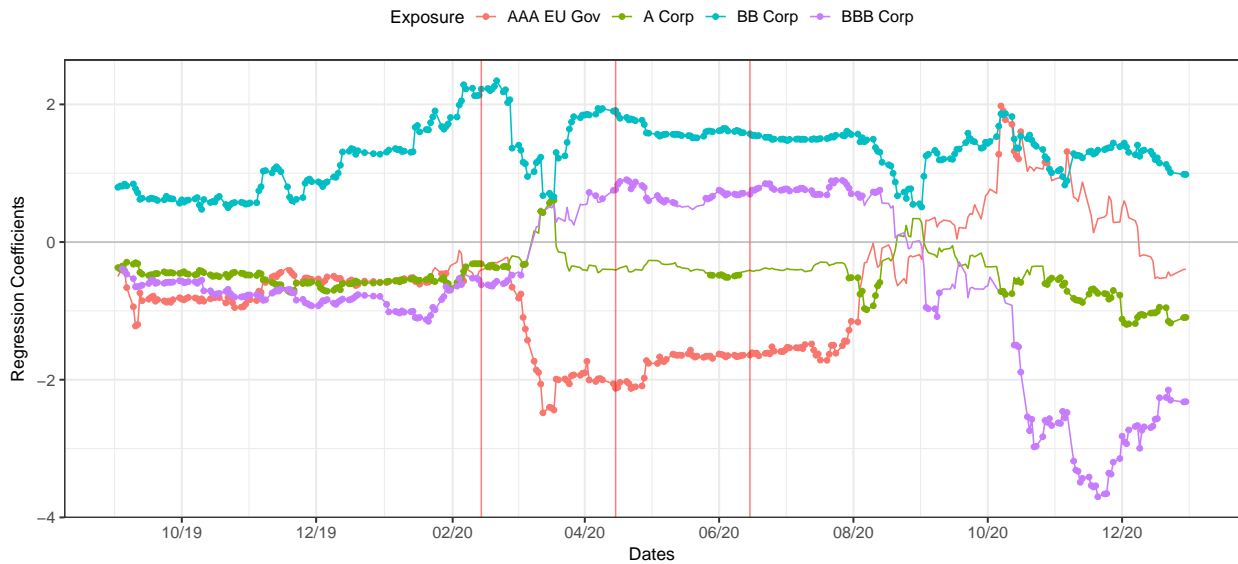


Figure 4: Rolling Regression Results

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 signals significance with respect to 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.

Panel 1 – Regression Coefficients over time



Panel 2 – adjusted R^2 over time

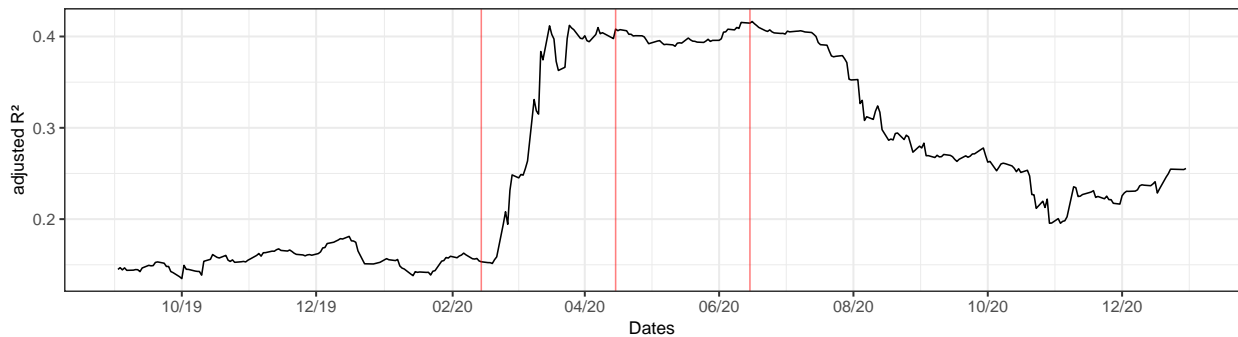


Figure 5: Corporate Debt Issuer Credit Rating Downgrades

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 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](#).

