A Data-Driven Assessment of Financial Market Risks Based on Historical Financial Crises

Master Thesis

Joël Luca Glässer

Chair of Entrepreneurial Risks

Department of Management, Technology, and Economics

ETH Zurich

Supervision

Prof. Dr. Didier Sornette

Dr. Peter Middelkamp

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Contents

Abstract

In this thesis, we develop a financial market risk model based on historical financial crises from the 20. and 21. century. We base this assessment on an extensive historical data set that combines historical data from a multitude of different sources. This thesis aims to develop a financial crisis model that is mostly independent of any single crisis.
To analyze the market risks, we track 12 different risk indicators for each crisis and divide the world into three economic regions. Based on these 12 parameters, we can project losses of any historic crisis on any simplified investment portfolio. Furthermore, we also identify relationships between our parameters and leverage them to build a Monte Carlo simulation. This simulation can build new crises that have not yet occurred but could potentially occur.
Based on these models, we calculate the value at risk (VaR) and expected shortfall (ES) estimation. In the next step, we then start adding and removing specific crises to observe the changes in our VaR and ES estimations.
Generally, we found that three crises are so unique that their features must be represented in our model. These are the Global Financial Crisis, the Dot-Com bubble, and the Black Monday crash. Furthermore, we were able to identify that our model greatly benefits if we at least include data until 1970.

Nomenclature

Symbols

ADP	Average daily performance of equity index
CS	Credit Spread
CSI	Credit spread increase
PtT_E	Peak to trough of equity index
PtT_P	Peak to trough of property index
YTM	Yield to maturity

Acronyms and Abbreviations

AAR	All affected regions of a crisis
CDF	Cumulative Distribution Function
ES	Expected shortfall (Conditional value at risk)
GFD	Global Financial Data
MVM	Market value margin
NAV	Net asset value
RBC	Risk bearing capital
SST	Standard Model Market Risk of the Swiss Solvency Test
S&P 500	Standard & Poor's 500 Stock Index
TC	Target capital
VaR	Value at risk

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Chapter 1

Introduction

In this chapter, we explain the relevance of this thesis, give an introduction to the Swiss Solvency Test (SST), and define market risks. Furthermore, we state the research questions and provide an outline of the structure of the thesis.

1.1 Background

Since 1992, more and more major economies have transitioned their capital requirements for insurance companies to a risk-based approach. In Switzerland, where the insurance industry is one of the largest institutional investors, the Swiss Solvency Test was introduced in 2006 (Eling et al. 2008, Meier et al. 2015).

However, one of the most significant critique points of the SST is that it only includes historical financial data back to May 2005 (FINMA 2019). This limited time frame of the data set leads to a serious dependency on the financial crisis of 2007-08 (Global Financial Crisis). The Global Financial Crisis is by far the largest crisis within the observed time frame of the SST. However, while the Global Financial Crisis has some similarities to previous crises, it also features significant differences such as the widespread use of opaque and complex financial instruments (Claessens et al. 2010). Due to the small sample data, these unique features of the Global Financial Crisis are over-represented in the SST and features of other crises are missing. For this reason, many experts question whether the SST will need to undergo a significant re-calibration as soon as a new crisis will arise which needs to be included in the model.

In our analysis, we investigate the potential of building a robust financial crisis model, which includes a lot of different financial crises. We will use a data-driven approach to quantify losses in various financial crises of the 20. and 21. centuries. In theory, this model should be robust enough so that the outcome of the model stays within a predefined range as specific crises are removed or added. Note, this theses will not explain the economic reasoning behind the data relationships that are found.

1.2 Overview of the SST

The goal of the SST is to ensure the solvency of Swiss insurance companies. For this, the SST defines a target capital (TC) and a risk-bearing capital (RBC). An insurance company will pass the SST if the RBC is at least as large as the TC.

$$TC \leq RBC \tag{1.1}$$

Another way a lot of industry experts state the condition in Equation 1.1 is by saying that $\frac{RBC}{TC} \geq 1$. Furthermore, the SST defines the RBC as:

$$RBC_t = MVM_t + NAV_t \tag{1.2}$$

where:

MVM_t = Market value margin (runoff costs) at time t
NAV_t = Net asset value at time t

Furthermore, when assuming that MVM_{t+1} can be determined, the SST defines:

$$TC_t = MVM_{t+1} - ES_t(\Delta RBC) \tag{1.3}$$

where:

MVM_{t+1} = Market value margin (runoff costs) at time t+1
$ES_t(\Delta RBC)$ = Expected shortfall of the change of the RBC over a one-year risk assessment

By inserting Equation 1.2 and 1.3 into 1.1 we see that an insurance company passes the SST if:

$$MVM_{t+1} - ES_t(\Delta RBC) \leq MVM_t + NAV_t \tag{1.4}$$

where:

MVM_t = Market value margin (runoff costs) at time t
$ES_t(\Delta RBC)$ = Expected shortfall of the change of the RBC over a one-year risk assessment
NAV_t = Net asset value at time t

Under the assumption that MVM remains more or less constant it becomes apparent that changes in the risk-bearing capital (recorded in Equation 1.4 as $ES_t(\Delta RBC)$) have a

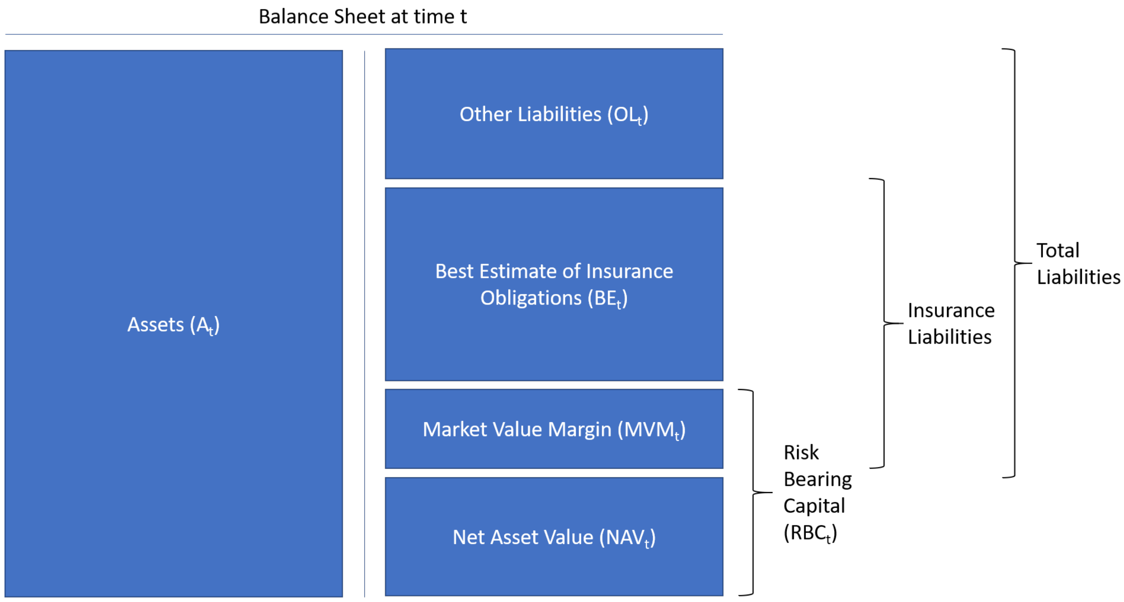

Figure 1.1: This figure presents a simplified balance sheet of an insurance company at time t and is an English translation of Figure 1 from FINMA (2019). Note that MVM is defined in Art. 41 Sec. 3 of the "Verordnung über die Beaufsichtigung von privaten Versicherungsunternehmen." According to Eling et al. (2008), the MVM can be viewed as the runoff costs in case of insolvency.

significant impact on the passing of the SST. While the Swiss Solvency Test has a lot of different models to calculate MVM_t, this thesis will solely focus on market risks and its impact on the risk-bearing capital. The SST measures this with the Standard Model Market Risk. Thus, from now on, when we refer to the SST, we concretely mean the Standard Model Market Risk of the Swiss Solvency Test.

As our focus is on the Standard Model Market Risk, we use the same market risk definition as the SST. Thus, we define the market risk as the risk of change in the value of the risk-bearing capital caused by a change in market risk variables (FINMA 2019). The risk is quantified as expected shortfall (ES), which we define in Section 4.4 of this thesis. To measure the expected shortfall, the SST includes 41 market risk variables. However, due to the limited time-scope of this thesis, we will only look at twelve market risk variables. To be more precise, we differentiate between 3 economic regions (the United States, Europe, and Japan) and track for each region the average daily equity performance, total equity value losses, credit spread increase, and total real estate value losses throughout each financial crisis. These indicators allow us to calculate the expected shortfall of equity, corporate bond, and real estate investments. By limiting ourselves to these indicators, we include three of the four most important market risk indicators (European Insurance and Occupational Pensions Authority 2011). The missing market risk from the list of the four most important ones is the interest rate risk. However, as interest rates on government bonds tend to fall in worsening economic situations (Akhilesh & Gordin 2020), we can ignore this risk in our model that solely focuses on financial crises.

1.3 Research Question

As previously described, the main goal of this thesis is to develop a robust financial crisis model that is independent of a single financial crisis. For this reason, we are especially interested in how the various financial crises impact the result of our model. Furthermore, we try to define a minimum time frame that should be used to achieve a minimal level of robustness in our model. For our analysis, we assess the model stability by tracking the changes in the expected shortfall of equity, corporate bond, and real estate investments. We will use a Monte Carlo simulation to answer the following questions:

1. Can we build a robust financial crisis model that is mainly independent of one financial crisis?
2. What time frame is appropriate to establish a robust model that is mainly independent of any single crisis?
3. How does the addition of the Covid-19 crisis affect our model outcome?

1.4 Thesis Outline

Following this introduction, we use Chapter 2 to describe the economic situation, and monetary policy changes that led to the 15 financial crises considered in our model. Afterwards, in Chapter 3, we describe our data set as well as the parameters we use to track the impact of financial crises. Continuing, in Chapter 4, we introduce our model and the risk indicators. We distinguish between a model that simulates historic crises on a predefined investment portfolio and a Monte Carlo simulation that generates 100'000 simulated financial crises based on our historical observations. In Chapter 5, we present the results from our two models and discuss them. Lastly, in Chapter 6, we conclude the thesis and give an outlook on further research to be conducted.

Chapter 2

Crises Overview

This chapter aims at describing the economic environment of the crises as well as the crises themselves. Even though, our data driven analysis later will not reuse this input to a great extent, it is important that the reader has this information for the completeness of the thesis. Note, at the end of each description we will always define all affected regions (AAR) of each crisis.

2.1 Panic of 1907

The Panic of 1907 originated in New York through a bank run and eventually spread to a nation wide stock market crash (Reinhart & Rogoff 2011*c*). In the run up to the crisis there was an increase in international credit restrictions and the Bank of England raised its interest from 4% to 6%. This caused more funds than expected to remain in London. As a result, New York City had a rather tight cash position in the fall of 1907 and with the run on the Knickerbocker Trust Company the actual panic began (Moen & Tillman 1990).
The Panic of 1907 was the most severe financial crash before the Great Depression and eventually led to the creation of the Federal Reserve (Moen & Tallman 1992).
For our analysis we will look at this event as a regionally isolated event in the US.

2.2 Depression of 1920-21

Shortly after the end of World War I, the United States and other economies entered into a deflationary recession. Economic research suggests that this recession was caused by three factors. Firstly, the unemployment rate increased world wide as troops returned home leading to a wage stagnation (Vernon 1991). Secondly, the commodity prices started to

decrease as the output of Europe returned to pre-war heights (Vernon 1991). Thirdly, in a fight to combat post-war inflation, the Federal Reserve Bank of New York began raising interest rates from 4.75% to 7%, a high that was only topped in the 1970s and 1980s (Friedman et al. 1971*a*).
For this thesis, the depression of 1920-21 will be regarded as an intercontinental crisis in the US and Japan. We exclude Europe as several European countries, especially Germany, were suffering from hyperinflation at the time (McIndoe-Calder et al. 2019). The hyperinflation in Germany is an exclusion factor as we use non inflation adjusted indexes. The reason for not using inflation adjusted indices will be further explained in Chapter 3.

2.3 Recession of 1923-24

The years from 1921 to 1929 were generally speaking years of relative steady growth. Nevertheless, these six years were interrupted by two recessions, both of which were rather mild and short (Friedman et al. 1971*b*). In our analysis we will only include the recession from May 1923 to July 1924 as it caused a greater reduction in economic activity (Moore 1958). The onset of the 1923-24 recession was followed by an increased sale of government securities and a rise in discount rates by the Federal Reserve in early 1923 (Friedman et al. 1971*b*).
In this thesis we will regard this recession as a regional recession in the United States. This is mainly due to the mildness of the recession and the fact that several European countries, especially Germany, were suffering from hyperinflation at the time (McIndoe-Calder et al. 2019). Furthermore, our historic data suggests that Japan was unaffected by the crisis.

