The Impact of Extreme Cyber Events on Capital Markets and Insurers' Asset Portfolios

Martin Eling, Werner Schnell*

Management Summary

The intention of this paper is to study in how far extreme (cyber risk) events affect capital markets and to propose a concrete model framework that might be implemented in internal risk models of insurance companies. The analysis is done in three steps. First, we review the relevant literature on the impact of disaster events on capital markets. Second, we propose two concrete models. Third, we empirically illustrate the potential impact of selected extreme scenarios on a stylized insurer's asset portfolio based on these two models.

The literature shows that extreme events in general affect capital markets, but the economic magnitude of the extreme events discussed in the academic literature is larger than what was previously discussed in the cyber context. The literature on disaster risks looks at extreme scenarios in an area of 15% or larger decline in GDP (world wars, financial crisis), while the cyber scenarios discussed in the academic literature and industry studies are typically of smaller magnitude, that is up to 2% of GDP on average; only some very extreme cyber scenarios go up to 10% of GDP.

To empirically analyze the relationship between extreme events and capital markets, we implemented two models, a simple one based on historical data (an extended version of the dataset presented in Barro (2006)) showing an impact of up to -4.26% on the insurer's asset for a stylized asset portfolio and two predefined cyber scenarios. In an extended model we additionally implement the response of monetary policy and a consumption based stock market response function based on the macroeconomic model by Swanson (2019). This model provides economically more sound estimators for the central parameters of interest (risk free interest rate, credit spreads, stock returns) and shows an impact of up to -1.99% for the stylized insurers asset portfolio.

We conclude that the impact of extreme cyber risk events on capital markets exists, but considering the asset side of insurance companies in isolation remains limited. This is mainly due to the hedging properties of different asset classes and the response of monetary policy: While the value of stocks decline and credit risk goes up, the risk-free interest rate decreases which increases the value of government bonds and other relatively risk free investments. This important hedging property may exist when we only look at the asset side of the balance sheet of a (re-)insurer, but particularly lower interest rates may lead to a large increase of the market values of liabilities and materially impact solvency (via discounting used for market value margin/ risk margin calculation).

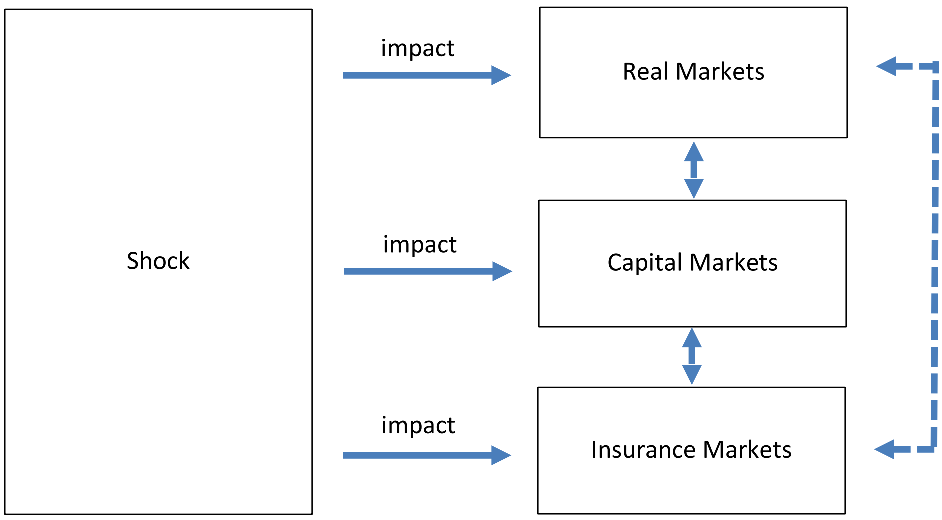
*: We acknowledge the support of Marcel Freyschmidt, Patricia Lehmann and Dingchen Ning (University of St. Gallen) as well as comments and support from Eric Durand, Peter Middelkamp, Stephan Schreckenberg and Jolanta Tubis (Swiss Re).

1 Research Question and Research Design

We study the impact of extreme (cyber) scenarios on the asset side of the insurer's balance sheet. While the effects of extreme scenarios on the liabilities are relatively well understood and are a core feature of the insurer's risk modelling, relatively little is known about the potential effects on the insurer's asset side.[1] For the purpose of this paper, we consider a representative, hypothetical insurer which holds a globally diversified portfolio with different asset classes among which are stocks (equity), government bonds and corporate bonds. We consider the asset side of the insurer's balance sheet in isolation, keeping in mind that for the interpretation of the results also the interaction with the liabilities side is important. We develop a general model to analyze the impact of extreme scenarios that we calibrate with information on extreme cyber scenarios. The model as such however is formulated so general way that it can be applied to different extreme events.[2]

In Figure 1, we consider different types of shocks and their effect on the real economy, capital markets and insurance markets. A shock can in principle be any extreme event such as natural or man-made catastrophes, pandemics, extreme cyber events, and wars. While our application of interest is cyber risk, other shocks have similar economic transmission mechanisms and we can thus use historical observations from such other events to better understand the potential impact of an extreme cyber incident. The motivation to do this is that extreme cyber risks have not yet been observed historically so that a direct empirical analysis is not possible.

Figure 1: Impact of a Shock on Real Markets, Capital Markets and Insurance Markets



A shock might have a direct impact on real markets. On the one hand, a shock can reduce economic activity by hindering production (typically damaging the capital stock) and reducing consumer spending. On the other hand, a shock might also increase economic activity by the need of rebuilding the damaged capital stock (i.e. reconstruction after a catastrophic event). Because of these different effects, the impact on sectors might differ as well. Some studies found that for cyber events, affected companies lose market value while at the same time IT security providers gain in market value.[3] Similarly it is well possible that biotech firms benefit from the COVID-19 pandemic or construction firms benefit from big natural catastrophes.

A shock can also directly affect capital markets. The uncertainty created by an extreme event changes investor confidence and expectations, for example about monetary and political interventions. Different types of events (e.g. natural vs. man-made) might induce different changes in expectations, especially also depending on the diversification potential. Regionally limited natural catastrophes can be diversified in a global portfolio, as long as they do not hit a critical economic center such as San Francisco or Tokyo and as long as the effect does not ripple through major supply chains.[4] Global events like the current pandemic, in contrast, are undiversifiable.

1 In most internal risk models the link is either neglected or modelled in a simplistic way based on expert judgement.

2 An application to pandemic risk is presented in Appendix B.

3 Cavusoglu et al. (2004) show that stock prices of information security providers increase on average by 1.36% after the announcement of another company's security breach.

4 According to a study by Risk Management Solutions (1995) cited in Cummins (2006) a severe earthquake in Tokyo could cause losses in the range of $2.1 to $3.3 trillion, constituting from 44 to 70 percent of the GDP of Japan.

Via the underwriting, a shock also has a direct effect on the insurer's liabilities. The direct loss (property loss and lives lost) is relevant for both the life and non-life insurance industry. There also could be various indirect links we need to keep in mind as well, possible going into both directions.[5]

In the following we first review the existing academic literature (Section 2). Then we present the methodology proposed to analyze the impact of extreme cyber events (Section 3) and the resulting empirical analysis (Section 4). Finally, conclusions, limitations and future research opportunities are discussed (Section 5).

2 Literature Review

Existing cyber risk research uses the event study methodology to investigate the impact of data breaches or other cyber risk events on the market value of firms. For example, Cavusoglu et al. (2004) show in an event study that a security breach negatively affects a company's stock price. They estimate the loss to be 2.1 percent of the market value or 1.65 billion USD per security breach. On the contrary, Campbell et al. (2003) as well as Hovav & D'Arcy (2003) find only limited evidence that data breaches or DoS attacks negatively influence the company's stock price. However, Campbell et al. (2003) provide evidence that a breach of confidential data has a larger negative effect on the stock price than a breach of non-classified information; Hovav & D'Arcy (2003) show a negative price effect for companies with a business model that is heavily based on the Internet. Thus, the markets seem to behave rationally, as the discount is proportional to the expected loss associated with different data.

To overcome data limitation and to raise attention for the potential relevance of cyber risks among policymakers, media, the public, and executives, a variety of scenarios have been proposed in the applied business literature and in industry studies. These worst-case scenarios include various incidents that lead to a disruption of critical infrastructure and thus to more extreme economic losses. The economic effects of the scenarios show some extreme variations, ranging from 0.2% to 2% of the GDP in the year of the event with a few extreme scenarios going as far as 10% of world GDP (Eling et al., 2020; Ruffle et al., 2014).

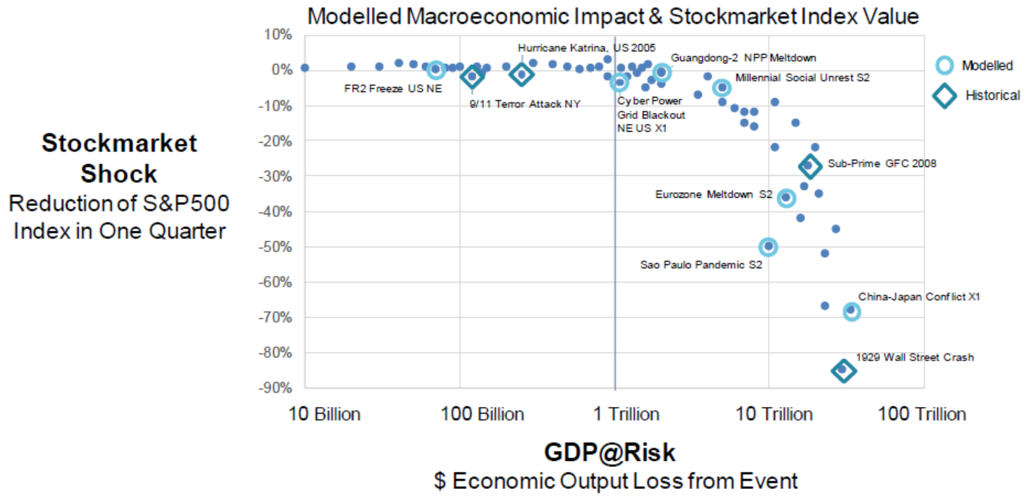
Overall, since there have been no extreme cyber events so far, the literature that investigates the effect of cyber risk on the economy and financial markets remains relatively limited. The largest cyber loss has been Wannacry with 8 billion USD economic loss (Gallin, 2017). Based on Figure 2, one might argue that for an event to be so extreme to create an impact on the capital market, at least an economic loss of 1 trillion USD (or 1-2% of world GDP) is necessary. This extreme magnitude is very likely also the reason why event studies for other catastrophic events come to mixed and inconclusive results.[6]

---

5 For example, a decline in economic activities on real markets might affect expectations on capital markets and reduce insurance demand, while an adverse development on the capital market might worsen the capital supply for the real economy and reduce the investment result of insurance companies. A difficult underwriting situation might force insurers to liquidate some assets, putting pressure on the capital market and might increase insurance prices for the real economy.

6 The results of event studies for catastrophic events depend on the country, industry, and disaster type. For natural disasters, Wang & Kutan (2013) find no wealth effects in the US and Japanese stock markets, indicating that these markets can well diversify the impact of natural disasters on stock returns. However, there are significant wealth effects in the US and Japanese insurance sectors. While US investors in the insurance sector lose in case of a disaster, those in Japan gain. All markets except the composite stock market in Japan face risk effects of natural disasters. For Australia, Worthington & Valadkhani (2004) find that bushfires, cyclones and earthquakes have a major effect on market returns, unlike severe storms and floods. The net effects can be positive and negative, though. Thomann (2013) shows in a US event study that natural catastrophes increase the volatility of insurance stocks and reduce the correlation of insurance stocks and the market. Investors can, consequently, diversify natural catastrophe risk by additionally holdings of the market portfolio. However, this result does not hold for 9-11 that led to an increase in volatility and, simultaneously, to an increase in correlation. Chesney et al. (2011) investigate the impact of terrorism on financial markets, again with mixed results.

Figure 2: Impact of Selected Events on GDP and Stock Market



Note: Taken from Mahalingam et al. (2018)

The fact that there has been no systematic impact of shock events for cyber risk or other types of risk does, however, not necessarily mean that such an impact does not exist. It might well be that investors on capital markets anticipate that large extreme events might happen and thus require a disaster risk premium especially for companies that are more exposed to selected aspects of disaster risk. This idea has been included in recent asset pricing models which show that rare disasters influence financial markets and are relevant for pricing. Barro (2006, 2009) uses rare disasters leading to a GDP loss of more than 15% such as world wars, great depression, oil price shock over more than 100 years to explain the risk premia observed in the financial market. He shows that investors ask for a disaster risk premium in the sense that higher risk premiums are required to compensate investors for bearing the risk of extreme events. Since data on real disasters are scarce, Berkman et al. (2011) propose a crisis index that reflects expectations about potential disasters (disaster risk) instead of actual observations. They show that their disaster index has a large impact on the mean and volatility of stock markets and that industries with higher exposure to disasters yield higher returns.