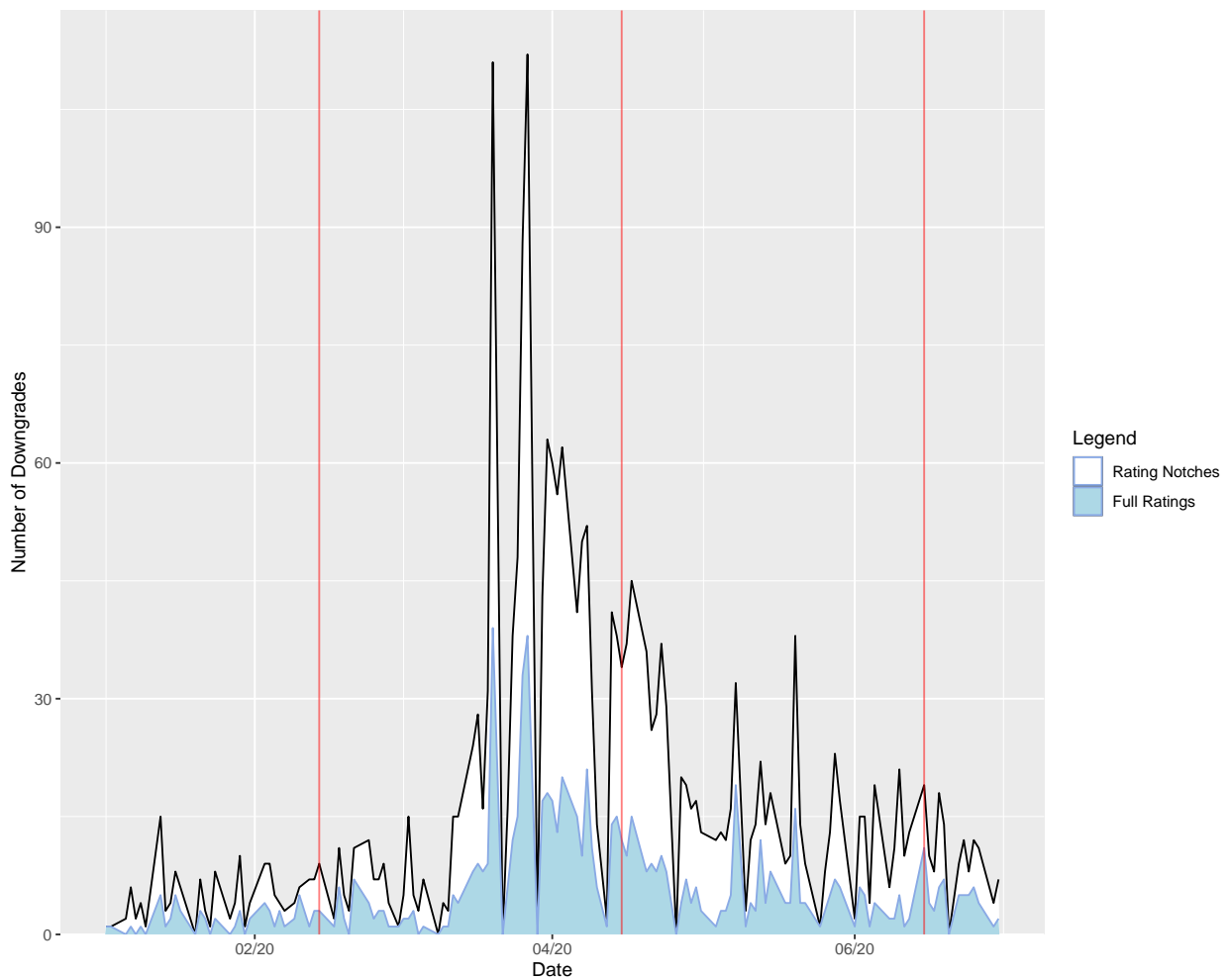
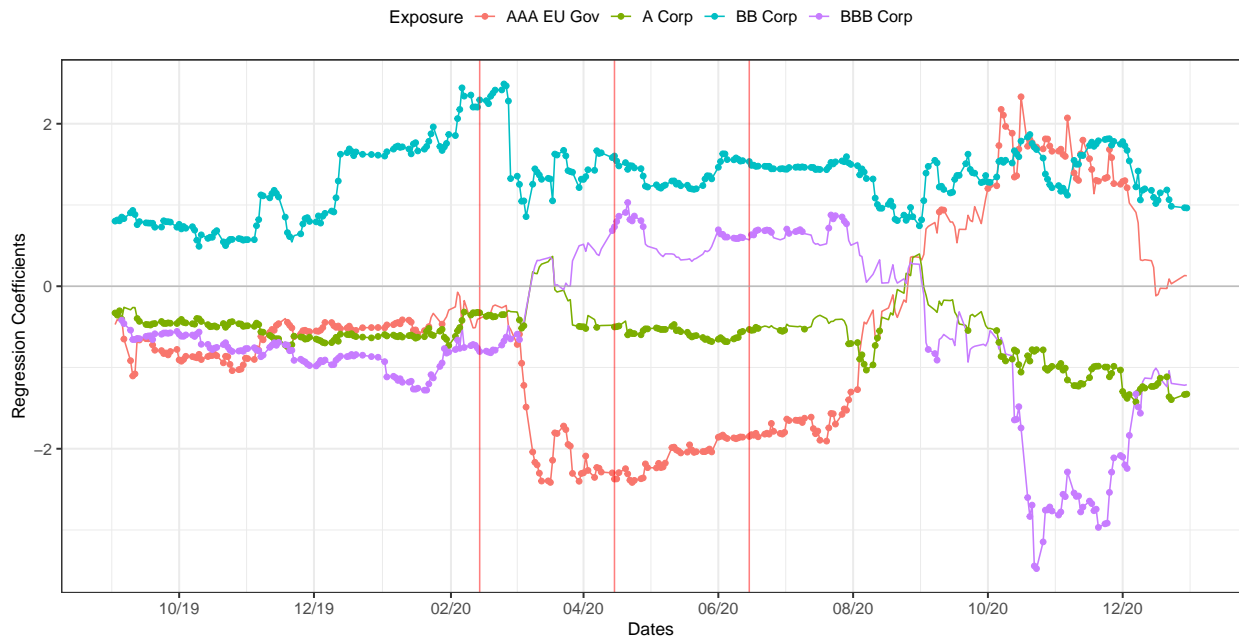


Figure 6: Downgrade Analysis Regression Results

This figure shows the results of the rolling regression when controlling for credit rating downgrades as specified in formula (2). 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. Each point reflects the average exposure of the sample firms to respective returns over the past 100 days. A dot signals significance with respect to 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.



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