2.4 Great Depression (1929-1933)

The Great Depression was the most severe global financial crises in the 20. and 21. century so far (Reinhart & Rogoff 2011*c*). The Great Depression marks the end of the roaring twenties. During these years, extensive money supply and margin trading led to the creation of a stock market bubble (Rappoport & White 1993). While the actual cause for the burst of the bubble in October 1929 is still debated, it is clear that the New York stock market already started to fall in the beginning of September 1929. This was after the US monetary policy began to tighten significantly in 1928 and the Federal Reserve Bank of New York further increased the interest rate from 5% to 6% in August 1929 (Hamilton 1987). However, it is important to note that this could not have been the only factor for the heavy downturn in 1929 (Hamilton 1987).
As the crisis spread across international boarders, interest rates dropped until the summer

of 1930. However, it was only after the first banking crisis at the end of 1930 that the monetary policies stated to take more severe measures to counter the crisis (Hamilton 1987).
The Great Depression is a global financial crisis (Reinhart & Rogoff 2011*b*) by which all of our 3 regions were affected.

2.5 Recession of 1937

Just as the United States started to recover from the Great Depression a new recession hit in 1937. Glasner (1997) determined three causes for the recession. First, more restrictive fiscal policies started the recession. To be more concrete, this refers to the fact that World War 1 veterans lost their bonus payment and the fact that social security taxes for employers rose by 2 percentage points to 3% in 1937. Second, the monetary policies were tightened. More concrete, the FED doubled the reserve requirements for banks between July 1936 and May 1937. Third, profits of companies were declining as labor and commodity prices rose sharply and were not accompanied by productivity or price increases. This then led to a decrease in capital investments by businesses. However, there is no consensus on which of theses three factors was the main cause of the crisis.
As no similar recessions occurred anywhere in the world (Glasner 1997), we will also treat this recession as a local recession in the United States.

2.6 Stock Market Crash of 1973-74

In the 1970s a period of relative calm and blooming growth came to an end (Reinhart & Rogoff 2011*c*).
The beginning of the 1970s was characterized by extremely rapid output growth causing share prices to increase. However, after the oil price rapidly increased by the end of 1973, a sharp recession started to unfold (Davis 2003). Of course, the oil price is not the only contributing factor to the recession but is considered to be a major contributor (Alpanda & Peralta-Alva 2010). The termination of the Bretton Woods system and high levels of inflation across the world caused further stress on the financial sector (Reinhart & Rogoff 2011*c*, Davis 2003).
The affects of this stock market crash were felt worldwide. For this reason we will treat it as a global recession.

2.7 Early 1980s Recession

The early 1980s recession resulted mainly from tightened monetary polices that aimed at fighting high inflation levels and the collaps of global commodity prices (Reinhart & Rogoff 2011*c*, Sablik 2013).
The high inflation was a result of the monetary policy in the 70s when economists believed in the Phillips Curve, which states that higher inflation lowers unemployment. As Paul Volcker took the office as Chairmen of the Fed this regime started to change. His Fed policies started to target the money supply rather than previously the interest rates. However, the tightening of money supply initially caused interest rates to increase and in the third quarter of 1981 the US entered into a recession. Even though Paul Volcker was faced with pressure from Congress, he persistently followed his policies. In October 1982 it finally paid off. Inflation had fallen and interest rates began to decline (Sablik 2013).
The early 1980s recession mainly affected the US, however there was also a minor impact on the Japanese economy. For this reason, we limit the crises to these two economic regions.

2.8 Black Monday (1987)

Most of our financial crises coincided with other economic crises. However, the Black Monday crash of 1987 is a pure stock market crash that is mainly unrelated to any other crisis period (Reinhart & Rogoff 2011*c*).
After the early 1980s recession, the 1980s were marked by an increase in international investors and the emergence of new investment products called "portfolio insurance" (Bernhardt & Eckblad 2013). All together it led to a steady market growth until August 1987, when the Dow Jones and other indexes peaked.
After some small and steady declines from the peak, the markets across the world faced a severe and sudden crash on October 19, 1987 (Roll 1988). With a loss of 20.47 % it is still the biggest one day percentage loss of the S&P 500 index until today (S&P Dow Jones Indices LLC. 2020). Today it is thought that computer programs at the heart of portfolio insurances accelerated the crash. The reason being that programs began to liquidate stocks as loss thresholds were exceeded. However, due to this selling prices fell further, leading to more stop-loss selling (Segal 2020). After the Black Monday crash, circuit-breakers were introduced to prevent panic selling (Greenwald & Stein 1988).
As Roll (1988) show, all of our economic regions have been impacted by the Black Monday crash. Thus, we view it as a global crisis.

2.9 Japanese Asset Price Bubble (1990-92)

The Plaza Accord of 1985 led to a 50% appreciation of the yen compared to the USD and triggered an endaka recession in Japan. In efforts to prevent any further appreciation of the yen, the Japanese government used an aggressive monetary easing strategy. In January 1986, the Bank of Japan (BOJ) started to lower the discount rates. Within 14 months the discount rates fell from 5% to 2.5% (Okina et al. 2001). As the counter measures started to work and asset prices increased, the BOJ considered to raise interest rates again in the summer of 1987. However, due to Black Monday, plans to increase interest rates were suspended. It was not until 1989 when the BOJ finally started increasing interest rates again. However, by that time Japanese stocks and urban land values had already tripled their 1985 values. In 1990 the bubble reached its peak and stock prices began to fall. The burst of the Japanese Asset Bubble thereby initiated the Lost Decade in Japan (Okina et al. 2001).
This crisis is specific to Japan and is thus treated as a regional crisis in our thesis.

2.10 Early 1990s Recession

The world entered into a recession in the beginning of the 1990s. The recession unfolded after the Federal Reserve began rising interest rates from 1986 to 1989. The aim of these restrictive monetary policies was to reduce inflation to zero. It was generally believed at the time that zero inflation would lead to higher real economic growth. While these monetary changes did slow the economy, they did not stop growth. However, the combination of these monetary policies, the 1990 increase in oil prices, the high levels of debt accumulations originating in 1980s and increased consumer pessimism due to the Gulf Crisis, led to the creation of a recession (Walsh 1993).
The impact of the early 1990s recession was felt in the whole Western world and thus we also treat it as a global crisis in this thesis.

2.11 Asian Financial Crisis of 1997

In 1995 the governments of the US, Germany and Japan agreed to a reversal of the Plaza Accord and coordinated an appreciation of the USD compared to the German Mark and the Japanese yen. This appreciation caused also an appreciation of all currencies pegged to the USD. Especially for East Asian countries, this appreciation caused a major issue, as their exports became more expensive when compared to Japanese and German exports. As exports plummeted and corporate profits declined, the pressure on the East Asian

governments increased. In July 1997, the Thai government decided to get rid of the peg to the USD and soon other East Asian countries followed. With this policy change, the currencies of most East Asian countries devalued. However, not only the currencies were devalued but also stocks and other assets lost up to 60% of their value (Chappelow & Scott 2020, Yamazawa 1998).
Note, we view the Asian Financial crisis as a regional crisis represented by the economic region of Japan.

2.12 Market Correction of 1998

This crisis is probably the least known crisis we include in this thesis. It represents a short and small crash in 1998. Today it is sometimes also viewed as a market correction (CNN 1998). This correction occurred in the US and Europe when the markets faced falling oil prices, a debt crisis in Russia, rapid currency deterioration in emerging markets and a financial crisis in Asia (Kolakowski 2019).
Note, while the Asian financial markets were also suffering at the same time, we do not include them in this market correction of 1998. This enables us to strictly separate between the ongoing Asian financial crisis and this emerging market correction in Europe and the US.

2.13 Dot-Com Bubble (2000-02)

The development of graphical user interfaces, the easier information exchange via CDs and the internet greatly increased the usability of personal computers. As this trend emerged, the number of US households owning a computer grew from 15% in 1990 to 35% in 1997 (Bureau of Labor Statistics 1999). Subsequently this shifted the economy into the Information Age and expectations on how technology will shape the future increased.
Additionally, in 1997 the interest rates were lowered and the Taxpayer Relief Act of 1997 was passed. The Taxpayer Relief Act lowered the tax on capital gains and thereby incentivized more speculative investments (Kasich 1997). Furthermore, Alan Greenspan allegedly put a positive spin on stock valuations and thereby further fueled the stock market (Teeter & Sandberg 2017). As a result of this, many investors were eager to invest into technology companies.
The bubble started to burst in the first quarter of 2000 as the Federal Reserve announced that it would increase interest rates (Goldman 2000) and Japan entered into a new recession (CNN 2000).

Due to the global nature of the stock selling in March 2020 (CNN 2000), this thesis looks at the Dot-Com bubble as a global crisis.

2.14 Global Financial Crisis (2007-09)

The Global Financial Crisis is generally considered to be the largest economic downturn since the Great Depression. The crisis itself originated from the bursting of the bubble in the US housing prices. When house owners were then unable to pay their mortgages, mortgage-backed securities began to loose their value. This then caused the crisis to spread into the financial sector causing an international banking crisis (Bernanke 2010). The crisis caused a multitude of financial firms to collapse, including Lehman Brothers.
Furthermore, as already stated in the introduction, the Global Financial Crisis was characterized by the widespread use of opaque and complex financial instruments (Claessens et al. 2010).
It is well known that this was a a global crisis that affected all economic regions. Thus we also treat it as such in our model.

2.15 European Sovereign Debt Crisis (2009-12)

The European sovereign debt crisis is a crisis that has affected the European Union between 2009 and 2012. The crisis started to unfold in October 2009 after Greece revealed that the size of its fiscal deficit was estimated at 12.7%, much larger than previously claimed. As a result, Fitch, Moody's and Standard & Poor's downgraded the sovereign debt rating of Greece. When the interest rate on sovereign debt reached 8.7% in April 2010, it became clear that Greece needed a bail-out by the EU and IMF (Petrakis et al. 2013).
After the crisis originated in Greece it subsequently spread to other European countries, such as Ireland and Portugal. Furthermore, the crisis also raised concerns about the sovereign debt status of Italy and Spain (Nelson et al. 2012).
Even though the crisis hit many European countries, other regions such as Asia or the US were less affected. Thus, this thesis views the European Sovereign debt crisis as a European crisis and does not assess its impact on Japan or the US.

2.16 Summary

As we can see from this chapter, financial crises can originate from a multitude of different economic factors. However, while most of the time a single event causes the unfolding of a crisis, it is usually not the sole cause of a crisis. Often, a number of various economic factors change in the run-up of a crisis and the event actually causing the crisis to unfold is simply the last stroke.

In our model we will include a variety of different crises. These will include economic recessions, stock market crashes and sovereign debt crises. In this thesis we will not differentiate by different types of crises, as we solely try to quantify the market risk and this risk is subject to any of this crises or combinations thereof. For this reason we will not alter our economic indicators for different types of crises, as the reader will see in the next chapter.

The only differentiation we are making in our crisis model, is by the affected geographic regions. Table 2.1, presents a brief overview of which crises affected which economic region. This will become especially important in our historic crisis model.

Table 2.1: This table breaks down which economic region was affected by which crisis. An x marks that the region was affected while a blank space means we consider the region to be unaffected.

Crisis	**United States**	**Europe**	**Japan**
European Sovereign Debt Crisis (2009-12)		x	
Global Financial Crisis (2007-09)	x	x	x
Dot-Com Bubble (2000-02)	x	x	x
Market Correction of 1998	x	x	
Asian Financial Crisis of 1997			x
Early 1990s Recession	x	x	x
Japanese Asset Price Bubble (1990-92)			x
Black Monday (1987)	x	x	x
Early 1980s Recession	x	x	x
Stock Market Crash of 1973-74	x	x	x
Recession of 1937	x		
Great Depression (1929-1933)	x	x	x
Recession of 1923-24	x		
Depression of 1920-21	x		x
Panic of 1907	x		

Chapter 3

Data Set Description & Crises Parameters

This chapter aims at providing the reader with an in depth understanding of the data set we used and the crises parameters we derived from it.

3.1 Data Set

A large part of conducting this research included the gathering of a large data set on historical financial crises. Similarly to the SST standard model for market risk, this thesis maps different geographical regions to the closest economic area. Meaning:

- North and South America are mapped on to the US financial market
- East Asia and Oceania are mapped on to Japan's financial market
- Europe, the Middle East, Africa and CIS countries are mapped on to the European financial market

The only difference of this mapping to the mapping of the SST is that we do not regard Switzerland and Great Britain as independent economic areas. The reason being the extensive research already required to develop a long and historical time-series for the three mentioned economic areas.