In conclusion, several papers address the potential of rare disasters to explain the aggregate stock market development such as mean returns and their variances; disaster risk is relevant for asset pricing and helps to explains a part of some widely discussed asset pricing puzzles (such as the equity premium puzzle). It is also notable that the economic magnitude of the extreme cyber scenarios at this moment does not seem large enough to expect a big impact of these events on the capital market; the above studies usually consider shocks in an area of 15% decline in a countries GDP, while our extreme cyber scenarios are typically around 2% of GDP. Event studies show that for a large diversified portfolio the impact of severe catastrophes on the capital market should not be extreme. However, usually natural catastrophes are considered which can be diversified globally, while cyber risk might not be diversified globally. Furthermore, the results for man-made catastrophes such as 9/11 show that there could be some impact on volatility and correlation, maybe because of the political responses that investors anticipate.[7]

We also note that the above event study literature for cyber risk mostly focuses on stock prices, while we are interested not only in stock prices, but also in risk free interest rates and credit spreads. The only paper we found that looks at the topic more holistically (not only stocks) is the working paper by Swanson (2019), but this is a theoretical model and not an empirical paper. We will implement some aspects of the model by Swanson (2019) to analyze the potential impact of extreme scenarios empirically.[8]

7 Also for 9/11 most market indices recovered to pre-9/11 levels within a month (Mahalingam et al., 2018, p. 10). More recently the impact of other extreme non-diversifiable events such as pandemic risk might be considered; the maximum drawdown for the MSCI World has been 1/3 (from 2400 to 1600 from mid February to mid March), but by the end of May it has already been back to 2200. See Figure A1 and Table A2 in Appendix A. It is difficult to disentangle the effect of the pandemic crisis in isolation from certain response measures like the activities of central banks. For this reason, it is important to also model the response of the monetary authority when analyzing extreme events.

8 Swanson (2019) also notes that traditional macroeconomic models typically ignore asset prices and risk premia, while at the same time, traditional finance models typically ignore the real economy, emphasizing the lack of holistic research.

3 Methodology

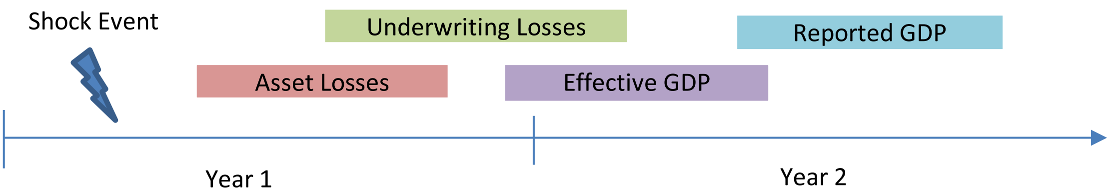
We build on previous scenarios that model extreme cyber events and their impact on the economy. Most of these cyber scenarios do not estimate the effect on financial markets, but provide an estimate for the potential losses to the economy. These numbers and the applied methodologies are very heterogeneous across different scenarios. Some estimate the loss for a certain sector or a certain region. What kind of costs are included in these estimates also diverges. Some contain estimates for liabilities, some for the business interruption, and only a few estimate comprehensive aggregate economic losses. To derive the effect on the overall capital market, we aggregate the losses to country or global level, i.e. the country GDP and "world GDP" (as done in the input-output model by Eling et al., 2020), taking the geographical and sectoral dependencies into account. We use the two scenarios presented in Table 1 to illustrate our approach.

Table 1: Cyber Scenarios

Eling et al. (2020)	**Ruffle et al. (2014, p. 4)**
Scenarios based on Input – Output – Model	Sybil logic bomb scenario analzed using the Oxford Economics Model
Modelling of inoperability and recovery time across sectors including spillover effects	Estimate the potential shock to the global GDP when a critical IT provider is compromised
0.64%-1.55% of GDP	4.7%-10.1% of world GDP

A model needs to consider shocks due to cyber risk scenarios to both the underwriting and an insurer's asset. Thus, we need to model the connection between the estimated aggregated losses and the financial markets. However, it is difficult to identify an empirical relationship between the real economy and stock market. The reason is that the forward-looking characteristics of the stock market and mitigations by monetary policy blunt the empirical relationship. For a stylized two period model (that is a short-term shock) the situation could be described as shown in Figure 3.[9]

Figure 3: Shock Timeline



The assets would react quickly to the shock, long before the real economy (especially the delayed economic indicators) are reflecting the new situation. Theoretical asset pricing model would suggest a connection of the prices on financial markets p_t to the real GDP, Y_{t+1} (see, e.g., Cochrane, 2009, p. 150):

$$p_t = E_t(m_{t+1}\, X_{t+1}),\, m_{t+1} = f_1(Y_{t+1}),\; X_{t+1} = f_2(Y_{t+1})$$

where m_{t+1} is the stochastic discount factor, X the payoff of any risky financial assets and f positive definite functions. Thus, participants in financial markets price according to their expectation about the future GDP development. Since there is data on expected GDP available, some papers try to uncover this relationship directly. Alternatively, we can assume that financial markets do not make systematic errors (rational expectation, an assumption frequently made in economics and finance). Then, we would have:

$$Y_{t+1} = E_t(Y_{t+1}) + \varepsilon_{t+1},$$

where ε_{t+1} is a random error (i.e. $E(\varepsilon_{t+1}) = 0$ and $E(\varepsilon_{t+1} E_t(Y_{t+1})) = 0$, meaning there is no systematic error in the expectations and the error and $E_t(Y_{t+1})$ are independent). Thus, on average the realized GDP in period $t+1$

9 To understand the empirical relationship between GDP and stock markets, we also consider the empirical correlation between GDP and stock markets (e.g. World GDP against MSCI World). Our results confirm what is known from Ritter (2005), i.e. the correlation is negative; with a lag of 1 year the correlation is positive (0.27 for the World GDP against MSCI World), confirming the relationship illustrated on Figure 3.

would be equal to the expected GDP in period t and we can empirically estimate the backward-looking relationship between the asset market price, p_t, and the realized GDP, Y_{t+1}. Then, we evaluate this empirical model with the cyber-GDP shock to derive an asset price reaction. The severity of the cyber scenario, measured by a shock in GDP, is mapped on the severity of previous events. The financial market reaction of previous mapped events is then used as an estimate for the effects of a cyber scenario on financial markets. The models we use in the following all build exactly on this assumption. As for any other statistical interference, we need to assume that a cyber scenario's effect on the asset market is comparable to other extreme events observed in the past.

4 Empirical Analysis

4.1 Simple Model

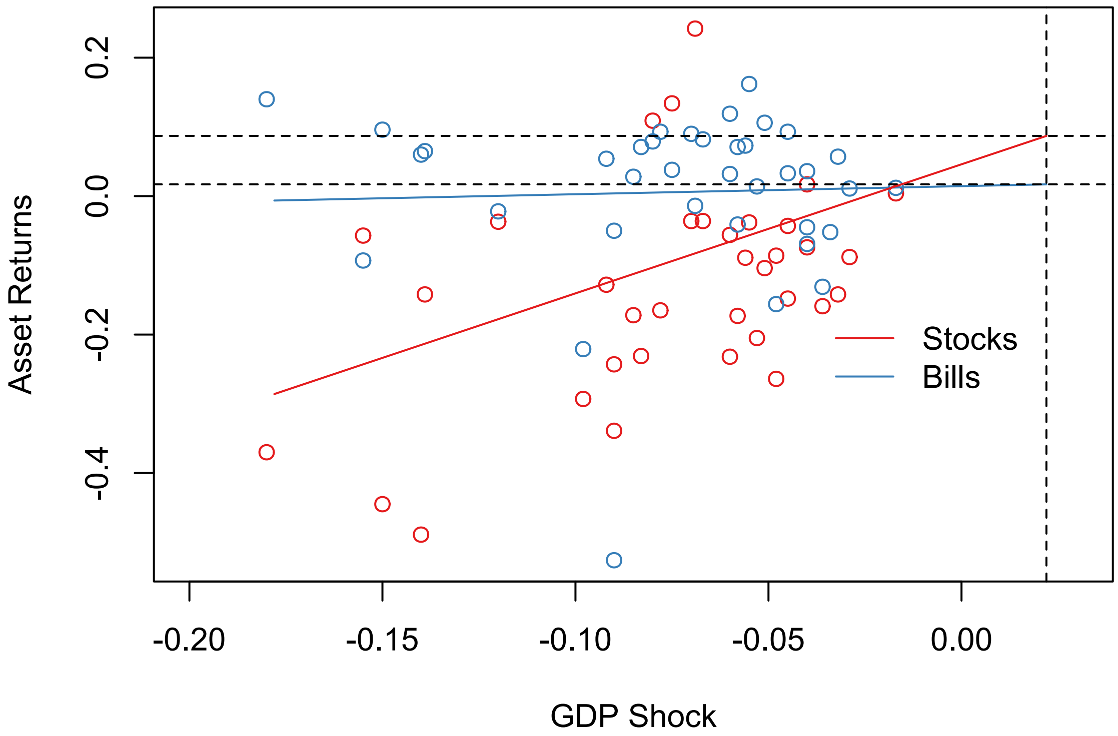
By purely looking at the empirical relationship between realized GDP losses and asset prices, one advantage of the empirical approach is that it not only incorporates the shock on asset returns due to a change in fundamentals, but implicitly also due to changes in other pricing relevant parameters (such as change in risk premium, risk aversion, sentiment, monetary policy). Moreover, our approach can take into account possible nonlinearities (nonlinear dependence between assets and shock severity) and does not use (linear) approximation used for asset pricing; that is especially important at the extreme end of the distribution (as starting point we use a linear approximation below, though; in robustness tests (Section 4.3.3) we also consider alternative functional forms). First, we estimate the following linear model:

$$r = \beta_0 + \beta_r(\Delta y),$$

where r stands for the asset returns (eighter stocks or bonds), Y for the GDP, y for logarithm of Y, and Δy for the %-changes in the GDP. Using extended data from Barro (2006) for 53 global events between 1900-2016, we derive the relationship between GDP shocks (x-axis) and reaction in the stock and bond market (y-axis; see Figure 4 and Appendix A for the data).[10]

[10] Here we use real values for the asset returns, r, and GDP shocks, Δy. Thus, the regression equation in real terms would read $r_t = \beta_0 + \beta_y \cdot \Delta y_t$. If we assume that inflation, π, affects asset prices and GDP numbers equally, the nominal regression equation would read $r_t + \pi_t = \beta_0 + \beta_y \cdot (\Delta y_t + \pi_t)$. This shows that the parameters estimated from the real numbers is also applicable the nominal model. Thus, considering inflation does not change the results. While the effect of inflation might be negligible in our analysis, we note that claims inflation is an important problem for the underwriting side of insurance and reinsurance companies.

Figure 4: Asset Prices (y-axis) vs. GDP Shock (x-axis)



Note: The data contains a selection of asset returns and GDP shocks for the period between 1900-2016 for different countries (US among others; see Appendix A). Both asset returns and GDP are annualized.

As expected, the extreme events have led to a negative return on the stock market. Moreover, the treasury interest rates decrease with the shock size. This can be explained by flight-to-security and monetary interventions in times of crises. Lower short-term interest rates would mean an increase in risk free bond prices with short-term maturity. Thus, the allocation to government bonds serves as a hedge against the shock to the other assets and liabilities.

We approximate the shocks to the value of government bonds Δgb as the shock to the risk-free interest rate Δi_{rf} (treasury bill) times the interest rate sensitivity D (modified duration; Ruffle et al., 2014, p. 33):

$$\Delta gb \approx -D(\Delta i_{rf}). \tag{1}$$

For corporate bonds we use a similar approach. However, we need to account additionally for the change in credit spreads ψ_c. The credit spread is the difference in the yields on corporate and government bonds. Thus, the corporate bonds yield is defined as:

$$i_{cb} = i_{rf} + \psi_{cb}. \tag{2}$$

In times of crisis it is likely that the default probability of companies increases and so does the credit spread. Thus, we have $\psi_{cb} = \widehat{\psi}_{cb} + \hat{\beta}_{\psi_{cb}}\Delta y$). We assume that the credit spread ψ_{cb} increases linearly with negative GDP shocks (see, e.g., Gilchrist & Zakrajšek, 2012; Swanson, 2019).[11] The change in value of corporate bonds would then be proportional to the change in risk free interest rate plus the change in credit spreads, i.e.:

$$\Delta cb \approx -D(\Delta i_{rf} + \Delta\psi_{cb}). \tag{3}$$

The duration is again set as for government bonds. The change in stock prices is modeled according to the regression underlying Figure 4 (i.e. the sensitivity to GDP changes is 2.0073).

[11] Gilchrist & Zakrajšek (2012) measure the difference between investment grade corporate bonds and government bonds as historical average from 1973 to 2010 for US corporate bonds (excluding financials). It would be intriguing to add credit spreads to Figure 4, but due to data limitations this is only possible for some of the points plotted in Figure 4 (historical credit spreads are only available for the US, but not for many of the markets plotted in Figure 4 and Appendix A).

Table 2: Parameter Choice for Simple Model

Parameter		**Value**	**Sources**
GDP growth	$\overline{\Delta y}$	2.2%	Historical average global yearly GDP growth (Barro, 2006, p. 840)
Risk free interest rate	$\hat{\imath}_{rf}$	1.7%	Historical average risk free (treasury bill) interest rate (Barro, 2006, p. 842)
Duration	D	5.7	Average duration of non-life insurers' assets in 2019 (EIOPA, 2019, p. 71)
Credit spread	$\hat{\psi}_{cb}$	2.0%	Difference between investment grade corporate bonds and government bonds, historical average (1973-2010) for US corporate bonds (excl. financials) (Gilchrist and Zakrajšek 2012, p. 1695)
Credit spread cyclicality	$\hat{\beta}_{\psi_{cb}}$	-0.34	Empirical credit spread sensitivity for US corporate bonds (see Gilchrist and Zakrajšek 2012, p. 1699).

Note: $\psi_{cb} = i_{cb} - i_{rf}$.

For the two cyber scenarios introduced above, we calculate the change in the value of a typical insurance investment portfolio (see, e.g., Gal, Gründl, and Dong, 2016) and assume a 50% allocation to risk free investments (government bonds, other relatively risk free investments), 20% to stocks (equity) and 30% to corporate bonds (or other investment with a credit spread; for simplification we do not model other investment classes such as real estate or alternative investments). The chosen parameters and results are presented in Table 2 and 3.

We thus build a prototypical portfolio for an insurer' assets composed of government bonds, corporate bonds and stocks and calculate the change in the portfolio as $\Delta p = \Delta \cdot w$, where the vector of returns on different assets is $\Delta = (\Delta gb, \Delta cb, \Delta e)$ and w are the portfolio weights.

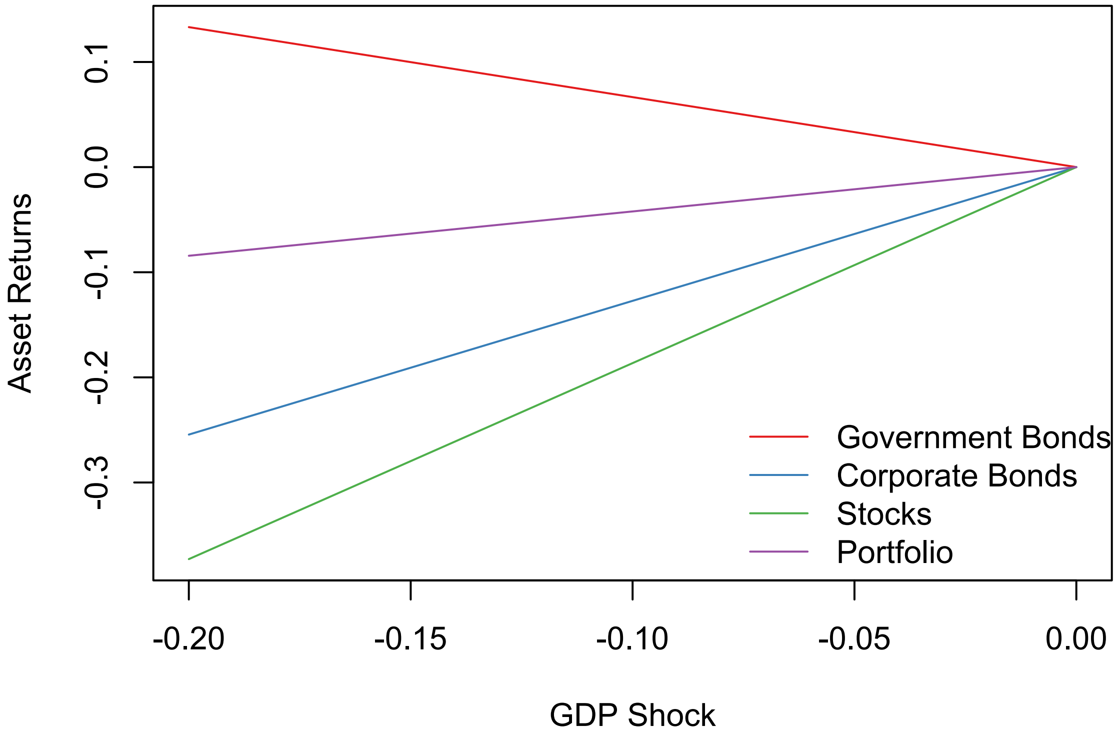
Table 3: Input Parameters and Results for the Simple Model

Variable		Basis Scenario	Eling et al. (2020) Scenarios		Ruffle et al. (2014, p. 4) Sybil logic bomb		Asset weight
Absolute GDP growth	Δy	2.20%	1.56%	0.65%	-2.50%	-7.90%	
Relative Shock GDP	$\widetilde{\Delta y}$	0.00%	-0.64%	-1.55%	-4.70%	-10.10%	
Risk free interest rate	i_{rf}	1.70%	1.63%	1.52%	1.15%	0.52%	
Government bonds return	Δgb	0.00%	0.43%	1.03%	3.13%	6.72%	50.00%
Corporate bond yield	i_{cb}	3.70%	3.84%	4.05%	4.75%	5.95%	
Corporate bonds return	Δcb	0.00%	-0.81%	-1.97%	-5.98%	-12.85%	30.00%
Stock market return	i_e	8.70%	7.51%	5.81%	-0.06%	-10.13%	
Equity return	Δe	0.00%	-1.19%	-2.89%	-8.76%	-18.83%	20.00%
Insurer's portfolio return	Δp	0.00%	-0.27%	-0.65%	-1.98%	-4.26%	

Note: The data for the basis scenario is based on long-term global data by Barro (2006). For the asset allocation weights see, e.g., Gal, Gründl, and Dong (2016) and the absolute GDP shock is defined as $\Delta y = \widetilde{\Delta y} + \overline{\Delta y}$.

The analysis shows that government bonds generally perform well and increase in value in the cyber scenarios. We also see that the shock to corporate bonds is composed of two elements: First, the reduction in interest rate increases bond values. Second, the increase in credit spreads decreases the bond value. In our case, the second effect dominates the first one. Still the hedging property of government bonds would compensate most of the losses on the other positions so that also for the most extreme scenario (-10.1% GDP) the value of the insurer's assets would only decrease by -4.26%. The magnitude of this decline seems plausible in light of the above described results of the literature review (see, e.g., Figure 2 for the effect on the stock market). We also present the results for a continuum of shock sizes in Figure 5.

Figure 5: Asset Returns for different GDP Shocks



While this first empirical analysis is useful to give some feeling for a possible direction and economic magnitude, there are manifold limitations we need to address to come to an economically more profound analysis. The modified duration only applies to incremental changes, not to 10% changes. Furthermore, we need to take the interaction with the liability side into account (the modified duration used here only applies to the asset side, but to understand the economic impact of an interest rate change, we need to look at both sides of the balance sheet). The results presented here are also sensitive to outliers in the data and to changes in the input parameters (e.g. modified duration, asset weights). More detailed specifications would be required to model the assets of a specific insurer adequately. First, the weight for different asset classes would need to be adapted. Second, differentiation between bonds with different rating (i.e. AAA, BBB, non-investment grade) would yield more realistic results. Finally, the geographical asset allocation needs to be taken into account. The data used in Barro (2006) makes projections for individual economies, but not for the world GDP. For a worldwide diversified portfolio, we might thus expect fewer extreme effects.[12] However, it is also not fully clear in how far extreme cyber scenarios can be diversified globally. One disadvantage of our empirical approach is that we assume that a cyber event would affect the economy and financial markets in a similar way as previous events. For example, the financial crisis 2008 that had a large impact on the financial markets but a relatively small impact on the real economy and thus might not be representative for a cyber event that affects real economy (i.e. reduction in production efficiency). For this reason, we recommend digging deeper on the modelling side (see extended model).

[12] We note, however that the US accounts for approximately 50% of the MSCI World and 25% of global GDP. In this respect, there are also strict limits to diversifiable for the global market portfolio.

4.2 Extended Model

The extended model relies on the macroeconomic model presented by Swanson (2019). In this model a core question is what the shock to the production technology is under a certain (cyber risk) scenario. To this end, we assume that a cyber event reduces the efficiency of production via a technological factor. We consider a classical (Cobb-Douglas) production function, where the production Y is a function of labor l, capital k and the employed technology A:

$$Y = A \cdot k^{1-\theta} \cdot l^{\theta}.$$

We assume in a first approximation that the labor and capital supply is exogenous and does therefore not change due to the shock. Then, change of the output would be approximately:

$$\Delta y \approx (1-\theta) \cdot \Delta ln(k) + \theta \cdot \Delta ln(l) + \Delta ln(A).$$

Next, we consider estimates for the businesses operability that could be at risk due to a cyber event. For example, Bounfour, Dieye, and Kammoun (2018) estimate a shock to productivity of 10%-40%. In our case considered here, the shock to the technology factor translates one to one to a shock in the production; moreover, we assume that, in equilibrium, production equals consumption. Note that we do not account for the economic multiplier effect, where the initial shock to the output would reduce the income, consumption, and finally output further. The shock to output would be larger when the multiplier effect is considered.

With respect to the GDP dynamics over time, we assume that after the initial shock, $\widetilde{\Delta y}$, in the first period the output returns to the long-term growth path. This would mean that the growth rate in period 2 is bigger than the long-term growth rate in order to compensate for the output lost. To summarize, the GDP growth rates would be $\{\Delta y_0, \Delta y_1, \Delta y_2, \Delta y_3, \dots\} = \left\{2.2\%, \widetilde{\Delta y}, \frac{1.022^2}{1+\widetilde{\Delta y}} - 1 > \widetilde{\Delta y}, 2.2\%, \dots\right\}$. In Appendix D we consider alternative scenarios by allowing the GDP to deviate from the long term growth path by more than one period.

We start by modeling the behavior of the monetary authority by using the so called Taylor rule (see, e.g. Swanson 2019). The Taylor rule describes how the short-term interest rates (target rate such as the 3-month Libor) are changed in response to a shock to the GDP. It has been shown that nonlinear versions of the Taylor rule fit the behavior of monetary authority best (see, e.g., Nitschka & Markov, 2016). The most frequently used nonlinear model is the logistic function (see, e.g., Gerlach & Lewis, 2014):

$$\Delta i_{rf} = \frac{i_{max}}{1+e^{-\beta_M \cdot \Delta y}} - i_{min},$$

where i_{max} and i_{min} are the upper and lower limits for the possible interest rates, β_M is the slope of the response function, and $\Delta y = \Delta ln(Y)$ is the output gap (in %).[13] Thus, a negative output gap $\Delta y < 0$ would cause central banks to lower interest rates. However, compared to a simple linear Taylor rule, this function describes a s-shaped reaction, meaning central banks are reluctant to lower already low interest rates further or even push them into negative territory. The reason is that while there is little evidence that lowering interest rates below zero would further stimulate the economy (see liquidity trap; Krugman et al., 1998), negative interest rates harms society by reducing pension and savings.[14]

To complete the modelling of the interest rates we need to analyze the effect of the short-term interest rates on the longer end of the yield curve. Thus, we use the monetary reaction function as an input to model yield curves for government bills (risk free), corporate bonds, and stocks. We refer to Appendix C for more details about modeling yield curves.