Additionally, the reader should note that this thesis uses non-inflation adjusted indices. The reason for this is that the SST aims at ensuring that an insurance provider can cover all his contractual obligations for the next year. However, these obligations are usually bound to fixed limits, which will not be inflation-adjusted throughout a fiscal year. For this reason, we can neglect any inflation adjustments.

Lastly, the reader should note that we focus our analysis on three different asset classes, equities, bonds and real estates. The following section describes the data-sets for each asset class in more detail.

3.1.1 Equity Data

For the modelling of equity risk we will use the main stock market index of each economic area. Generally note that we do not differentiate between total return and price indices. The reason for this is that our crises usually cause sudden and large losses, where the differences between total returns and price indices become neglectable.

For the US, we track the losses of each crisis after 1928 with the S&P 500 index. Due to the unavailability of the S&P 500 before 1928, we use the Dow Jones Industrial Average for all crises prior to the Great Depression.

For Europe, we use the Euro Stoxx 50 index back until 1987. However, for all the crises before 1987 we are unable to find an European stock index. To compensate for this issue, we use the German DAX index as a representation of all European countries before 1987. Germany is one of the largest economies in Europe and thus it makes sense to track Germany's performance.

For Japan, we use the Nikkei data from 1914 until 2020 to track the equity performance during financial crises.

Note, for more details Table A.1 in Appendix A presents a detailed listing of all the used stock indices, their frequencies and their sources.

3.1.2 Credit Spread Data

Another market risk factor a lot of insurances are exposed to, is the credit spread risk of bonds. Note, in this thesis we define the credit spread as the difference in yield to maturity between a corporate bond and a risk-free government bond.

$$CS = YTM_{\text{corporate bond}} - YTM_{\text{government bond}} \tag{3.1}$$

where:

CS = Credit Spread
YTM = Yield to Maturity

For modeling the credit spread, we will use two indices per economic area. The first index will track the yield to maturity of corporate bonds and the second index will track the yield to maturity for (risk-free) government bonds. In Tables A.2 and A.3 of Appendix A a detailed list of the used bond indices can be found for each economic area.

When looking at Tables A.2 and A.3, we need to point out two special cases. First, the US Government bond yields are missing for the years between 1944 and 1960. However, for this thesis, this will not pose a problem as we did not observe an US financial crisis within these years. Reinhart & Rogoff (2011*c*) explain this world wide calm period with a combination of booming growth, repression of domestic financial markets and heavy use of capital controls (note, neither this thesis nor Reinhart & Rogoff (2011*c*) are implying these controls to be the right approach to dealing with financial market risks). Secondly, for US Corporate Bonds, we did not find a bond yield index covering bonds of different credit ratings before 1994. However, as an increasing number of bonds change their ratings during a financial crisis (Benmelech & Dlugosz 2010), it is important to track the spread changes on an overall average rather than on a credit rating basis. To compensate for the missing overall average, we followed the spread changes for AAA as well as BAA rate bonds from 1919 to 1994 and average the two credit spread increases for each crisis. We know that this still does not include all credit ratings. However, it still gives some degree of cross rating overview and is the broadest available overview that could have been established, especially for the years before World War II.

3.1.3 Property Data

To track the property risk exposure of real estate investments, this thesis tracks one price index for each region. This means we track the actual real estate price fluctuations during a crisis rather than the industry performance. This is important as an insurance also reports the asset value and not the revenue potential on their balance sheet.

To track the price fluctuations, the FRED St. Louis publishes property real estate price indices. For the European Area, this index is available since 1975. For Japan it is available since 1955 and for the US it is available since 1970. However, to track the US real estate price developments before 1970 we were able to leverage the Case Shiller Price Index back until 1890.

Note, for more details Table A.4 in Appendix A presents a detailed listing of all the used real estate indices, their frequencies and their sources.

3.1.4 Investment Portfolio

This thesis will use Swiss Re's investment portfolio as an example. Note, our investment portfolio is a heavily simplified version of Swiss Re's investment portfolio. Due to the public nature of this thesis we only use publicly available data from Swiss Re Ltd. (2020).

A more detailed breakdown of the investment portfolio would be possible with internal data. In Table 3.1 the portfolio details are listed.

Table 3.1: Swiss Re's investment in Mio USD broken down to 3 economic areas (Swiss Re Ltd. 2020).

Economic Area	**Government Bonds**	**Corporate Bonds**	**Equity**	**Real Estate**
United States	28763	23268	3209	1537
Europe	20303	16425	2265	2977
Japan	7332	5931	818	288

To arrive at such a granular investment portfolio, we make the following assumptions:

- Regional split of government bonds also holds for corporate bonds and equity
- The maturity of all bonds is equal to 10 years
- Rest of the World, other countries and indirect real estate investments are split equally to all three economic regions

Note, as Swiss Re Ltd. (2020) specifies the credit spread sensitives of the portfolio, we can use Equation 4.4 to verify our maturity assumption for the bond maturity. By solving Equation 4.4 for t and plugging in the three specified credit spread sensitives we conclude that the average bond maturity must lie between 9 and 10 years. Therefore, making our assumption of an average bond maturity of 10 years realistic.

3.2 Crisis Parameters

In Chapter 2 we have seen how different financial crises can be and how they emerge from different sources. Even though the sources of the crises are extremely different, this thesis is only interested in the expected losses of each crisis. Thus, we will not vary our risk indicators for different types of crises but rather stick with the same indicators for all crises.

3.2.1 Equity Losses

The equity risk is the risk of sudden losses in the value of equities and alternative investments (Höring 2013). To quantify this risk, this thesis will preliminary use the average daily performance (ADP) of the stock market. We define ADP as:

$$ADP = \frac{1}{N} \sum_{n} \frac{I_n^c - I_{n-1}^c}{I_{n-1}^c} \tag{3.2}$$

where:

ADP = Average daily performance
I_n^c = Index closing value on day n
n = A trading day of the crises
N = Number of trading days between observation start and end

However, as seen from Table A.1 in Appendix A for Europe and Japan we miss daily recordings of the stock indices in the early part of the 20. century. To compensate for this issue, we assume a constant exponential growth between the two recordings. This is a typical long-term assumption in finance and coincides with Gibrat's law of proportional growth (Gibrat 1931).

Additionally, to tracking ADP, this thesis also follows the peak to trough value for each crisis.

$$PtT_E = \frac{I_{\text{Peak}} - I_{\text{Trough}}}{I_{\text{Peak}}} \tag{3.3}$$

where:

PtT_E = Peak to trough value of equity indices
I_{Peak} = Peak value of the index
I_{Trough} = Trough value of the index

As previously described, for some historical months we only have monthly equity data. For the peak to trough value drop, we simply assume that the actual peak to trough value was close to the lowest recorded data point of this crisis. However, it is essential to note that this is only an approximation and the real peak to trough value might be somewhat larger than what we find.

Considered Time-frame

To calculate the average daily performance and peak to trough value of each crisis, we need to define the time frame we consider. Generally we define the market peak and market trough as the start and end data of all crises. However, there are some special cases where no clear peak or trough is agreed upon and there we just defined in each individual situation which one we choose. Furthermore, not all crisis occur in all economic areas at exactly the same time, for this reason we define a lead indicator to define the time frames we consider. As the United States stock market has the largest market capitalization of all considered geographic regions, we use it as the lead indicator. However, there are three crisis where the US was not part of the AAR but all of them only affected a single region. This makes it easy for us and we can just alternate the lead indicator for these three crises to the actually affected region. In Table 3.2 you can find the defined crises time frames in more detail.

Table 3.2: A detailed list of all the start and end dates we consider for the equity market of each crisis.

Crisis	Start	End
European Sovereign Debt Crisis (2009-12)	2009-12-01	2012-07-04
Global Financial Crisis (2007-09)	2007-10-09	2009-03-09
Dot-Com Bubble (2000-02)	2000-03-24	2002-10-09
Market Correction of 1998	1998-07-17	1998-08-31
Asian Financial Crisis of 1997	1997-06-16	1998-10-09
Early 1990s Recession	1990-07-16	1991-01-09
Japanese Asset Price Bubble (1990-92)	1989-12-29	1992-08-18
Black Monday (1987)	1987-10-05	1987-12-04
Early 1980s Recession	1980-11-28	1982-08-12
Stock Market Crash of 1973-74	1973-01-11	1974-10-03
Recession of 1937	1937-03-10	1938-03-31
Great Depression (1929-1933)	1929-09-16	1932-07-08
Recession of 1923-24	1923-03-20	1924-05-20
Depression of 1920-21	1919-11-03	1921-08-24
Panic of 1907	1907-07-06	1907-11-22

3.2.2 Bond Losses

When looking at losses from bonds, the focus lies on sudden losses in the value of bonds due to a widening of the credit spread. Höring (2013) defines this as the credit spread risk.

The reason we focus solely on credit spread risk is that if the economic conditions worsen, investors will flee to safer government bonds and sell risky corporate bonds. This will cause government bond to face rising prices and falling yields, while corporate bonds face falling prices and rising yields (Akhilesh & Gordin 2020). However, as we make the basic assumption that profit expectations do not protect against losses, we will solely focus on the falling prices of corporate bonds and will assume the government bond prices to remain constant throughout a crises, even though they are likely to rise.

$$CSI = \max_{S<t\leq E}(CS_{\mathrm{t}} - CS_S) \tag{3.4}$$

where:

CSI = Credit Spread Increase
CS_t = $YTM_{\text{corporate bond, }t} - YTM_{\text{government bond, }t}$
YTM = Yield to Maturity
S = Start of credit spread crisis
E = End of credit spread crisis

Considered Time-frame

The crisis in the bond market will not occur at exactly the same time as in the equity market. Thus the question remains at what point in time our observation starts and ends. The easiest way to do this would be by relating the observation time frame to the equity market, where we already defined our observation time.

To test by how much the credit spreads lead or lag the equity market, we used a Granger causality test. To be more precise we test whether the time series Y_t Granger-causes the time series X_t with a lag T. For this we start of by estimating the univariate autoregression.

$$X_t = \sum_{i=1}^{T} a_j X_{t-i} + \epsilon_t \tag{3.5}$$

where:

X_t = Time series Value of X at time t
ϵ_t = Uncorrelated white-noise at time t
T = Maximum lag-time

In the next step, we then estimate the augmented model:

$$X_t = \sum_{i=1}^{T} b_j X_{t-i} + \sum_{i=1}^{T} c_j Y_{t-i} + \nu_t \tag{3.6}$$

where:

X_t = Time series Value of X at time t
Y_t = Time series Value of Y at time t
ν_t = Uncorrelated white-noise at time t
T = Maximum lag-time

With the help of an F-Test we are then able to test if the lagged variables collectively benefit to the model accuracy. Our null hypothesis is that "Y_t does not Granger cause X_t". It is rejected if the group of coefficients $\{c_1, c_2, c_3, ..., c_n\}$ are statistically different from zero.
In Tables A.5, A.6 and A.7 of Appendix A the Granger causality test results for all our three economic regions can be found. We are unable to show a consistent lead-lag structure of credit spreads over stock markets.
One potential explanation why we are unable to find a lead or lag of the credit spread over equity is the regime shift that Leiss et al. (2015) found. This regime shift causes the previously leading indicator of treasury bond yields to become a lagging one at the end of the financial crisis. Of course credit spreads and government bond yields are not exactly the same, however they are related (see Equation 3.1) and the question arises whether a similar shift might be occurring for credit spreads. However, to proof or disproof this theory, more research is needed.

For the case of defining our start and end of our credit spread observation we went back to a visual assessment of the time-difference between the equity trough and credit spread peak. Our visual assessment showed that the peak of the credit spreads sometimes occurs before the trough of the equity market in the origin country, however most of the time it lags a little behind. However, the lag is never greater than six months. Additionally, we noticed that we can assume the same start date for the credit spread crises as the trough is mostly reached simultaneously with the peak of the equity market. To summarize this means we add an additional 6 months to observation ends defined in Table 3.2 to ensure observing the credit spread peak.

3.2.3 Real Estate Losses

The real estate risk is the risk of sudden losses in the value of properties (Höring 2013). To quantify this risk for each crises we measure the peak to trough values of the real estate market.

$$PtT_P = \max_{S<t\leq E} \frac{P_{\mathrm{t}} - P_S}{P_S} \tag{3.7}$$

where:

PtT_P = Peak to trough value of the property prices
P_t = Property price index value at time t
S = Start of credit spread crisis
E = End of credit spread crisis

Considered Time-frame

Similar to the timeframe we defined for the credit spread increase, we also need to define the observation timeframe of the real estate market. Bordo & Jeanne (2002) found that (banking) crises tend to occur at the peak or shortly after the peak in real estate prices. Thus, we can make the reasonable assumption that the start of the real estate price deterioration coincides with the start of the stock market downturn. However, the downturn of the real estate market usually takes between four and six years (Reinhart & Rogoff 2011*a*). To compensate that, we extend the search for the trough value to six years after the start of the crises.