Combined with the interest rate sensitivity (Equation 1) we calculate the shock to government bonds. For the corporate bonds we again consider countercyclical credit spreads (see Equation 2) and define them as above. For stocks, we discount the companies' future cash flows, to attain the present value with a shock ($\tilde{S}$) and without a shock (S). We consider stocks as a leveraged claim on the overall consumption C^{λ} where λ is the leverage (see,

---

13 To calibrate the logistic function, we use long term average maximum ($i_{max} = 6\%$) and minima (i_{min} =0.5%) for the interest rate. This is the range observed for FED rate since 2008. We also note that Swanson (2019) explicitly models the monetary response as a function of the output gap (i.e. in our context the GDP reduction) and inflation. As noted earlier, we do not explicitly model inflation and focus on the effect of the GDP reduction.

14 Note that the Taylor rule describes short term interest rates only; it would be possible to also include monetary interventions at the longer end of the yield curve (so called quantitative easing, yield curve control), which might reduce long-term interest rates and credit spreads. A more aggressive monetary intervention would thus generally support asset prices and further dampen the shock to the insurer's portfolio.

e.g., Abel, 1999; Bansal & Yaron, 2004; Gourio, 2012; Swanson, 2019).[15] In equilibrium, we can assume $C = Y$ (Swanson 2019), and thus the long-term cash flow grows according to the long-term GDP growth rate, $\overline{\Delta y}$. The Gordon growth model, where the cash flows grow with a constant rate $\overline{\Delta y}$ infinitely, would well describe the income stream without a shock:

$$S = \frac{Y^{\lambda}}{i_e - \overline{\Delta y}},$$

where i_e is the risk-adjusted interest rate if there is no shock. In the case of a shock, we assume that the shock in companies' cash flows $\tilde{C}$ sustains for one period only and the cash flow returns to the pre-shock value C afterwards. To reflect this income stream, we use a cashflow dividend model that combines a shock period with a residual component:

$$\tilde{S} = \frac{\tilde{Y}^{\lambda}}{1+\tilde{\iota}_e} + \frac{Y^{\lambda}(1+\overline{\Delta y})}{(i_e - \overline{\Delta y})(1+\tilde{\iota}_e)},$$

where $\tilde{\iota}_e$ is the risk adjusted interest rate for the shock. While the shock to the income stream is transitionary, we assume that the shock in interest rates is long lasting in the sense that it affects how the cash flows are discounted (residual term). Our analysis shows that the change in the residual value due to change in the discounting factor dominate the results.

Table 4: Parameter Choice for Extended Model

Parameter		Value	Sources
Monetary policy response	$\hat{\beta}_M$	0.70	Carvalho et al., (2018, table 1a) for US; other sources: 0.75 (Swanson 2019, p.13), 0.5-1 (Taylor 1993, 1999); empirical for Switzerland (2000-2012) 0.58-0.63 (Nitschka & Markov, 2016, table A.3)
Min. interest rates	i_{min}	0.5%	Nominal short term interest rates observed for the US.
Duration	D	5.7	Average duration of non-life insurers' assets in 2019 (EIOPA, 2019, p. 71)
Risk premium cyclicality	$\hat{\beta}_{\psi_e}$	-0.97	Empirical sensitivity of the equity risk premium to shocks in GDP for US equity (1948-2005) (Cooper & Priestley, 2009, p. 2808)
Leverage	$\hat{\lambda}$	3.0	Assumption by Swanson (2019, p. 18) based on estimated / model derived values in Abel (1999) / Bansal and Yaron (2004)

Note: $\psi_e = i_e - i_{rf}$.

The expected return for stocks is composed of the risk-free interest rate and the equity risk premium, $i_e = i_{rf} + \psi_e$. Like the credit spread above, we assume that the equity risk premium increases in times of crisis, thus $\psi_e = \hat{\psi}_e + \hat{\beta}_{\psi_e}\Delta y$. Such a countercyclical equity risk premium is well documented in the literature (see, e.g., Campbell & Cochrane, 1999; Cooper & Priestley, 2009; Fama & French, 1989; Swanson, 2019). The explanation for a varying risk premium can be changed in market sentiment (risk aversion). Finally, the change in the insurer's stock investment would be:

$$\Delta s = ln(\tilde{S}) - ln(S),$$

$$\Delta s = ln\left(\frac{\frac{\tilde{Y}^{\lambda}}{1+\tilde{\iota}_e} + \frac{Y^{\lambda}(1+\overline{\Delta y})}{(1+\tilde{\iota}_e)(i_e-\overline{\Delta y})}}{\frac{Y^{\lambda}}{i_e-\overline{\Delta y}}}\right) = ln\left(\frac{\tilde{Y}^{\lambda}(i_e-\overline{\Delta y})}{Y^{\lambda}(1+\tilde{\iota}_e)} + \frac{(1+g)(i_e-\overline{\Delta y})}{(1+\tilde{\iota}_e)(i_e-\overline{\Delta y})}\right) = ln\left((1+\lambda\cdot\Delta Y)\frac{(i_e-\overline{\Delta y})}{(1+\tilde{\iota}_e)} + \frac{(1+\overline{\Delta y})}{1+\tilde{\iota}_e}\right), \quad (4)$$

where ΔY is the overall change in consumption due to the shock and $\lambda \cdot \Delta C$ the change in the dividends or cashflows (leveraged claim).

The table below reports the changes in the value of an insures' portfolio for different scenarios (the parameters are chosen as in Table 3 & 4).

[15] The leverage parameter describes the leveraged claim on a company's future cash flows. This is due to fixed costs (operation leverage) and fixed amount of debt (financial leverage) (Gourio, 2012).

Table 5: Input Parameters and Results for the Extended Model

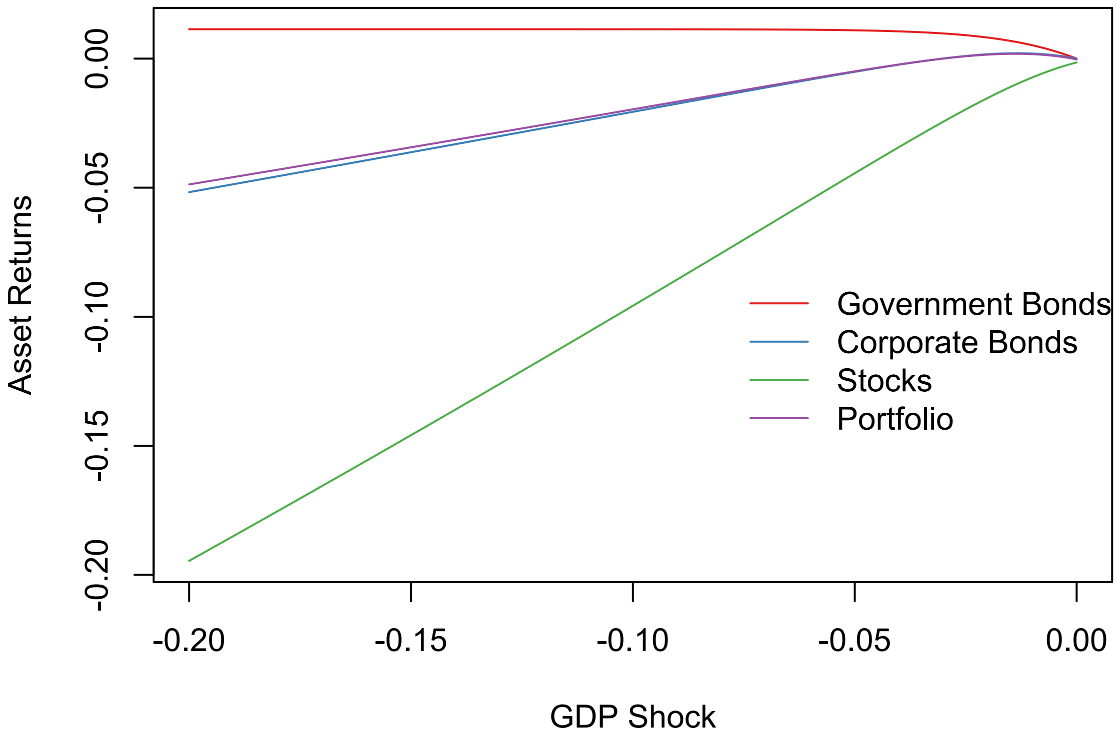
Variable		Basis Scenario	Eling et al. (2020) Scenarios		Ruffle et al. (2014, p.4) Sybil logic bomb		Asset weight
Absolute GDP growth	Δy	2.20%	1.57%	0.65%	-2.50%	-7.90%	
Relative shock GDP	$\widetilde{\Delta y}$	0.00%	-0.63%	-1.55%	-4.70%	-10.10%	
Risk free interest rate	i_{rf}	1.70%	1.32%	0.96%	0.55%	0.50%	
Government bonds return	Δgb	0.00%	0.36%	0.70%	1.09%	1.14%	50.00%
Corporate bond yield	i_{cb}	3.70%	3.54%	3.48%	4.15%	5.94%	
Corporate bonds return	Δcb	0.00%	0.15%	0.20%	-0.43%	-2.09%	30.00%
Equity premium	ψ_e	8.70%	8.93%	9.46%	12.11%	17.30%	
Equity return	Δe	-0.00%	-0.48%	-1.14%	-4.13%	-9.68%	20.00%
Insurer's portfolio return	Δp	-0.00%	0.13%	0.18%	-0.41%	-1.99%	

Note: The data for the basis scenario is based on long-term global data by Barro (2006). For the asset allocation weights see, e.g., Gal, Gründl, and Dong (2016) and the absolute GDP shock is defined as $\Delta y = \widetilde{\Delta y} + \overline{\Delta y}$.

While here the sensitivity of the insurer's portfolio to shocks is slightly lower than in the empirical model above, the results are quite similar. For the most extreme GDP shock (-10.1%), the portfolio return would be -1.99% (compared to -4.26% above). The difference between the simple and expanded model is mainly driven by the different interest rates used to calculate the assets sensitivity. Here we calculate the assets sensitivity to the longer end of the interest rate curve that is less sensitive to the shock than the short-term interest rates used as above.

Figure 6 shows the return on the insurer's portfolio for the whole space of different shocks. Compared to the results above, the curves are now concave and not linear anymore. The reason for that is that here we assumed that the monetary authority reaction is limited. For corporate bonds and the whole insurance portfolio the curves are first increasing and then decreasing for larger shocks. The reason is that for small shocks the monetary authority dominates (risk free rates) but for larger shocks the credit spreads and equity risk premium start to bend the curves downwards.

Figure 6: Asset Returns for different GDP Shocks (Extended Model)

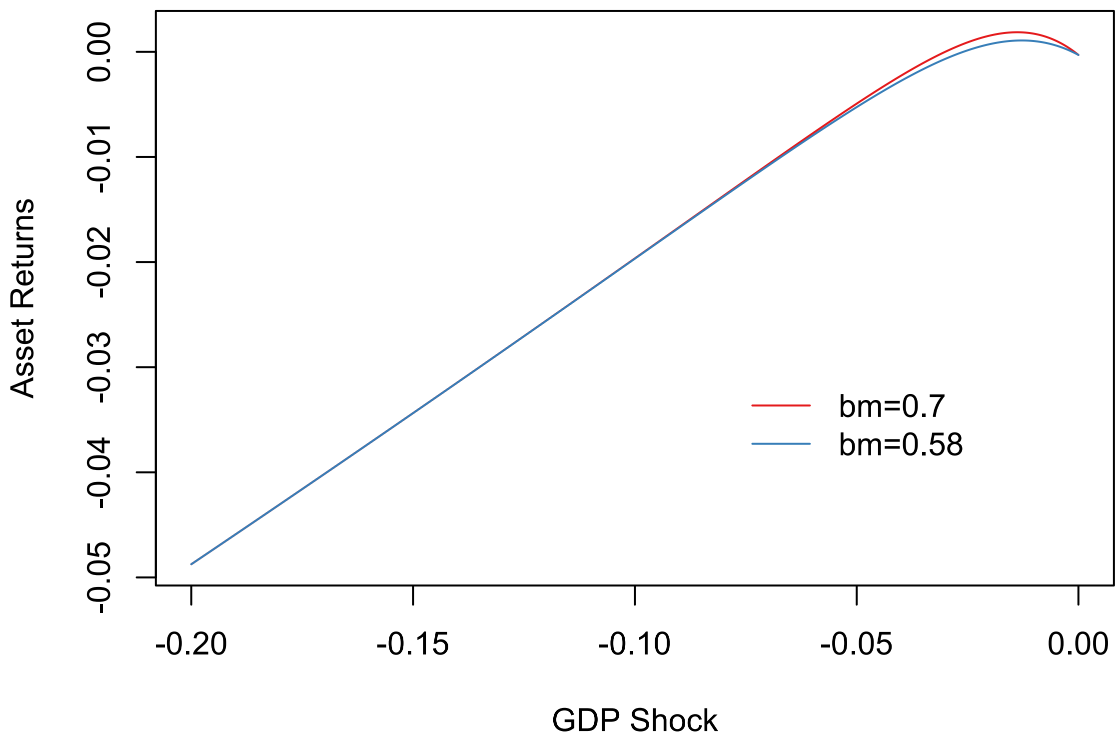


4.3 Robustness Checks

4.3.1 Different Monetary Response

To judge the reliability of our results, we let all estimated parameters vary over a meaningful range of values. One important parameter is how the monetary authority reacts with interest rates cuts to the shock, $\hat{\beta}_M$. Figure 7 shows the return on the insurer's assets for different $\hat{\beta}_M$. A less aggressive lowering of interest rates as a reaction to a shock ($\hat{\beta}_M = 0.58$) would decrease, ceteris paribus, the present value of all assets and the negative shock to the insurer's aggregated assets would be larger. Especially, the government bonds would benefit from lowering interest rates. So essentially if we believe that central banks will react to the shock, there will be no negative impact on asset returns. As mentioned above (note 14), it would be possible to also include monetary interventions at the longer end of the yield curve (so called quantitative easing), which might reduce long-term interest rates and credit spreads. A more aggressive monetary intervention would support asset prices and further dampen the shock to the insurer's portfolio.