3.2.4 Summary

We applied this logic for all our crises within our analysis. The results from these calculations are summarized in Table 3.3. Generally we note that even for our extensive data set we were unable to generate a complete set of our crisis parameters for all crises. The lack of data becomes especially apparent for crises before 1940.

Table 3.3: This table summarizes all derived crisis parameters from the data set. Please note that blank spaces mean that the region was unaffected while N/A means that the value is missing because of a lack of historical data. To fit this table on 1 page, all the crisis names have been abbreviated: ESD = European Sovereign Debt Crisis, GFC = Global Financial Crisis (2007-09), DCB = Dot-Com Bubble, MC = Market Correction of 1998, AFC = Asian Financial Crisis (1997), R90 = Early 1990s Recession, JAB = Japanese Asset Price Bubble Burst (1990-92), BM = Black Monday (1987), R80 = Early 1980s Recession, SMC = Stock Market Crash (1973-74), R37 = Recession of 1937, GD = Great Depression (1929-33), R23 = Recession of 1923-24, D20 = Depression of 1920-21, Po07 = Panic of 1907

Crisis	**Equity Crisis Duration [working days]**	**Credit Spread Increase [BPS]**			**Equity Average Daily Performance**			**Equity Peak to Trough**			**Real Estate Peak to Trough**		
		United States	**Europe**	**Japan**	**United States**	**Europe**	**Japan**	**United States**	**Europe**	**Japan**	**United States**	**Europe**	**Japan**
ESD	676		3			-6.8E-05			-25%			-10%	
GFC	369	314	234	92	-2.0E-03	-2.3E-03	-2.1E-03	-57%	-61%	-59%	-28%	-15%	-6%
DCB	663	81	164	20	-8.9E-04	-1.2E-03	-1.2E-03	-49%	-59%	-57%	0%	0%	-30%
MC	31	69	25		-6.5E-03	-6.0E-03		-19%	-19%		1%	0%	
AFC	344			58			-1.3E-03			-38%			-28%
R90	127	46	27	34	-1.3E-03	-2.2E-03	-2.7E-03	-20%	-27%	-39%	-10%	-1%	-12%
JAB	687			75			-1.4E-03			-63%			-8%
BM	44	23	45	100	-7.7E-03	-8.2E-03	-2.5E-03	-32%	-34%	-19%	-6%	1%	1%
R80	444	126	56	66	-6.9E-04	1.4E-04	-7.7E-05	-27%	-1%	-3%	-7%	-18%	1%
SMC	450	136	83	110	-1.4E-03	-4.5E-04	-6.0E-04	-48%	-19%	-28%	-5%	N/A	7%
R37	276	92			-2.7E-03			-54%			-6%		
GD	734	267	N/A	N/A	-2.4E-03	-1.1E-03	-3.1E-04	-86%	-56%	-33%	-25%	N/A	N/A
R23	305	28			-5.6E-04			-18%			-4%		
D20	472	48		N/A	-1.3E-03		-1.3E-03	-47%		-53%	1%		N/A
Po07	99	N/A			-4.3E-03			-35%			-8%		

Chapter 4

Methodology

As seen in Chapter 3 we were not able to achieve a complete data-set for every crises. Especially for crises before 1940, the data scarcity becomes apparent. For this reason, we build two models around the data we do have. The first model is the historic crises model. All this model does, is it generates a complete set of crisis parameter for every crisis. Secondly, we define a Monte Carlo simulation, where new crisis parameters are simulated based on our historical observations. Furthermore, we then define a methodology to convert our crisis parameters into actual financial losses and describe how we measure our model stability. Note, we always model and quantify the losses, VaR, and ES within one fiscal year. Some crises last for more than one year. However, due to the annual nature of the SST assessment we only have to model the first year.

4.1 Historic Crises Model

To quantify the impact of any historic crisis on any given portfolio in 2020, we will only need a complete set of all our parameters for all affected regions. As can be seen from Table 3.3, even our extensive data set is missing some critical data values.
To compensate for this issue, we decided to use a regression model to find a statistically significant regression relationship between our variables. With this regression model, we can complete our missing data points.

However, to start with our regression, we have to identify the parameters, which are available for all crises. These parameters are the equity crisis duration, the average daily performance, and the peak to trough value of the equity market. We can determine a statistically significant relationship between credit spread increases and peak to trough values of the equity market (see Figure 4.1). We will use this relationship to complete our credit spread data.

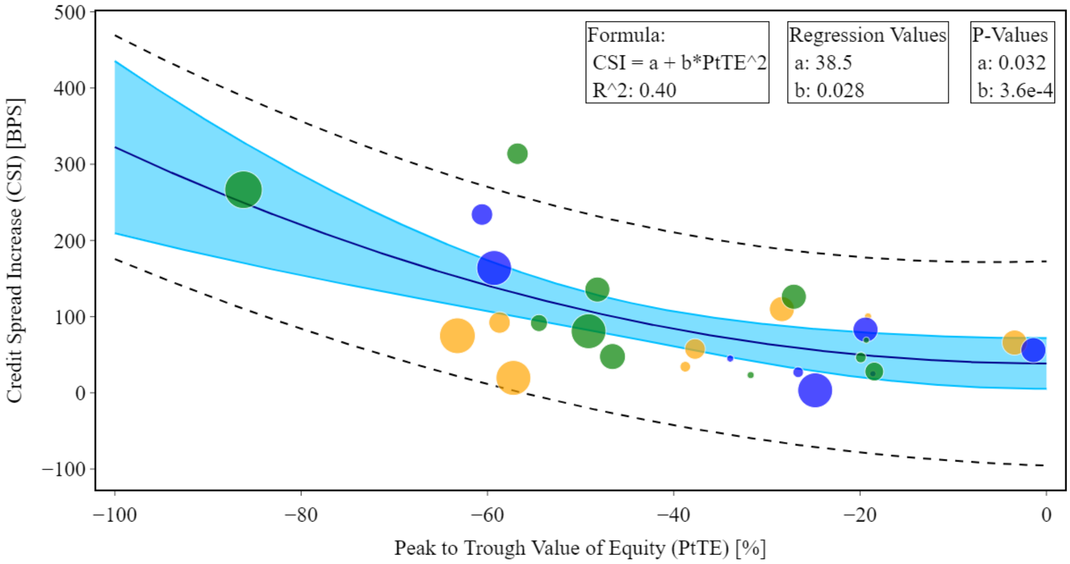

Figure 4.1: This figure presents the regression between the equity peak to trough value and the credit spread increase of various crises. The diameter of the data points is proportional to the duration of the equity crisis and colored according to their economic region (US - green, Europe - blue, Japan - yellow). The blue line represents the regression line, the light blue area the 95% confidence interval, and the area between the two dashed lines the 95% prediction interval.

After completing our CSI index for all crises, we only need to find a way to quantify the peak to trough values of the real estate market (PtTP). Also here we can find a statistically significant regression relationship between CSI and PtTP (see Figure 4.2). Similar to before, we leverage this regression relationship to complete our data set.

Upon having a complete data set for all crises, we leverage the relationships described in Chapter 4.3 to quantify the losses on any predefined portfolio. With this, we can quantify the impact of any crisis on the portfolio of Swiss Re today.
Note, when modeling a historic crisis in 2020, we stick with the original affected region. Meaning when we model the Asian Financial Crisis onto a portfolio in 2020, our model will only simulate losses in Japan. The reason for this is that we defined Japan to be the only affected region (see Table 2.1).

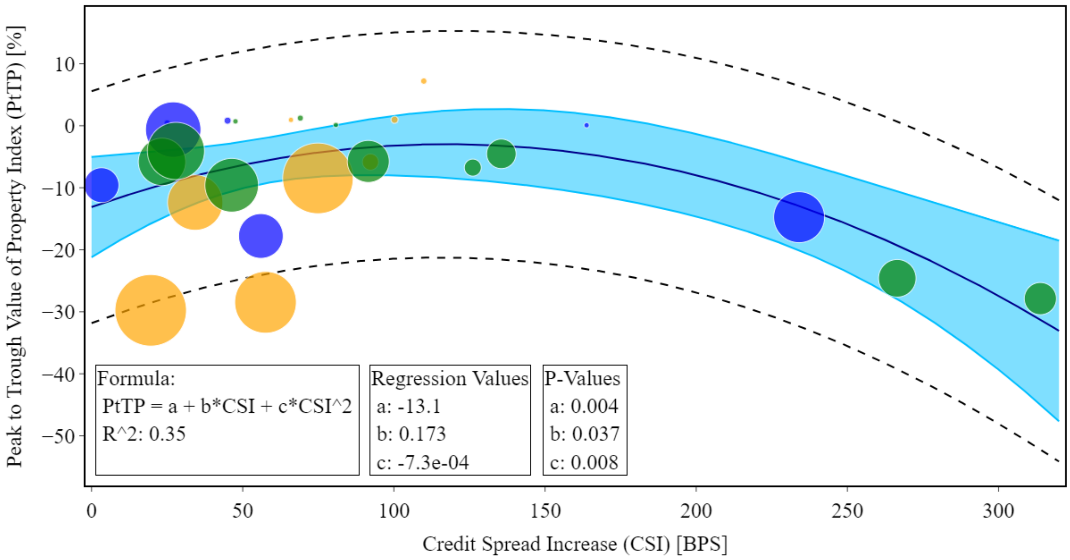

Figure 4.2: This figure presents the quadratic regression between the credit spread increase during a crisis and the peak to trough values in the six years following the crisis. The diameter of the data points is proportional to the time it takes until the trough value of the property index is reached. Additionally, the data points are colored according to their economic regions (US - green, Europe - blue, Japan - yellow). The blue line represents the regression line, the light blue area the 95% confidence interval, and the area between the two dashed lines the 95% prediction interval. Note that there are several crises where the property prices stayed steady and remained almost unaffected by the crises. These are usually referred to as pure stock market crashes and include Black Monday in 1987 and the bursting of the Dot-Com bubble in 2001 (Reinhart & Rogoff 2011*a*).

4.2 Monte Carlo Simulation

After showcasing how we complete our data set to quantify the impact of any crisis on a predefined portfolio, we would also like to build a model that simulates crises that have not previously occurred. For this, we can surely leverage the relationships we determined for our historic crisis model. However, we currently have no methodology to determine ADP or the peak to trough losses of the equity market. Through further assessments, we are able to identify a statistically significant relationship between the equity crisis duration and the average daily performance throughout the crisis (see Figure 4.3).

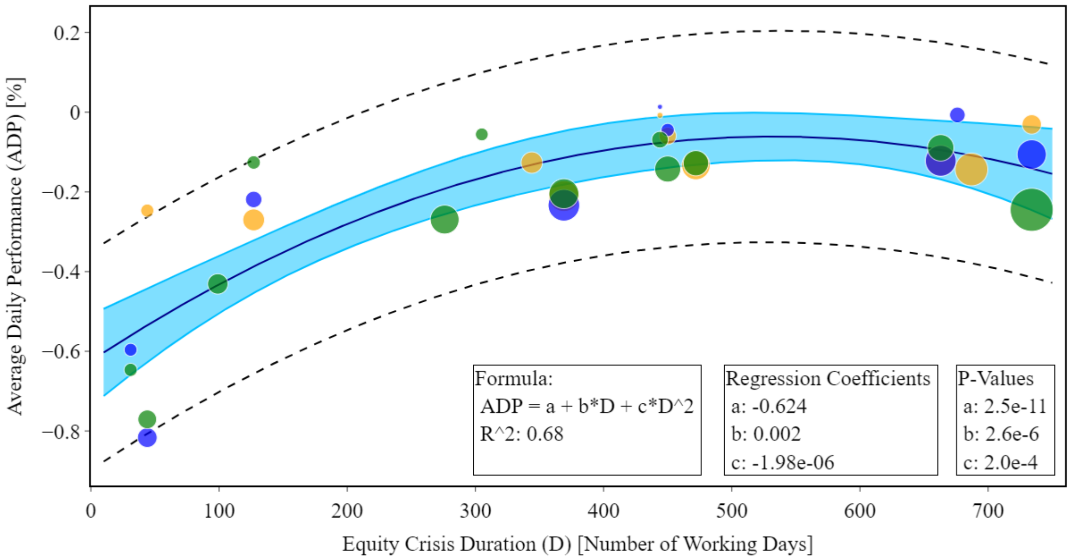

Figure 4.3: This figure presents the quadratic regression between equity crisis duration in working days and average daily performance. The diameter of the data points is proportional to the peak to trough value of the equity index and colored according to their economic region (US - green, Europe - blue, Japan - yellow). The blue line represents the regression line, the light blue area the 95% confidence interval, and the area between the two dashed lines the 95% prediction interval. Note that the Great Depression was the longest crisis in our data set and had the largest peak to trough value in the US. Additionally, we note that for all three economic regions, the ADP of the 2008 financial crises was lower, than the average regression would expect for a duration of 374 working days.

With this relationship, we sample a equity crisis duration from a uniform distribution between 30 and 750 days and generate an ADP estimation. Furthermore, we can approximate the peak to trough value of the equity market using the following equation:

$$PtT_E \approx (1 + ADP)^D \tag{4.1}$$

where:

PtT_E = Peak to Trough
ADP = Average daily performance as defined in Equation 3.2
N = Number of trading days between observation start and end
D = Duration of crises in trading days

Note, we limit the duration to a duration of 750 days as the longest crisis in our data set (the Great Depression) was 734 days long, and large extrapolations beyond the sample data should be avoided in regression models. Furthermore, we use a uniform distribution, as we do not want to influence the chance of the crisis being short or long.

As mentioned, with our three regressions we can generate any random crises with any given duration. However, as we can see from Figures 4.1, 4.2, and 4.3, there are few crisis values that land directly on our regression line. To compensate for this issue, we decided to add a certain degree of randomness to each parameter that is selected throughout our Monte Carlo simulation. We achieve this randomness by using the expected mean from the regression (μ) as well as the standard deviation (σ). We can use these two values and plug them into the normal distribution function described in Equation 4.2. We then randomly sample the exact used value from the resulting probability density function. Thereby we sample with a 95% chance a value within the 95% prediction interval plotted in Figures 4.1, 4.2 and 4.3.

$$p(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{4.2}$$

where:

$p(x)$ = Probability density function for any value x
μ = expected mean from regression
σ = Standard deviation from the regression

Note, as Figure 4.4 presents the property losses depend on the credit spread, and the credit spreads depend on ADP, the variance of our possible regression outcomes increases significantly as we add the randomness for each parameter. To make sure we run enough simulations, our Monte Carlo simulation will run 100'000 times.

Furthermore, the reader should note that for our Monte Carlo simulation, we will always simulate global crises. This means all economic areas are hit simultaneously.
To see how we transform our crisis parameters into actual losses, please refer to Chapter 4.3.

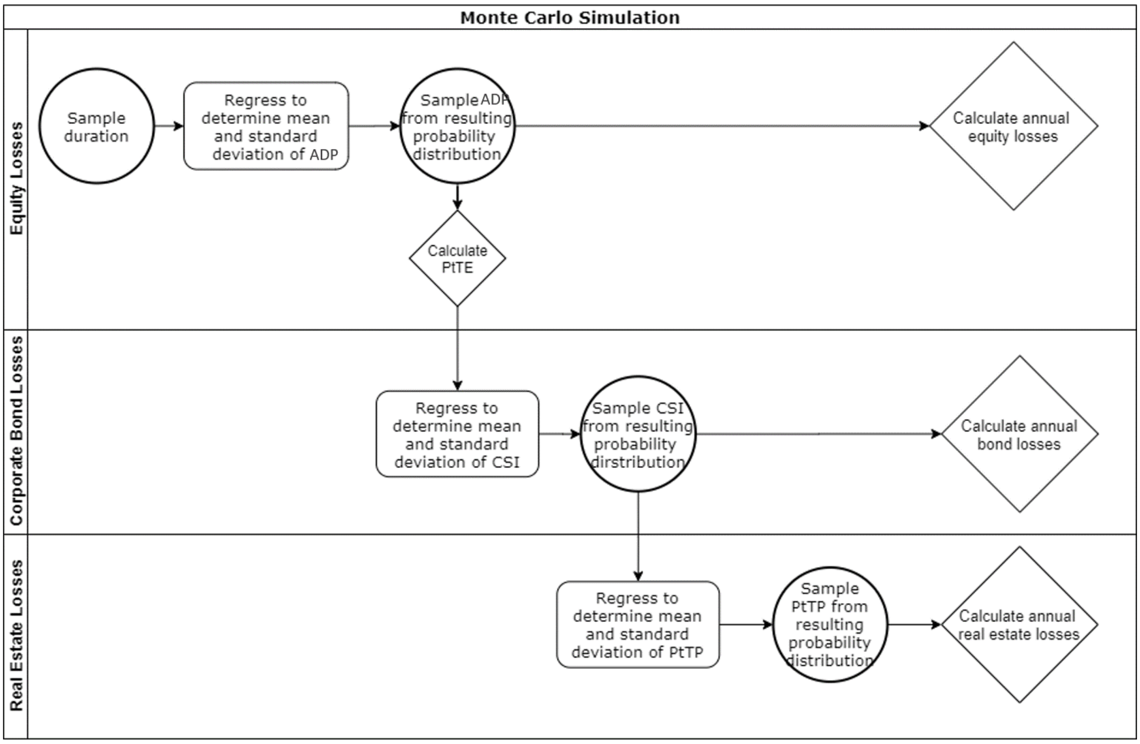

Figure 4.4: This figure presents a flow diagram of the Monte Carlo simulation. Circles represent a sampling from a distribution function, rectangles represent a regression model and squares represent a calculation. Note, property losses depend on the credit spread, and the credit spreads depend on the average daily performance, thereby greatly increasing the number of outcomes.

4.3 Financial Impact Quantification

So far, both our historic crisis model as well as our Monte Carlo simulation generate a complete set of crisis parameters. However, to determine the VaR and the ES, we need to transform our parameters into annual losses. This sub-chapter will explain the methodologies we use to determine the annual losses from our crisis parameters.

To convert the average daily performance into annual losses, we use a similar approach, as seen in Equation 4.1. This means, we will approximate the annual equity losses with the following equation:

$$AEL \approx (1 + ADP)^d \tag{4.3}$$

where:

AEL = Annual Equity Loss
ADP = Average daily performance as defined in Equation 3.2
d = min(n,D)
n = Number of working days in the current fiscal year
D = Duration of crises in working days

How we transform credit spread increases into corporate bond losses is a bit less straight forward. However, we can use an equation that Swiss Re uses internally to calculate the effects of credit spreads on corporate bond prices. A detailed explanation of the origin of this equation can be found in Appendix B.

$$\Delta P = -P(s_0)t\Delta s \tag{4.4}$$

where:

ΔP = Change in bond values
$P(s_0)$ = Bond value with a credit spread of s_0
Δs = increase in credit spread
t = time to maturity in years
Δs = credit spread increase

Note, if the credit spread increase is expressed in basis points [BPS], the result needs to be divided by 10'000.

Lastly, to transform the peak to trough value of the real estate prices into an annual loss, we will use the following equation:

$$APL = (1 + \frac{PtT_P \cdot n}{D})P_0 \tag{4.5}$$

where:

APL = Annual Property Value Loss
P_0 = Value of properties before the crises
PtT_P = Peak to trough property losses
n = Number of working days in a fiscal year
D = Number of days until the trough of the property market is reached

Note, if PtT_P is sampled from the regression model, our historic crisis model assumes that it takes six years until the trough of the property market is reached. This makes this model fully deterministic.
However, for our Monte Carlo simulation, we sample the number D from a normal distribution between 30 and 1500 days. This adds a further random parameter to our simulation.

4.4 Risk Analysis

After running both our models and calculating the financial impact, we will be able to calculate the value at risk (VaR) and the expected shortfall (ES). Both these indicators help us to assess the market risk.

VaR is a measure for the worst expected loss with a given level of confidence α over a certain period of time. In our case, the time frame is one year. Furthermore, our α is 99.5% for VaR.

$$VaR_\alpha = min\{x \in \mathbb{R} : F_X(x) > \alpha\} \tag{4.6}$$

where:

VaR_α = VaR for a given confidence α
X = a loss distribution
F_X = cumulative distribution function of X

However, one of the most significant drawbacks of VaR is that it only measures a single point of the tail risk and thus is not a coherent risk measure. To compensate for this, we will include the expected shortfall (ES), a measure for the average loss of the entire tail exceeding α. We measure the ES for one year at a confidence level of 99.0%. Sometimes, this risk measure is also referred to as conditional value at risk (CVaR).

$$ES_\alpha = \frac{1}{\alpha}\int_0^\alpha VaR_{1-\gamma} d\gamma \tag{4.7}$$

where:

$VaR_{1-\gamma}$ = VaR for a given confidence $1-\gamma$
$1-\alpha$ = Confidence of the expected shortfall

4.5 Model Robustness

In the next step of our analysis, we want to look at the robustness of our model. For this, we use three different approaches.

In the first approach, we will always delete one of the previous crises at a time and re-run our Monte Carlo simulation. This approach aims to see how much our VaR and ES calculations change if we exclude a single crisis.

In the second approach, we will start with a model that includes data until 1960 and run it forward. This means we add more and more crises as they occur throughout history and see how our VaR and ES change over time.

In the third model, we will start with a model that includes crises from today until 2000 and run it backward. This model aims to determine if we need to include data until 1907 to make our model robust or if we can see diminishing marginal benefits of including more and more crises. If we do find diminishing marginal benefits, we might be able to make recommendations on how far back a market risk model should look.

In all three approaches, we will always limit the equity crisis duration to be a maximum of 49 days larger than any crises that are included in the model. This approach aims to limit large extrapolations of the model. Furthermore, the reader should note that we do not reassess the model stability when we rerun each regression with different data. We aim to see how much the model outcome changes and not whether the model stability changes. Of course, the model stability will have an indirect impact because the standard deviation from the regression will become larger or smaller.

4.6 Addition of Covid-19 Crisis

While writing this thesis, a new financial crisis started to unfold due to Covid-19. This crisis creates an ideal testbed to see how significant the impact of the addition of the Covid-19 crisis is on our model. For this reason, we add what we observed until the end of June 2020 into our model. In case that Covid-19 will not have any further impact on the financial markets, this data can then be used in future research to see whether our model stability is greater than the stability of the SST model.
Note, the Covid-19 crisis is not necessarily over, and further stock market losses might still follow throughout the next years. However, for this analysis, we limit ourselves to market data until the market losses and behavior from February 19, 2020, to the end of March 2020.

Chapter 5

Results & Discussion

Throughout this chapter we will present the results from our analysis and discuss them critically. Note, like all models, our models are a simplification of the real world and subject to limitations. The most significant limitations will be discussed at the end of this chapter.

5.1 Historic Crises Model

To start, we present the results of our historic crisis model. This model replicates the market behavior from any given crisis on a current investment portfolio. As an example portfolio, we use publicly available information about Swiss Re's investment portfolio (see Chapter 3.1.4). However, this method can be applied to any other investment portfolio. Note, as described in Chapter 4, this model only creates losses in the regions that have also been initially affected by the crisis.

5.1.1 Results

Our historic crises model enables us to understand the risk of individual asset class and transform them into potential losses of any given investment portfolio. Furthermore, it helps us to identify the most significant risks within the specified portfolio. Keep in mind that our model simulates the annual losses of a crisis and not the total losses throughout a crisis. With this, we are inline with the run-off assumption of the SST (FINMA 2019).

In Figure 5.1, we can see the average annual losses across AAR of each asset class expressed as a percentage of the original value of the asset class. Generally, it is apparent that equity investments are exposed to the most significant annual percentage drop, followed by corporate bonds and the real estate market. This is in line with general expectations.

On closer consideration, we can see that for some crises, the real estate market had a continuous value appreciation instead of a price decline. This has to do with the fact, that the real estate markets often face a more significant volume impact than price impact (Strohm David 2020). This means that prices are less affected by a crisis.
Furthermore, the real estate prices move much slower than other asset classes. This means that high inflation rates become a more significant influence factor. This becomes especially apparent when deep diving into the real estate value increases throughout the stock market crash of 1973-74. During this crisis, Japan faced high inflation rates, causing the nominal value of the real estate markets to increase, while the real values decreased. In future research this could be avoided by using inflation adjusted indices to track the real estate losses.