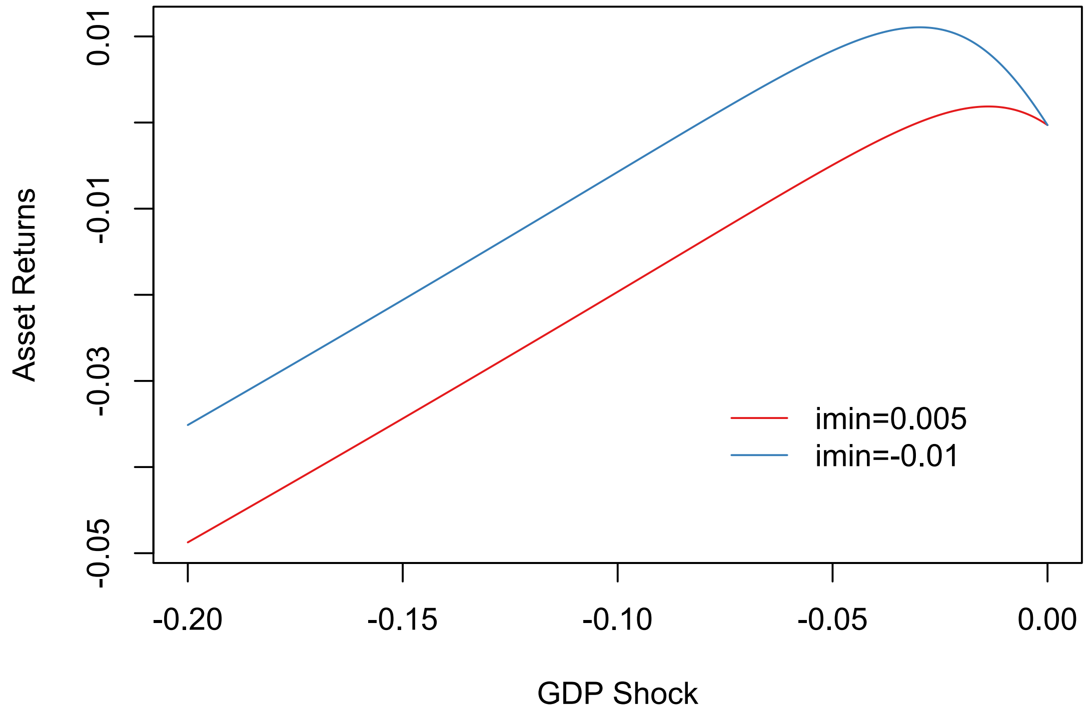
Figure 7: Portfolio Returns for different Monetary Policies (bm)



Note: The figure compares the outcome for $\hat{\beta}_M = \{0.7, 0.58\}$ as discussed in Table 4.

Another important parameter is how the monetary authority reacts with interest rates cuts to the shock, i_{min}. Figure 8 shows the return on the insurer's assets for different i_{min}. A more aggressive lowering of interest rates as a reaction to a shock ($i_{min} = -1\%$) would increase, ceteris paribus, the present value of all assets and the negative shock to the insurer's aggregated assets would be smaller. So essentially if we believe that central banks will react to the shock stronger, there will be less negative impact on asset returns.

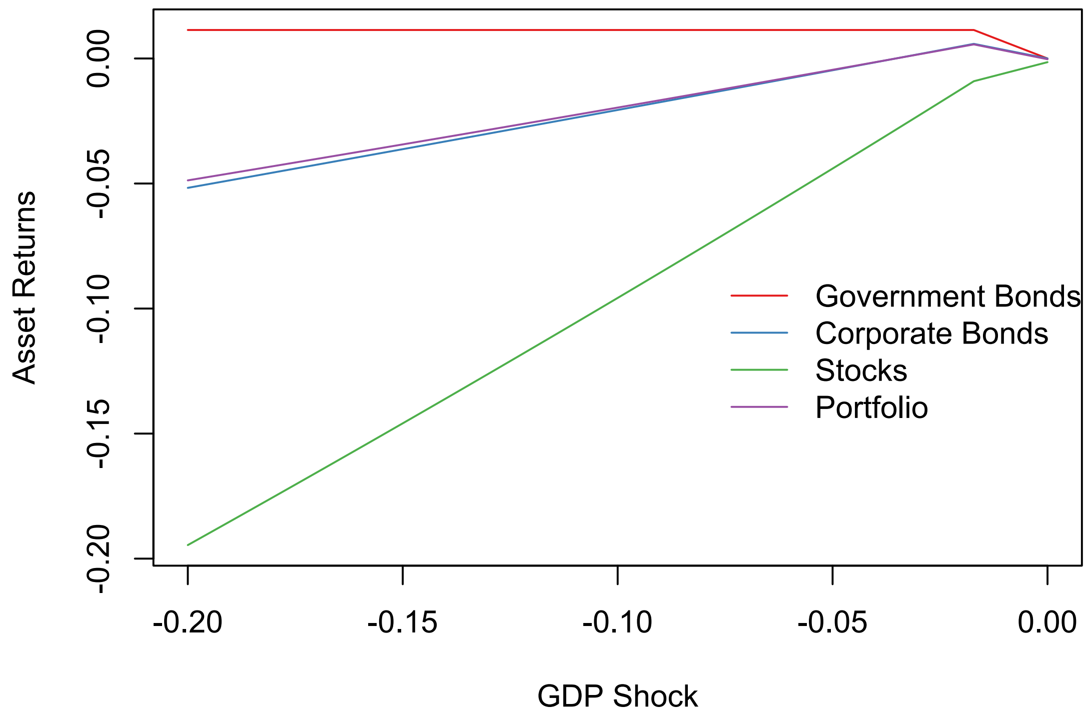
Figure 8: Portfolio Returns for different Monetary Policies (Extended Model; i_{min})



Note: The figure compares the outcome for $i_{min} = \{0.5\%, -1\%\}$ as discussed in Table 4.

We let not only the parameter values vary to analyze parameter risk, but we also vary the modelling itself to get some feeling for potential model risk. An alternative to the logistic model for the monetary response is to use a simple linear function which is cut off at the min and max interest rates, again showing robust results.

Figure 9: Portfolio Returns for linear Taylor rule

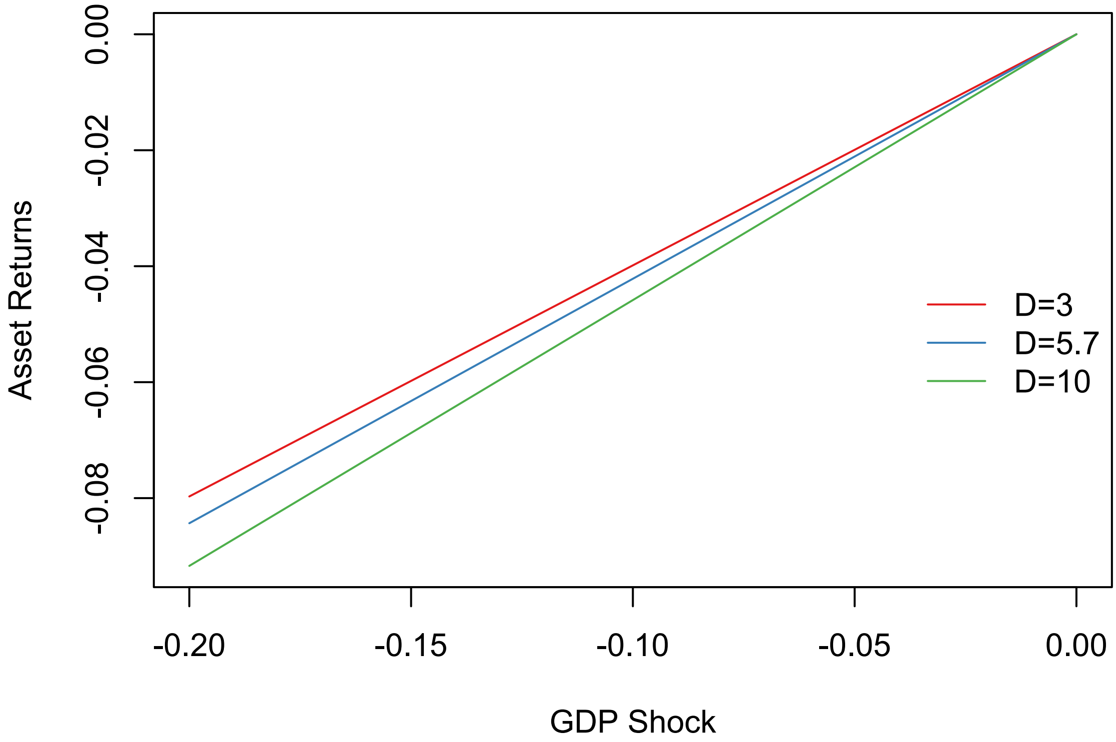


Note: The figure shows the outcome for a linear Taylor rule with $\{i_{min}, bm\} = \{0.005, 0.7\}$.

4.3.2 Different Durations

We also analyze the sensitivity of our result to the duration (focusing on the effect on the assets only; for the influence of the interest rate change on the entire risk capital of an insurer the liabilities are relevant too). Figure 10 presents the return on the insurer's asset portfolio for different duration levels based on the simple model. A portfolio with higher duration would perform relatively worse.

Figure 10: Portfolio Returns for different Durations (Simple Model)



Note: the figure compares the outcome for $D = \{3, 5.7, 10\}$.

5 Conclusion, Limitations, Future Research

We propose a general framework to model the effect of extreme risks on an insurer's assets and apply it in the context of extreme cyber risk events. We reviewed a wide range of literature, mainly for non cyber disasters, and show how we can apply the respective insights to future extreme cyber disasters and their effect on financial markets. Extreme cyber scenarios might have a profound effect on an insurer's assets, but the overall effect remains to some extend limited mainly due to hedging properties of different asset classes. First, such an event would lower current and expected interest rates and thus increase the value of (risk free) government bonds. Due to this property, government bonds have frequently served as a safe haven in times of crisis. Second, the effect on corporate bonds is ambiguous, since in times of crisis, we frequently observe spikes in credit spreads. Third, stocks would suffer major losses. The reason is that a cyber disaster would reduce the economy's productivity and capital stock. After the initial hit to the production, the economic multiplier would cause demand and production to plunge further. All this hurts companies' earnings and increases in the risk premium would further reduce the value of future cash flows. Overall, the value of stocks decline and credit risk goes up, but the risk-free interest rate decreases which increases the value of government bonds and other relatively risk free investments. This important hedging property may exist when we only look at the asset side of the balance sheet of a (re-)insurer, but particularly lower interest rates may lead to a large increase of the market values of liabilities and materially impact solvency (via discounting used for market value margin/ risk margin calculation).

There are a number of limitations to our analyses that might serve as motivation for future research. First, since we have never observed a catastrophic cyber event, we do not exactly know whether previous disasters are representative and different types of cyber events will have different effects on assets.[16] Second, for a real life implementation, insurers need to adapt our model to reflect their concrete asset portfolio with respect to the geographic, asset class, strategic, and duration allocation. As mentioned, there might be sectors that could even benefit from a cyber event (e.g. cyber security providers). From an empirical perspective, we illustrated that the main challenge is to identify the time dimension of the connections between an event and the financial market reaction. Since financial markets are forward-looking, their reactions run in front of other relevant economic measures. By looking at several periods and using unexpected shocks, we could mitigate this problem to some extent. It also means that insurers should be aware that asset shocks might precede underwriting losses for cyber risks. The timing of the losses is thus different, which again might cause some diversification potential. However, insurers will need to put provisions on the balance sheet as soon as the cyber event occurs.

Future research could aim at providing better estimates for the potential economic damage a cyber disaster could cause. We addressed the uncertainty so far by providing results for a whole range of shock severities, as measured by the GDP decline. Clearly, for risk management purposes, we should have a more sophisticated understanding about the size of the shock, the time for the crisis to resolve, and the likelihood of such an event. Moreover, to apply our model to the concrete exposure of an insurer, we would need to be more precise about the sectoral and geographical regions that are affected. An input-output model as presented in Eling et al. (2020) could be informative on such questions. Furthermore, this analysis is limited to study the effect on the asset side of an insurance company. To understand the full impact on the insurance balance sheet, the liability side needs to be incorporated in the analysis, which is not the focus of this analysis. Apart from the impact of an extreme scenario on the insured losses, also the interest rate effect needs to be considered. Also, the increase in credit spreads might have effects on the underwriting side.

Another promising avenue for future research might be to apply our model to other institutions in the financial services sector, especially to the banking industry. The findings in this paper indicate that the impact of extreme scenarios on the asset side of the insurers balance sheet is relatively limited because of hedging effects, but it is not clear how the model would behave for example in the context of a banking balance sheet. The outcome of such an analysis might also provide some relevant policy implications on differences and commonalities in the business model of banks and insurance companies.

The results of the paper can be useful to improve internal capital models with respect to the link between extreme (cyber) events and the capital markets. The general results derived here are also relevant in light of the discussion around the development of solvency models that assume a linear correlation of 0.25 between the investment and underwriting.[17] Given the results we have seen so far, this seems to conservative. Moreover, the relation should be modeled non-linear (that is in normal times the correlation is very likely lower and closer to 0, while in extreme scenarios we might expect to observe a link (e.g. 9/11), at least in the short to medium term. Given that the time horizon of solvency models is not short term (daily, weekly), but one year, the strengths of the actual correlation might again be questioned in light of the results presented here.

[16] For example we look at scenarios where stock prices go down, but what we have not considered is what happens if a cyber-attack directly disrupts trading on the capital market; e.g. what happens if virulent malware stops the NYSE exchange for two weeks; or what happens if malware disconnects an insurance company from the capital market for two weeks. This is implicitly part of our scenarios, but we have not discussed this in detail so far. What if liquidity issues arise, if an insurance company cannot trade for two weeks anymore? The scenario has both systemic (the case that the whole market is disrupted) as well as idiosyncratic components (the case that only one company is disconnected). In general, the empirical approach presented here can only be calibrated with existing data and data for big cyber events is not existent. We thus implicitly assume that those disasters are to some extend also representative for other disastrous events. While for the pandemic scenario presented in Appendix B a comparison with wars has been made regularly, for the cyber events the comparison might only hold for very extreme scenarios such as the decline of -10.1 % in GDP presented in the sybil logic bomb scenario.

[17] A linear correlation of 0.25 is the assumptions in many regulatory standard models such as Solvency II in the European Union; see Eling & Jung (2018). Insurance companies that work with internal models use our specific dependencies, including dependencies between investment and underwriting risks.

References

Abel, A. B. (1999). Risk premia and term premia in general equilibrium. *Journal of Monetary Economics*, *43*(1), 3–33.

Bansal, R., & Yaron, A. (2004). Risks for the long run: A potential resolution of asset pricing puzzles. *Journal of Finance*, *59*(4), 1481–1509.

Barro, R. J. (2006). Rare Disasters and Asset Markets in the Twentieth Century. *Quarterly Journal of Economics*, *121*(3), 823–866.

Barro, R. J. (2009). Rare disasters, asset prices, and welfare costs. *American Economic Review*, *99*(1), 243–264.

Berkman, H., Jacobsen, B., & Lee, J. B. (2011). Time-varying rare disaster risk and stock returns. *Journal of Financial Economics*, *101*(2), 313–332.

Bounfour, A., Dieye, R., & Kammoun, N. (2018). *Macro estimates of intangibles cyber-risks*. https://www.hermeneut.eu/wp-content/uploads/2018/08/HERMENEUT-D3.2-Macro-estimates-of-intangibles-cyber-risks.pdf

Campbell, J. Y., & Cochrane, J. H. (1999). By force of habit: A consumption-based explanation of aggregate stock market behavior. *Journal of Political Economy*, *107*(2), 205–251.

Campbell, K., Gordon, L. A., Loeb, M. P., & Zhou, L. (2003). The economic cost of publicly announced information security breaches: empirical evidence from the stock market. *Journal of Computer Security*, *11*(3), 431–448.

Carvalho, C., Nechio, F., Francisco, S., Tristao, T., Fernanda, P.-R., Frb, N., & Tristão, T. (2018). *Taylor Rule Estimation by OLS Taylor Rule Estimation by OLS*.

Cavusoglu, H., Mishra, B., & Raghunathan, S. (2004). The effect of internet security breach announcements on market value: Capital market reactions for breached firms and internet security developers. *International Journal of Electronic Commerce*, *9*(1), 70–104.

Chesney, M., Reshetar, G., & Karaman, M. (2011). The impact of terrorism on financial markets: An empirical study. *Journal of Banking and Finance*, *35*(2), 253–267.

Cochrane, J. H. (2009). *Asset pricing: Revised edition*. Princeton university press.

Cooper, I., & Priestley, R. (2009). Time-Varying Risk Premiums and the Output Gap. *Review of Financial Studies*, *22*(7), 2801–2833.

Copeland, T. E., Weston, J. F., & Shastri, K. (2005). *Financial theory and corporate policy* (Vol. 4). Pearson Addison Wesley.

Cummins, J. D. (2006). Should the government provide insurance for catastrophes? *Federal Reserve Bank of St. Louis Review*, *88*(4), 337–379.

EIOPA. (2019). *Report on insurers ' asset and liability management in relation to the illiquidity of their liabilities*. *December*.

Eling, M., Elvedi, M., & Falco, G. (2020). The economic impact of extreme cyber risk scenarios. *Working Paper*.

Eling, M., & Jung, K. (2018). Risk aggregation in non-life insurance: standard models vs. internal models. *Working Paper*.

Fama, E. F., & French, K. R. (1989). Business conditions and expected returns on stocks and bonds. *Journal of Financial Economics*, *25*(1), 23–49.

Gal, J., Gründl, H., & Dong, M. (2016). The evolution of insurer portfolio investment strategies for long-term investing. *OECD Journal: Financial Market Trends*, *2016*(2), 1–55.

Gallin, L. (2017). *Re/insurance to take minimal share of $8 billion WannaCry economic loss: A.M. Best*. https://www.reinsurancene.ws/reinsurance-take-minimal-share-8-billion-wannacry-economic-loss-m-best/

Gerlach, S., & Lewis, J. (2014). Zero lower bound, ECB interest rate policy and the financial crisis. *Empirical Economics*, *46*(3), 865–886.

Gilchrist, S., & Zakrajšek, E. (2012). Credit spreads and business cycle fluctuations. *American Economic Review*, *102*(4), 1692–1720.

Gourio, F. (2012). Disaster risk and business cycles. *American Economic Review*, *102*(6), 2734–2766.

Hovav, A., & D'Arcy, J. (2003). The impact of denial-of-service attack announcements on the market value of firms. *Risk Management and Insurance Review*, *6*(2), 97–121.

IFO. (2020). *Branchenatlas*. https://www.ifo.de/branchenatlas

IMF. (2020). *World economic outlook update*. https://www.imf.org/en/Publications/WEO/Issues/2020/06/24/WEOUpdateJune2020

Jordà, Ò., Singh, S. R., & Taylor, A. M. (2020). Longer-Run Economic Consequences of Pandemics. *Federal Reserve Bank of San Francisco, Working Paper Series*, 01–16.

Krugman, P. R., Dominquez, K. M., & Rogoff, K. (1998). It's baaack: Japan's slump and the return of the liquidity trap. *Brookings Papers on Economic Activity*, *1998*(2), 137–205.

Mahalingam, A., Coburn, A., Jung, C. J., Yeo, J. Z., Cooper, G., & Evan, T. (2018). Impacts of severe natural catastrophes on financial markets. *Cambridge Centre for Risk Studies*.

Nitschka, T., & Markov, N. (2016). Semi-Parametric Estimates of Taylor Rules for a Small, Open Economy – Evidence from Switzerland. *German Economic Review*, *17*(4), 478–490.

Risk Management Solutions. (1995). What if the 1923 earthquake strikes again? A five-prefecture Tokyo region scenario. *Topical Issue Series*.

Ruffle, S. J., Bowman, G., Caccioli, F., Coburn, A. W., Kelly, S., Leslie, B., & Ralph, D. (2014). *Stress test scenario: sybil logic bomb cyber catastrophe*. Centre for Risk Studies, University of Cambridge.

Swanson, E. (2019). A Macroeconomic Model of Equities and Real, Nominal, and Defaultable Debt. *Working Paper*.

Taylor, J. B. (1993). Discretion versus policy rules in practice. *Carnegie-Rochester Confer. Series on Public Policy*, *39*(C), 195–214.

Taylor, J. B. (1999). A historical analysis of monetary policy rules. In *Monetary policy rules* (pp. 319–348). University of Chicago Press.

Thomann, C. (2013). The Impact of Catastrophes on Insurer Stock Volatility. *Journal of Risk and Insurance*, *80*(1), 65–94.

Wang, L., & Kutan, A. M. (2013). The impact of natural disasters on stock markets: Evidence from Japan and the US. *Comparative Economic Studies*, *55*(4), 672–686.

World Bank. (2020). *Global economic prospects*. https://openknowledge.worldbank.org/bitstream/handle/10986/33748/9781464815539.pdf

Worthington, A., & Valadkhani, A. (2004). Measuring the impact of natural disasters on capital markets: An empirical application using intervention analysis. *Applied Economics*, *36*(19), 2177–2186.