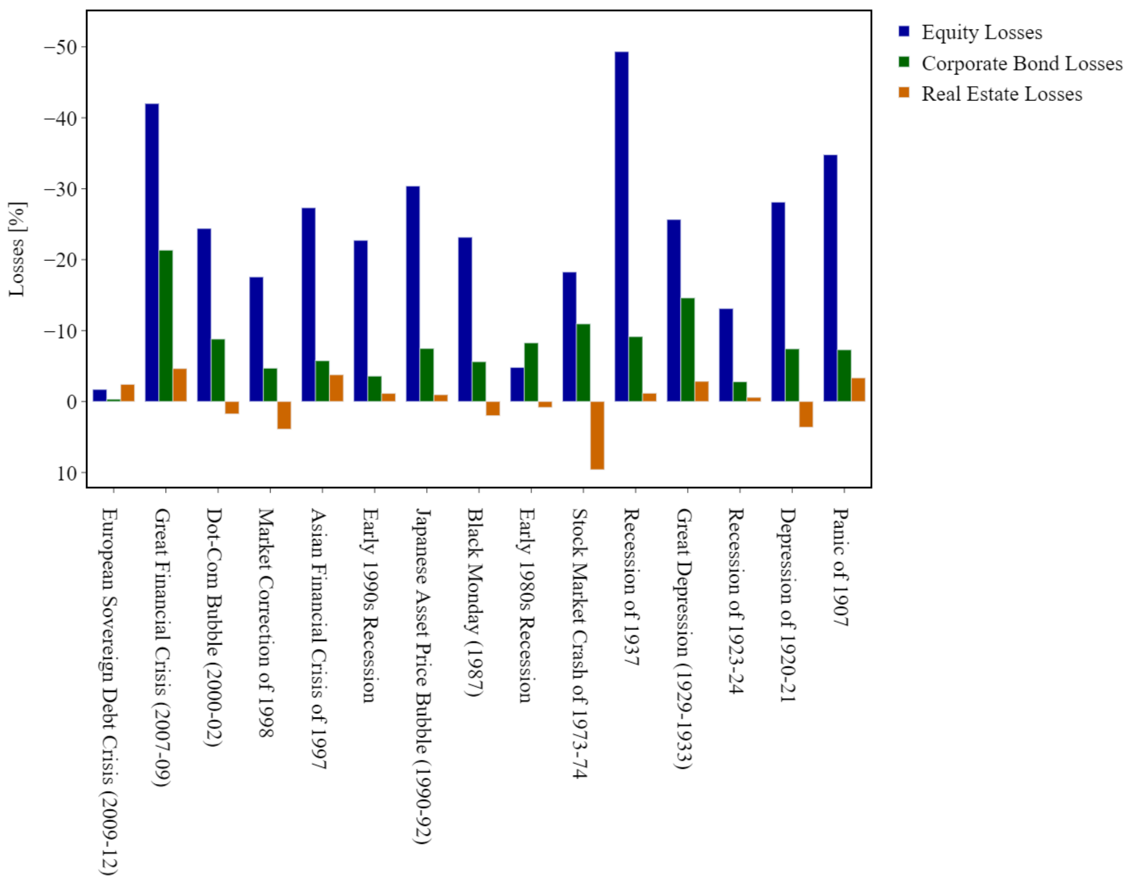

Figure 5.1: This figure presents the average one-year percentage of losses per asset class and per crisis. Note we exclude unaffected regions from the average, as we assume that these had no losses. From the figure, we can see that usually equity faces the most significant losses, followed by losses in corporate bond investments, followed by real estate investments. This pattern is expected. However, it is good to note that it can be found in the model.

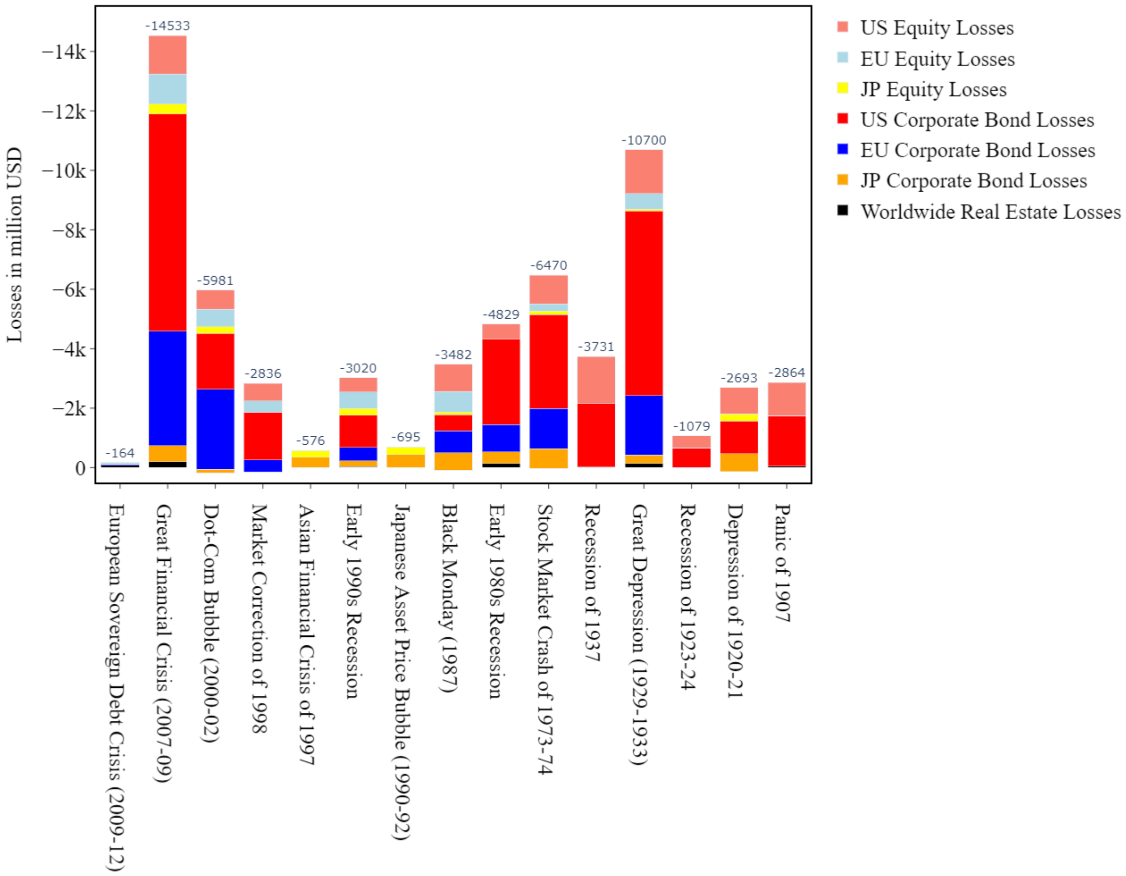

Figure 5.2: This figure presents the one-year losses of Swiss Re's investment portfolio based on our historic crises model. The value of the total losses is stated above each bar. The bars themselves are broken down by region and asset class. Due to the low value of real estate losses, we got rid of the color differentiation for this asset class and simply represented the global real estate losses in black. We note that our test portfolio has a significant exposure to credit spread risks. Furthermore, we can see that a crisis similar to the Global Financial Crisis would cause unprecedented annual losses to the portfolio.

Furthermore, we note that the European Sovereign Debt Crisis caused by far the lowest losses with a drop of only 1.7% for stock market investments, 0.3% for corporate bond investments, and 2.4% for real estate investments. The small financial impact of this crisis makes it questionable if this crisis should even be included in our model.

When we apply the described crises losses to our sample portfolio, we arrive at a loss structure, as presented in Figure 5.2. Immediately it becomes apparent that the investment portfolio of Swiss Re is mainly exposed to credit spread risks. For almost all crises, the losses due to credit spread increases are the highest. However, this is also somewhat unsurprising when considering the investment structure of Chapter 3.1.4.

When looking at the annual losses from each crisis, we need to compare them to the actual loss values of the crisis. For the fiscal year 2008, Swiss Re reported investment losses of roughly 16 billion CHF (Swiss Re 2009). Considering that the investment portfolio has changed a little since 2008 and comparing this to our simulated losses of roughly 14.5 billion USD, we can see that our simulation yields losses in a realistic value range.
Furthermore, it becomes apparent that our model shows the most significant losses for the Great Depression and the Global Financial Crisis. This makes sense as these two crises are generally considered the worst ones in our sample data.

5.1.2 Summary

Generally, the results of our historic crises model show that our approach yields losses in a realistic monetary value range. Furthermore, we showed a realistic behavior where the stock market is most exposed to losses, and real estate investments are the most stable.
Additionally, we were able to identify that our simplified investment portfolio of Swiss Re is mainly exposed to credit spread increases. However, this is also not surprising when considering the investment structure from Chapter 3.1.4.

5.2 Monte Carlo Simulation

After assessing the results from our historic crises model and deeming them in a realistic range, we will use this chapter to highlight the results from our Monte Carlo simulation.

5.2.1 Results

For this, we start by comparing the Cumulative Distribution Functions (CDF) of our Monte Carlo simulation to the CDF of our historic crises model (see Figure 5.3). When looking at the figure, it becomes apparent that the Monte Carlo simulation follows a similar trend line as the historic crises model.

On closer consideration, it becomes clear that the extreme loss scenarios tend to appear less frequently for credit spread risks in our Monte Carlo simulation. This becomes especially apparent when looking at the probability of corporate bond losses of over 20%. The historical CDF line is considerably higher in our result from the Monte Carlo simulation. However, to assess this in more detail, we should also consider our risk measures (VaR and ES), which are summarized in Table 5.1.

Table 5.1: This table presents the value at risk (VaR) and the expected shortfall (ES) values of our historic crises model and our Monte Carlo Simulation. Generally, we note that our Monte Carlo Simulation tends to slightly overestimate the VaR and ES of equity and real estate. For corporate bonds, both the model and historical observations match each other.

	$\mathbf{VaR}_{99.5\%}$		$\mathbf{ES}_{99.0\%}$	
	Historic Crises Model	Monte Carlo Simulation	Historic Crises Model	Monte Carlo Simulation
Equity	-48.8%	-56.9%	-49.3%	-57.7%
Bonds	-30.7%	-30.0%	-31.4%	-31.2%
Real Estate	-7.4%	-11.5%	-7.7%	-12.7%

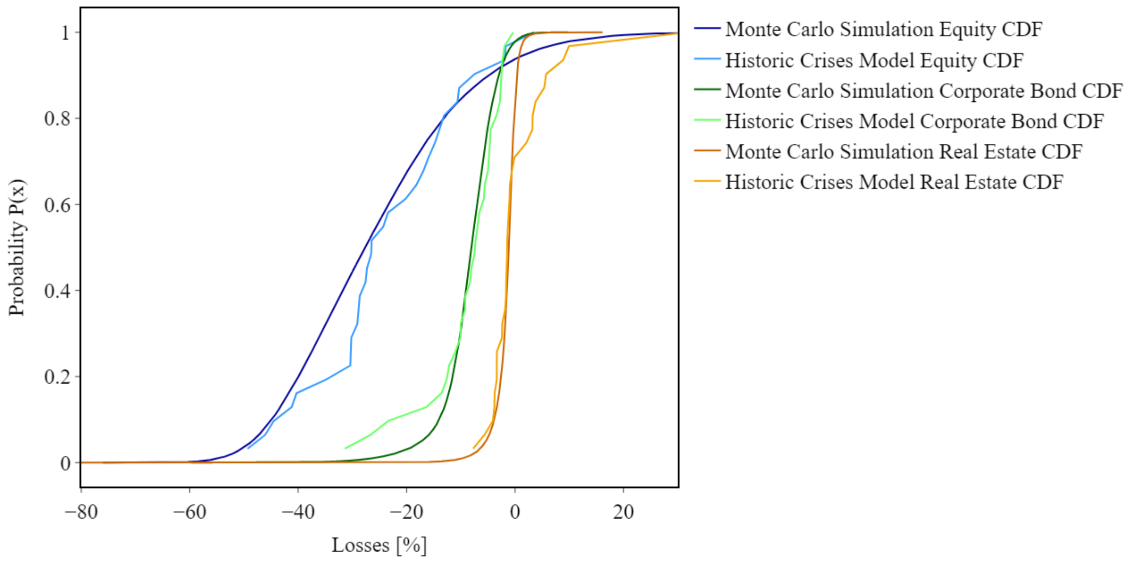

Figure 5.3: This figure presents the cumulative distribution function (CDF) for the three asset classes for both of our models. Generally, we note the CDF from our Monte Carlo Simulation tends to overlap with the CDF from our historic crises model nicely.

From Table 5.1, it becomes visible that the low probability of high losses occurring has no substantial impact on our VaR and ES values. Generally, both VaR and ES of corpoate bond investments are in a similar range for both models. However, when comparing it to equity and real estate investment it becomes apparent that our Monte Carlo simulation generally yields higher VaR and ES values. However, this is also understandable, as our model is able to simulate losses that were even greater than anything we observed so far.

5.2.2 Summary

In summary, we can show that our Monte Carlo simulation tends to follow similar trend lines. Furthermore, we are also able to see that our Monte Carlo simulation tends to yield higher values for VaR and ES. However, this is also understandable, as our Monte Carlo simulation is able to yield a much smoother CDF where more tail risks are simulated.