Appendix A: Data

Table A1: Data Used for Figure 4

Event	Country	Years	No. of years	Real per capita GDP growth	Real per capita GDP growth (per year)	Real stock return (per year)	Real bill return (per year)
Panel A: Data Used in Barro (2006)							
World War I	Austria	1913–1919	6	-0.350	-0.058		-0.041
	Belgium	1916–1918	2	-0.300	-0.150		
	Denmark	1914–1918	4	-0.160	-0.040		-0.069
	Finland	1913–1918	5	-0.350	-0.070		
	France	1916–1918	2	-0.310	-0.155	-0.057	-0.093
	Germany	1913–1919	6	-0.290	-0.048	-0.264	-0.156
	Netherlands	1913–1918	5	-0.170	-0.034		-0.052
	Sweden	1913–1918	5	-0.180	-0.036	-0.159	-0.131
Great Depression	Australia	1928–1931	3	-0.200	-0.067	-0.036	0.082
	Austria	1929–1933	4	-0.230	-0.058	-0.173	0.071
	Canada	1929–1933	4	-0.330	-0.083	-0.231	0.071
	Chile	1929–1931	2			-0.223	
	France	1929–1932	3	-0.160	-0.053	-0.205	0.014
	Germany	1928–1932	4	-0.180	-0.045	-0.148	0.093
	Netherlands	1929–1934	5	-0.160	-0.032	-0.142	0.057
	New Zealand	1929–1932	3	-0.180	-0.060	-0.056	0.119
	United States	1929–1933	4	-0.310	-0.078	-0.165	0.093
Spanish Civil War	Portugal	1934–1936	2	-0.150	-0.075	0.134	0.038
	Spain	1935–1938	3	-0.310	-0.103		
World War II	Austria	1944–1945	1	-0.580	-0.580		
	Belgium	1939–1943	4	-0.240	-0.060		
	Denmark	1939–1941	2	-0.240	-0.120	-0.037	-0.022
	France	1939–1944	5	-0.490	-0.098	-0.293	-0.221
	Germany	1944–1946	2	-0.640	-0.320		
	Greece	1939–1945	6	-0.640	-0.107		
	Italy	1940–1945	5	-0.450	-0.090	-0.339	-0.526
	Japan	1943–1945	2	-0.520	-0.260	-0.023	-0.087
	Netherlands	1939–1945	6	-0.520	-0.087		
	Norway	1939–1944	5	-0.200	-0.040	0.017	-0.045
Aftermaths of wars	Canada	1917–1921	4	-0.300	-0.075		
	Italy	1918–1921	3	-0.250	-0.083		
	United Kingdom	1918–1921	3	-0.190	-0.063		
	United Kingdom	1943–1947	4	-0.150	-0.038		
	United States	1944–1947	3	-0.280	-0.093		
Post-WWII Depressions	Argentina	1998–2001	3	-0.210	-0.070	-0.036	0.090
	Chile	1981–1982	1	-0.180	-0.180	-0.370	0.140
	Indonesia	1997–1998	1	-0.150	-0.150	-0.445	0.096
	Philippines	1982–1984	2	-0.180	-0.090	-0.243	-0.050
	Thailand	1996–1997	1	-0.140	-0.140	-0.489	0.060
	Venezuela	1976–1984	5	-0.240	-0.048	-0.086	
Panel B: Extended Data from 2001 onwards							
	Estonia	2007-2009	2	-0.184	-0.092	-0.128	0.054
	Latvia	2007-2010	3	-0.169	-0.056	-0.089	0.073
	Lithuania	2008-2009	1	-0.139	-0.139	-0.142	0.065
	Luxembourg	2007-2009	2	-0.090	-0.045	-0.043	0.033
	Spain	2007-2013	6	-0.105	-0.017	0.004	0.012
	Ireland	2007-2009	2	-0.121	-0.060	-0.232	0.032
	Finland	2008-2009	1	-0.085	-0.085	-0.172	0.028
	Greece	2007-2013	6	-0.240	-0.040	-0.074	0.036
	Iceland	2008-2010	2	-0.102	-0.051	-0.104	0.106
	Argentina	1998-2002	4	-0.219	-0.055	-0.038	0.162
		2008-2009	1	-0.069	-0.069	0.242	-0.014
	Brazil	2013-2016	3	-0.086	-0.029	-0.088	0.011
	Venezuela	2001-2003	2	-0.161	-0.080	0.109	0.079

Note: The data source for Panel B is the World Bank for the GDP and Bloomberg and FRED for the stocks and bills. We use 2017 constant international $ (based on purchasing power parity) for the GDP. Panel A is taken from Barro (2006).

The results in Table A1 show that short-term bonds / bills in general outperform stocks in extreme crisis scenarios. The mean stock return across the scenarios described is -13%, while the mean return of the bills is 0.5%. Considering the data one also might ask whether there are different regimes in the data, given that the mean return of the bills is driven by two extreme outliers which are Italy and France in World War II with a real bond return of -52.6% and -22.1% (the median of the returns are -16% for the stocks and +1% for the bills). These are driven by extreme inflation at that time. One might argue that there are two regimes in the data with the majority of the cases the monetary agency still has inflation under control, while in a few exceptional cases the monetary authority has lost control and high inflation rates appear. While this may be plausible from an economic point of view the sparsity of data does not allow us to empirically estimate such a relationship with the data at hand.

Appendix B: Application to Pandemic Risk

The World Bank (2020) estimates a -5.2% decline in the world GDP due to COVID 19, while the IMF (2020) estimates -4.9%. Both expect that the pre-crisis levels will almost be reached in 2021. We consider the overall effect on the economy here, although the impact will vary depending on the industry considered (e.g. IT firms have profited in the crisis, while labor intensive manufacturing industry has suffered during the crisis; see, e.g., IFO, 2020).

Table B1: Results for the Simple Model

Variable		Basis Scenario	IMF	World Bank
Absolute GDP growth	Δy	2.20%	-4.90%	-5.20%
Relative Shock GDP	$\widetilde{\Delta y}$	0.00%	-7.10%	-7.40%
Risk free interest rate	i_{rf}	1.70%	0.87%	0.84%
Government bonds return	Δgb	0.00%	4.73%	4.93%
Corporate bond yield	i_{cb}	3.70%	5.28%	5.35%
Corporate bonds return	Δcb	0.00%	-9.03%	-9.41%
Stock market return	i_e	8.70%	-4.54%	-5.10%
Equity return	Δe	0.00%	-13.24%	-13.80%
Insurer's portfolio return	Δp	0.00%	-2.99%	-3.12%

Note: For the asset allocation weights see, e.g., Gal, Gründl, and Dong (2016).

We note that the consideration here is an aggregated view relying on the World Bank (2020) and IMF (2020) estimates. An alternative could be a more detailed analysis based on input output inoperability considerations that considers the effect of pandemics on different industries (following the ideas presented in Eling et al., 2020). We also note that with a GDP reduction of 5% and an output gap of -7.2%, the monetary response parameter bm must take the value 0.098 (i.e. solving the Taylor rule for bm) to reduce interest rates by 50 basis points (which was what empirically happened at the beginning of the pandemics), emphasizing the need to model a non-linear response function for the monetary agency.

Appendix C: Modelling the Yield Curve (Model 2)

While we detailed in the main text how the monetary authority controls the short-term interest rates, we provide here a more comprehensive description on what this would mean for the longer end of the yield curve. Lowering short-term interest rates affects the whole curve. The yield curve is frequently modeled according to the liquidity preference theory (Copeland et al., 2005, p. 262). Refinancing yearly at the short-term (expected) interest rates should be equivalent to the interest rate on a long term (n-period) bond plus a liquidity premium lp:

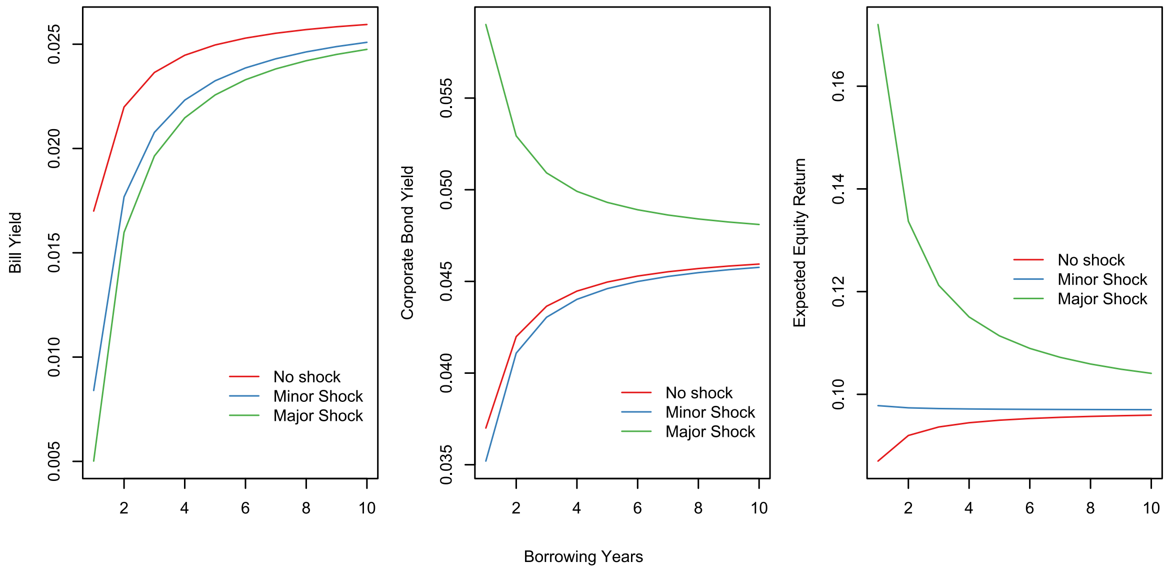
$$lp + \prod_{t=1}^{n}(1 + i_{1,t}) = (1 + i_{n,1})^{n},$$

where $i_{1,t}$ is the one-year (expected) yield in period t and $i_{n,1}$ is the spot yield for n periods. We can solve this equation for the yield curve, $i_{n,1}$, recursively:

$$i_{n,1} = \left(lp + (1 + i_{n-1,1})^{n-1}(1 + i_{1,n})\right)^{1/n} - 1$$

$i_{n,1}$, for different monetary interventions in the short-term rates are shown in Figure C1. We see that the yield curve is upward sloping as it has been observed in the recent history in "normal" times (called the "normal" yield curve). This characteristic is due investors demanding higher interest rates for longer durations and is controlled by the positive liquidity premium, lp. We also see that lowering the short-term yield $i_{1,1}$, even if temporary, drags down longer-term yields $i_{n>1,1}$ as well. We also report the yield curves for risky assets namely corporate bonds and stocks. There initial shock increases credit spreads and equity risk premiums more than it lowers risk free rates and thus the yield curves bend upwards. Finally, we assume that after the initial shock the short-term yields return to the long-term average. Thus, the yield curves for all assets converge in the long run, $\lim_{n\to\infty}(i_{n,1}) = a$.

Figure C1: Monetary Shock to Yield Curves



Note: the figures show the yield curve for t bills, corporate bonds, and stocks and how they react to different monetary shocks: no shock ($\Delta y = -0\%$), a minor shock ($\Delta y = -2\%$), and a major shock ($\Delta y = -10\%$) For the liquidity premium we choose $lp = 0.01$ based on US data (own estimations).

These yield curves are relevant to price the cashflows of government bonds, corporate bonds, and stocks. For the government and corporate bonds, we use again the duration to read the relevant interest rate from the yield curve in Figure C1, meaning we evaluate the yield curve for a maturity of 5.7 years. Then, we apply Equation (1-3) to calculate the changes in the bonds' values.

For the stocks we adapt the dividend discount model (Equation 4) to include more periods and to allow the interest rates to reflect the whole yield curve.

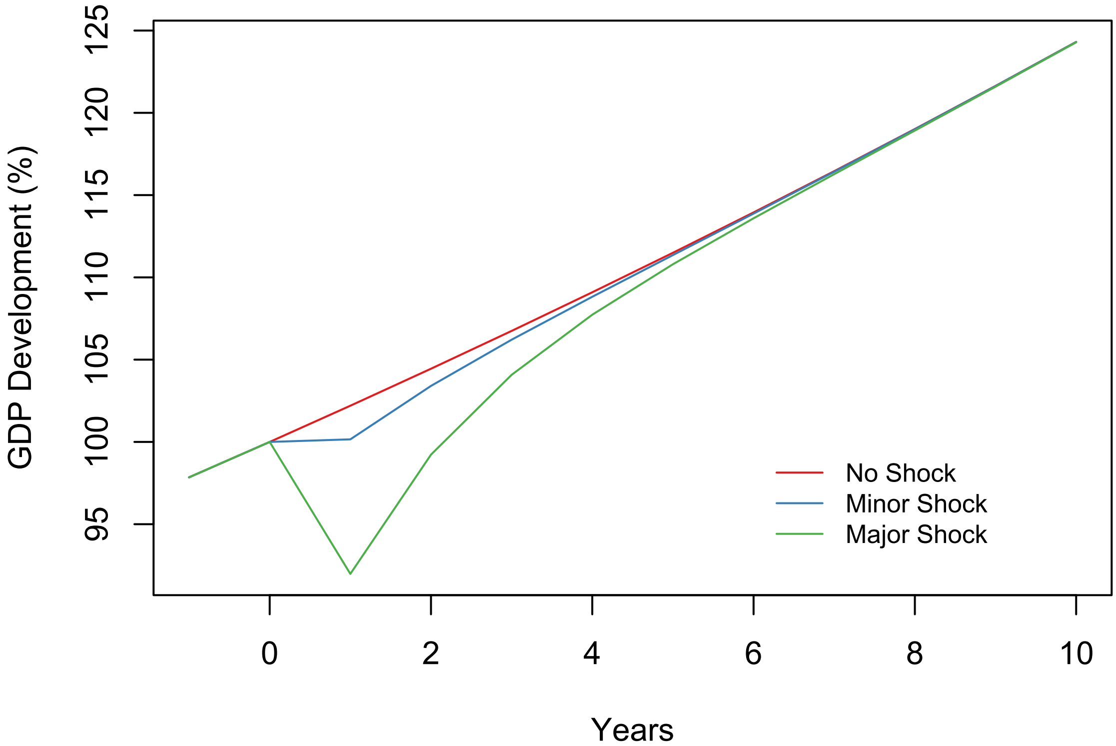
Appendix D: Multi-period Shock

While we assume in the main text that the GDP shock lasts only one period and then returns to the long-term growth path, we relax this assumption here. Especially large economic shocks can cause structural changes and thus more than one period is needed for the GDP to recover (see, e.g., Jordà et al., 2020). In the following we assume that the shock in the GDP due to a cyber event is long lasting (more than a year). For that we use a differential equation with mean reversion to describe the development of the GDP growth, Δy:

$$\Delta y_t = \Delta y_{t-1} + \rho_y(\overline{\Delta y} - \Delta y_{t-1}) + \varepsilon_t,$$

where ρ_y describes the speed of mean reversion (for the base line we choose $\rho_y = -0.5$. We use the same initial GDP shock $\varepsilon_1 < 0$ as above (and no shock otherwise, $\varepsilon_{t\neq 1} = 0$). Figure D1 shows the development of the GDP for different shock sizes over time. After the GDP deviated in the period $t = [0,1]$ it converges back (asymptotically) to the long-term growth trend over time. The GDP shock is reverted to a large degree after year 4 (from -10% back to -1%).

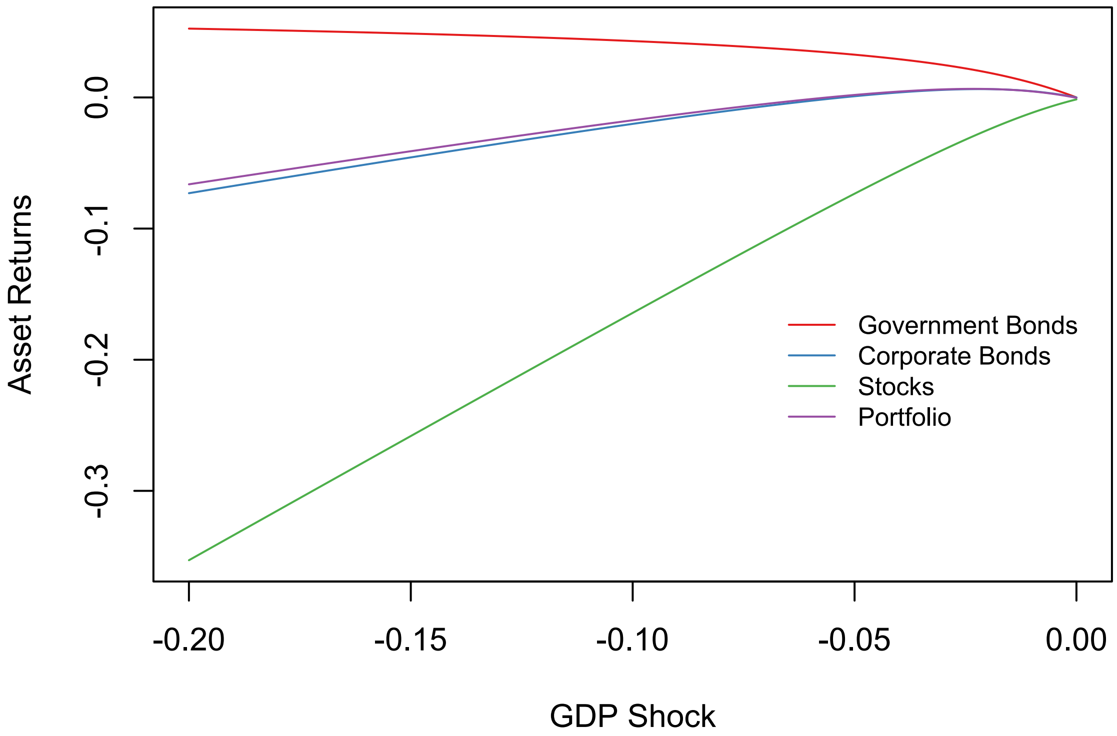
Figure D1: Multi-period GDP Shock



Note: the figure shows the GDP development for no shock, minor shock ($\Delta y = -2\%$), and a major shock ($\Delta y = -10\%$) over time. We choose the GDP before the shock as the basis (y_0=100).

Then we adapt Equation 4 to allow for multi-period shocks to the GDP and therefore to interest rates, risk premiums and dividends. Figure D2 shows the shock to the insurer's portfolio. When comparing the one period model in the main text (Model 2) with the multi-period shock model here, we see that the insurer's portfolio would be stronger negatively affected for more sustained shock. This is because the persistent shock would increase risk premiums and lower dividends.

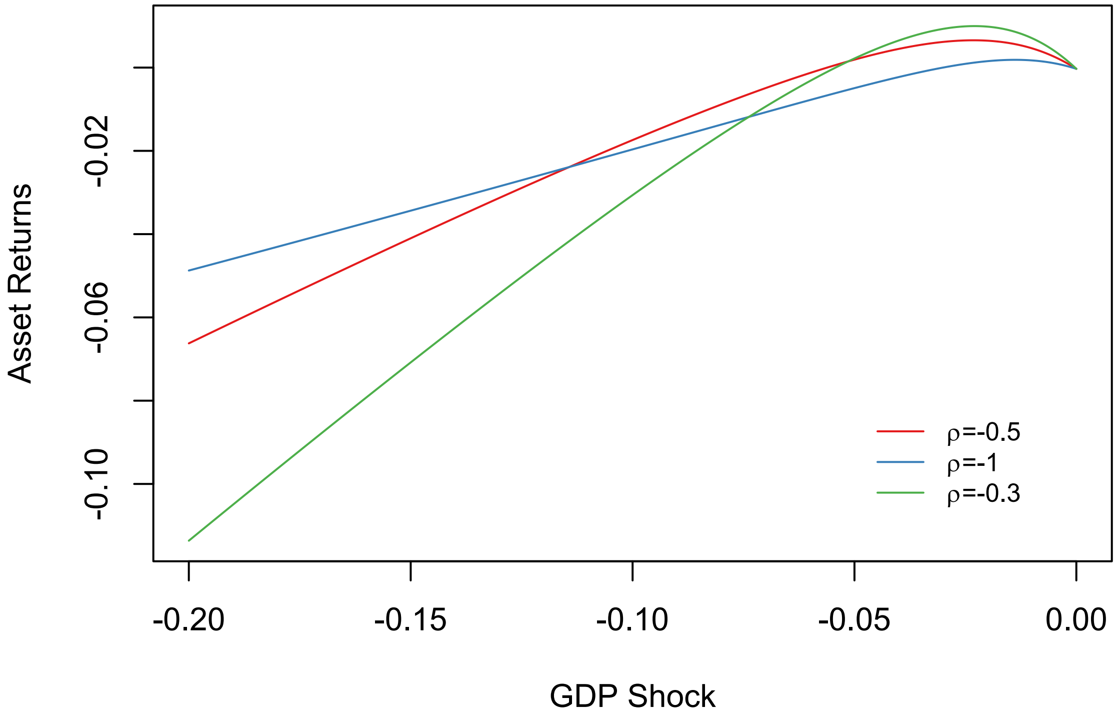
Figure D2: Portfolio Returns for Multi-period Shock (Model 2)



Note: we choose $\rho_y = -0.5$ for the GDP process.

In the next figure we show the results for GDP processes with different speed of mean reversion. The curve for $\rho_y = -0.5$ replicates the results in Figure D2. For $\rho_y = -1$ the shock is less persistence and the GDP would return to the long term path faster. Finally, for $\rho_y = -0.3$ the shock to the GDP is more persistent and it takes longer to normalize. More specifically, the shock is reverted largely by year 8 (from -10% back to -1%; compared to year 4 Figure D2 & year 2 in the main text).

Figure D3: Portfolio Returns for Multi-period Shock (different GDP processes)

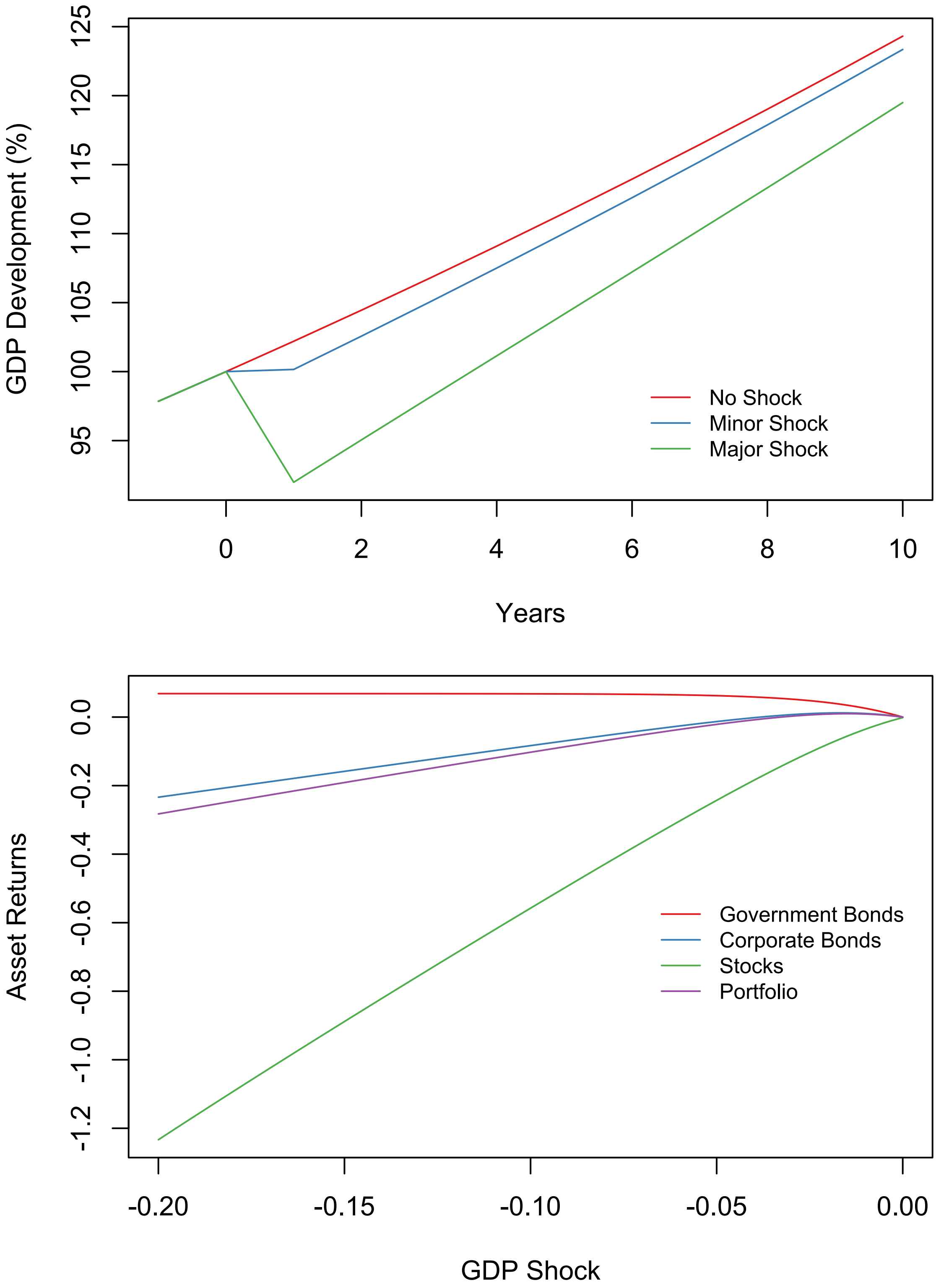


Note: we choose $\rho_y = \{-0.5 - 0.3, -1.0\}$ for the GDP processes.

The analysis shows that the persistency of the GDP shock has a bivalent effect on the insurer's portfolio return. While for larger shocks the portfolio would do worse, it would do better for smaller shocks. The reason is the nonlinearity of the monetary authority's reaction function. The aggressive lowering of interest rates for small shocks would causes asset values to increase. However, for larger shocks the monetary policy runs out of ammunition and the sustained effect on credit spreads, risk premiums, and dividends dominate.

While even more persistent shocks have been observed for example when capital is destructed by wars (see, e.g., Jordà et al., 2020), we think cyber catastrophes are probably not as persistent. Despite that, we report in Figure D4 the outcome for an even more persistent shock $\rho_y = \{-0.1\}$ where it would take decades for the GDP to return to the long-term growth path. In such a scenario the impact on the assets would be larger.

Figure D4: Extreme Persistent Shock



Note: we choose $\rho_y = \{-0.1\}$ for the GDP process.