5.3 Model Robustness

After assessing the results from our historic crises model and our Monte Carlo simulation, we start to look at the robustness of our model. For this, we use three different tests and look at the changes in expected shortfall as well as value at risk of our Monte Carlo simulation. However, as the results from VaR and ES are very similar, we only show the expected shortfall plots in this chapter. The plots for VaR can be found in Appendix C.

5.3.1 Results

To assess the robustness of our model, we start with the stability analysis. For this, we look at how the expected shortfall changes if a single crisis is removed (see Figure 5.4). Generally, we note that in 3 cases, our stability condition cannot be upheld for one asset class. In the case of equity losses, we exceed our stability limits if we remove the 1987 Black Monday crash. This is likely caused by the unique nature of the short, sudden, and large drops of the Black Monday crash. In the case of corporate bond losses, our stability cannot be upheld if we remove the Great Depression or the Dot-Com Bubble. The reason for this is likely twofold. Firstly, both crises had peak-to-trough equity losses of over 49% in all three economic regions. With that, they are the only crises besides the Great Depression to record equity losses of over 50% (see Table 3.3). Secondly, they had a considerably different CSI, which leads to an underestimation or overestimation of the equity - credit spread relationship for equity losses above 50% if one of them is removed. Note, more detailed data on the credit spread losses in Europe and Japan during the Great Depression would likely resolve this high interdependence of the two crises. However, throughout writing this thesis, we were unable to find reliable sources for such data.

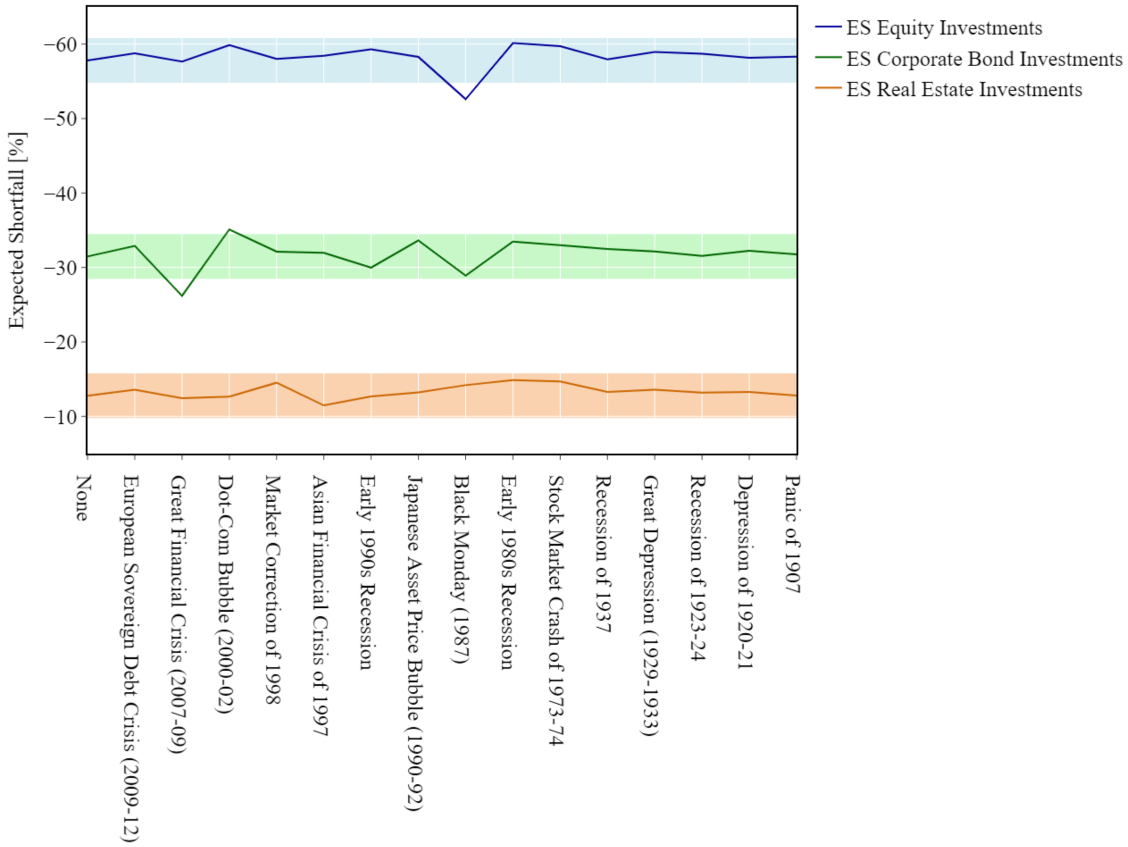

Figure 5.4: This figure presents the changes in the expected shortfall ($ES_{99.0\%}$) as a single crisis is removed. The x-axis states the name of the removed crisis. The lightly colored background represents a ±3% range of expected shortfall of our original model. We consider our model to be stable, as long as we stay within this defined range. Note, if we remove the Dot-Com Bubble or the Global Financial Crisis, our stability condition cannot be upheld for the expected shortfall due to the widening of the credit spread. Furthermore, if we remove the Black Monday crash, our model does not uphold our stability condition for the expected shortfall of equities.

To complement our stability analysis, we also conduct a historic run-through analysis. This analysis aims to see how our model would have evolved if it were already used in 1970, and more crises were added as they occur. Generally, our model tends to estimate a higher ES in the 1970s for equity and real estate investments. Over time, this value tends to decrease and approach our final estimation. For corporate bond investments, we cannot observe such a decreasing trend over time. This is probably caused by the fact that the 2008 financial crisis causes a significant increase in the ES of corporate bond investments.

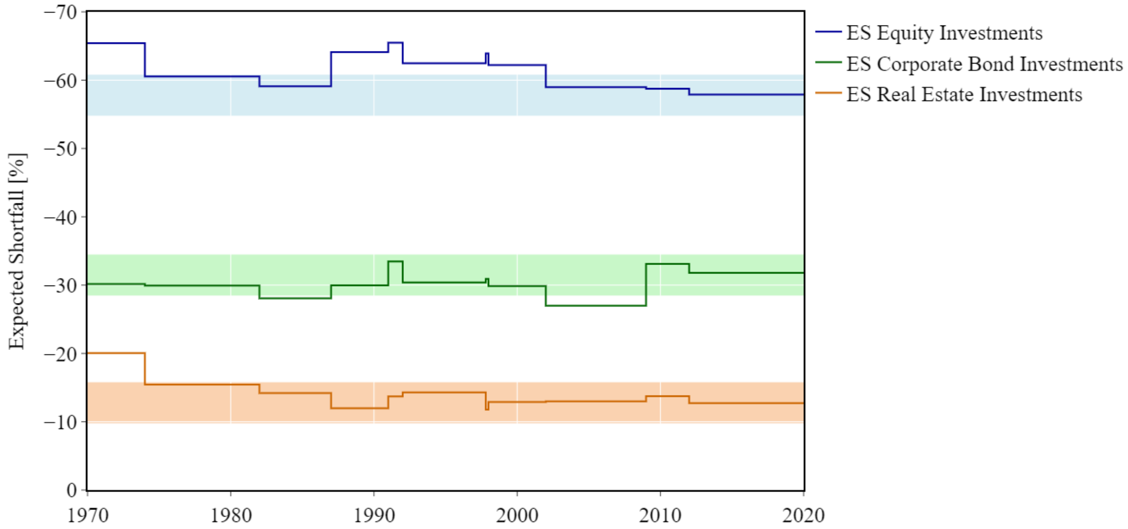

Figure 5.5: This figure presents the changes in the expected shortfall ($ES_{99.0\%}$) of our Monte Carlo simulation as we run through history. The lightly colored background represents a $\pm3\%$ range of expected shortfalls of our original model. We consider our model to be stable, as long as we stay within this defined range. We start in 1970 and add more crises as they occur. Generally, we note that the $ES_{99.0\%}$ for the equity and real estate investments tend to slowly and gradually approach our final value. For corporate bond investments, we especially note the high increase in the $ES_{99.0\%}$ after the 2008 crisis is added. However, the Great Financial Crisis has no substantial impact on the $ES_{99.0\%}$ estimation of equity and real estate investments.

Finally, we will present the results of our reversed history analysis. This analysis aims to determine if we can find a cut off year, where the addition of more historical data has a negligibly small benefit to the outcome of our model. In Figure 5.6, we summarize the changes in the expected shortfall as more and more historical data is added to our model. From the figure, it becomes apparent that if we include a historical time series that does not extend beyond the 1980s, our model becomes unstable. However, once we add data until the 1970s, our model outcomes tend to be extremely close to our $\pm3\%$ threshold. Furthermore, once we include data until 1929, all our parameters are well within our stability threshold, and the addition of data before the Great Depression could potentially be neglected.

Additionally, we note that, with the addition of more historic crises our model tends to decrease the expected shortfall estimation. This is likely caused by the reduction in the standard deviation within our regression model. As this standard deviation decreases, the randomness of our model decreases, and thereby, fewer data outliers are simulated.

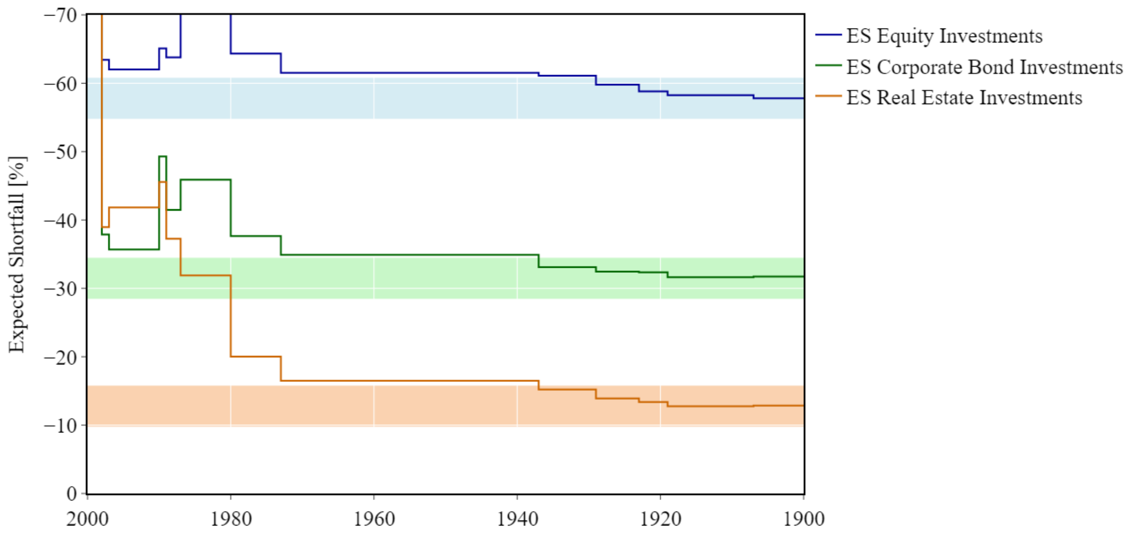

Figure 5.6: This figure presents the changes in the expected shortfall ($ES_{99.0\%}$) of our Monte Carlo simulation as we add more and more historical data. The lightly colored background represents a ±3% range of expected shortfalls of our original model. We consider our model to be stable, as long as we stay within this defined range. Note if we only include data until 1998, our model becomes heavily unstable. However, as we add more historical data, our model starts to approach our desired stability range. After we include data until 1929, all our parameters have reached our stability condition, and the benefit of any prior data is marginal.

5.3.2 Summary

Due to their unique features and their significant impact on the expected shortfall, we will consider the Global Financial Crisis, the Dot-Com bubble, and the 1987 Black Monday crash as important crises that must be included in our model. Furthermore, we were able to show that our model stability greatly benefits if at least data until the 1970s is included. The benefit of adding crises before 1970 is marginal. However, if one would like to do so, it would be advisable to add detailed data until the Great Depression.

5.4 Model Impact Covid-19

As previously described, the Covid-19 pandemic emerged while writing this thesis. This pandemic also had a substantial impact on the financial markets. We will use this impact as a testbed to see how much it would influence our model stability.

5.4.1 Results

We base the analysis on data retrieved at the end of June 2020. We calculate the spread increases, the average daily performance, and the equity peak to trough values for the Covid-19 crisis. These results are summarized in Table 5.2. Note, we exclude real estate losses, as it is too soon to see a price impact in the real estate sector.

Table 5.2: This table summarizes the derived crisis parameters for the Covid-19 Crisis for our three economic regions. Note, we excluded an analysis of the real estate market, as according to our reasoning in Chapter 3, the market would need more time to show price developments.

	Average Daily Performance	Equity PtT	Credit Spread Increase [BPS]
US	-7.4E-03	-33.6%	184
EU	-9.6E-03	-37.8%	98
JP	-7.0E-03	-28.6%	13

In the next step, we then use these results and plug them into our regression model to see how our ES and VaR estimation from our Monte Carlo simulation change. The results of this analysis are summarized in Figure 5.7. For simplicity, we only show the ES impact within this chapter. However, the impact on the VaR yields similar results. For completeness, the VaR results are included in Appendix C.
When looking at Figure 5.7, we can see that all our parameters stay within our predefined stability range. To be precise, the expected shortfall decreases by 2.8, 1.8, and -0.1 percentage points for equity, corporate bond, and real estate investments, respectively. This clearly shows that our model is robust to the addition of the Covid-19 crisis.

On closer examination of Table 5.2, and comparing it to Table 3.3, we start to observe similarities between the two crises. Firstly, both crises have a short duration of under 45 days. Secondly, both are global crises with a maximum stock loss between 30-40%. Thirdly, the average daily performance across our three observed economic areas only differed by 0.2 percentage points. However, there is one clear difference. The credit spread impact of the Covid-19 crisis is almost twice as large as the credit spread increase caused by the Black Monday crash. Nevertheless, this raises the question if the addition of the Covid-19 crisis can reduce the dependency on the Black Monday crash of 1987. To analyze this in more detail we preform one last variation of our regression model. In this version, we replace the Black Monday crash with the Covid-19 impact.

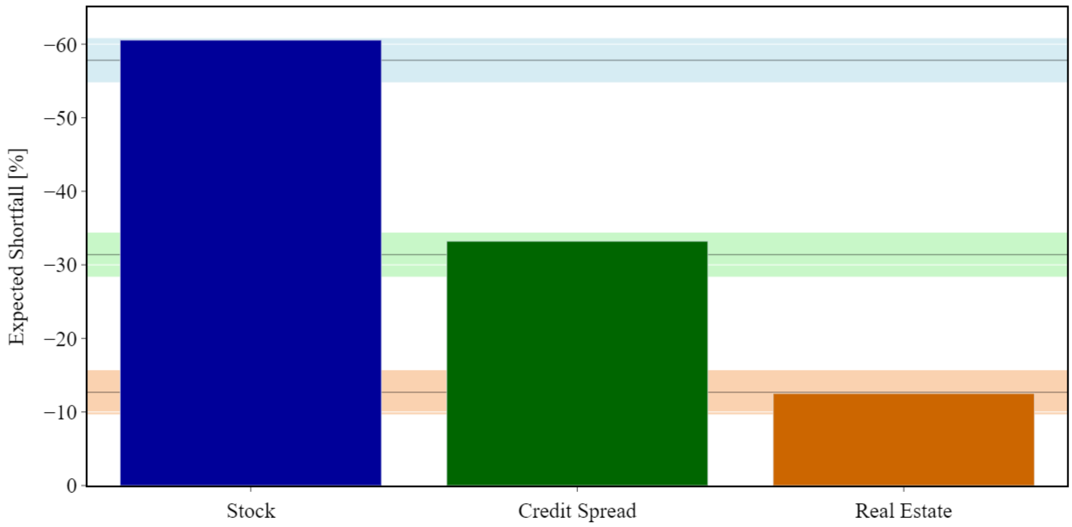

Figure 5.7: This figure presents the changes in the expected shortfall ($ES_{99.0\%}$) of our Monte Carlo simulation as we include the Covid-19 crisis. Blue refers to the $ES_{99.0\%}$ of equities, green to the $ES_{99.0\%}$ of corporate bonds and brown to the $ES_{99.0\%}$ of real estate investments. The lightly colored background represents a $\pm 3\%$ range of expected shortfalls of our original model. We consider our model to be stable, as long as we stay within this defined range. We can see that with the addition of the Covid-19 crisis, all ES values stay well within our stability condition. The most significant change is faced by the increase in the expected shortfall of equity investments.

In Figure 5.8, the new expected shortfall is presented. When comparing these results to the results from Figure 5.4, we can immediately observe that our model dependency on the Black Monday crash is drastically reduced with the inclusion of the Covid-19 crash. The expected shortfall decreases by 0.65, 0.75, and 0.9 percentage points for equity, corporate bond, and real estate investments when compared to our original model. This clearly shows that the addition of the Covid-19 crisis reduces the dependency on the Black Monday crash and that these crises are, to some degree, similar to each other.

5.4.2 Summary

We were able to show that the addition of the recently evolved Covid-19 crisis keeps our model within our target range. This means, no large re-calibration of the model is necessary. Furthermore, we were able to show that there are similarities between the Covid-19 crisis and the Black Monday crash of 1987. Our model can leverage these similarities and thereby reduces the dependencies on the Black Monday crash. Thus, as time evolves and more crises occur, our model will naturally further increase its robustness.
Note, with this analysis we are not stating or implying that the Covid-19 crisis within the financial system is over or that it has come to an end. We instead assess if what we have seen until the end of June 2020 fits into our model.

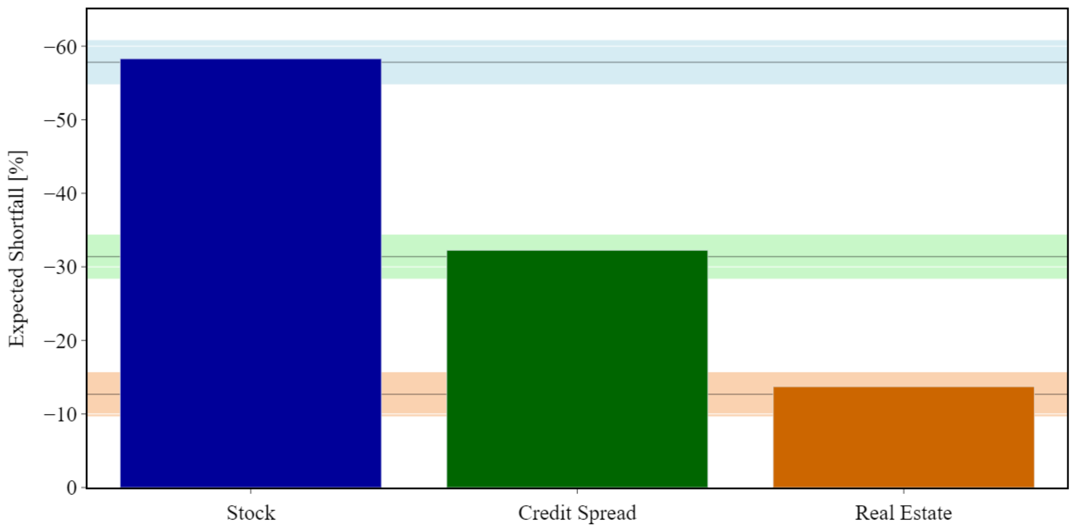

Figure 5.8: This figure presents the changes in the expected shortfall ($ES_{99.0\%}$) of our Monte Carlo simulation if we include the Covid-19 crisis and remove the Black Monday crash. Blue refers to the $ES_{99.0\%}$ of equities, green to the $ES_{99.0\%}$ of corporate bonds and brown to the $ES_{99.0\%}$ of real estate investments. The lightly colored background represents a $\pm 3\%$ range of expected shortfalls of our original model. We consider our model to be stable, as long as we stay within this defined range. We can see that with the addition of the Covid-19 crisis all ES values stay well within our stability condition. The most significant change is faced by the decrease in the expected shortfall of real estate investments.

5.5 Model Limitations

Like all models, our models are a simplification of the real world and subject to limitations. Before concluding our thesis, we would like to shed light on some of these limitations. Note, we do not state that the limitations we state throughout this section are exhaustive. However, in our view, these are some of the most important ones to consider. Additionally, some other limitations, such as the exclusion inflation or the fact that we do not differentiate between return and price indices, have already been mentioned in previous chapters and will not be repeated here.

To our knowledge, our historical data set is the largest of its kind, especially when considering the long retrieved history of credit spreads. However, even our data set has its limits, especially when considering the frequency.

Furthermore, it has to be mentioned that our approach of using the average daily performance to determine the losses of a crisis also has limitations. Most notably is the fact that we do not differentiate between different monthly performances. In other words, throughout longer crises, there are usually months where the markets perform bad and months where they are stable or even recover a little. This differentiation is not included in our model. However, when considering that our model always simulates the first 12 months of a crisis, it is reasonable that both bad and better performing months are within that year and that they average themselves out.

Additionally, we limit our model to three key risks. However, when looking at the investment structure of our simplified Swiss Re portfolio, it becomes apparent that there are significant government bond investments. These investments are exposed to interest rate risks as well as government default risks. However, when looking at government default risk, we exclude them as most of these investments are into government bonds of countries that have matured from default on sovereign debt (Reinhart & Rogoff 2011*a*). When looking at interest rate risks, we also have to consider recent trends in fiscal policies. In recent times governments tend to lower interest rates in periods of economic crises. These policies aim to incentivize more substantial investments that might yield higher returns and simultaneously stimulate the economy. Therefore, we ignore them in our model. However, this still raises the question if a separate model for losses due to interest rate increases might need to be developed.

To continue, we should also mention that we did not analyze the statistical significance of every single variation of our regression model. This is especially important when looking at our model robustness, as some of the regression indicators used there might not have a p-value smaller than 0.05. However, that being said, it still allows us to see how the model outcome would change in predefined situations. Additionally, it should also be noted that with the addition of the Covid-19 crises, all regression parameters have a p-value smaller than 0.05.

Lastly, as already stated in the introduction, our model aims to identify relationships we observe within the data. However, this also means that we do not provide a macro- or microeconomic explanation for our observed relationships. This means that the described and quantified relationships might appear random and without reasoning to many economists. Furthermore, we restrict our analysis to four economic measures across three geographic regions. However, other indicators, as the previously described macroeconomic situation or quantifiable indicators like the unemployment rate or inflation rate, might also have a significant impact on the performance of investments. However, that being said, the nature of finding regression relationships between different economic parameters might become more challenging once new economic parameters are added.

Chapter 6

Conclusion & Outlook

To end this thesis, we will revisit our research questions, come to a conclusion, and give an outlook on what future research should include.

6.1 Conclusion

In general, we have seen that financial crises have a multitude of different causes. This leads to the fact that if more historical data is included, more of the unique features of theses crises are incorporated into our model. However, whether the addition of these features lead to a decrease or increase in the expected shortfall or value at risk depends on the crisis itself.

Furthermore, we were able to show that we can build a robust financial crisis model. However, we also identified three crises that have a significant impact on the model outcome and should be included in any case. These crises are the Global Financial Crisis, the Dot-com bubble, and the Black Monday crash.

Additionally, we were able to identify that crisis data until 1970 greatly aid the model stability and, in our view, should be included in a financial risk model. Generally speaking, the more data, the better. However, there is also a clear decreasing marginal benefit of adding more data, meaning there is a cutoff point where the additional model accuracy will not outweigh the efforts to find reliable data. In our view, it would be good if at least data until 1970 is included. However, ideally data until 1928 would be included in our a crises model.

In the last step, we were also able to show that even with the addition of the recent Covid-19 pandemic, our model remains stable. Furthermore, we were able to identify numeric parallels between the Black Monday crash and the Covid-19 crisis.

To summarize, we were able to build a historic crises model that is mostly independent of individual crises. However, we have identified three crises that are critical to the outcome of our model. Furthermore, we were able to show that it would be good if our model would at least include data until 1970. Lastly, we were also able to show that our model remains stable with the addition of the Covid-19 crisis.
With this, we were able to answer all of our research questions.

6.2 Outlook

Science is a process of continuous improvement. For this reason, we want to give an outlook on what future research should include.

Let us start by looking at the number of risks we include in our model. As mentioned throughout our thesis, we use 12 risk indicators across three regions. However, we solely focus on equity, credit spread risk, and real estate risk. In future research, such a historic crises model could be extended to include exchange rate, interest rate, and commodity investment risks.

Furthermore, we were unable to identify a consultant lead or lag relationship between credit spreads and equity markets. It would be great if future research would investigate this relationship in more detail. To be more precise, it would be exciting to see whether a similar regime shift, as Leiss et al. (2015) identified for the treasury bond market, also occurs in the credit spread world.

Lastly, we also identified numeric parallels and differences between the Black Monday crash and the Covid-19 crisis. Future research should investigate these parallels and differences in more detail, as our analysis was still on a relatively high level.

Appendix A

Tables

Table A.1: This table reports the used stock indices, the available time period, the frequency, the source, and wherever available the ticker. Note that we do not differentiate between total return and price indices as we look at sudden and significant equity drops where the difference becomes negligible.

Economic Area	**Time Period**	**Indicator**	**Frequency**	**Source**	**Ticker**
United States	1928 - 2020	S&P 500	Daily	Bloomberg (2020)	SPX Index
	1901 - 1927	Dow Jones	Daily	Bloomberg (2020)	INDU Index
Europe	1987 - 2020	Euro Stoxx 50	Daily	Bloomberg (2020)	SXXE Index
	1870 - 1986	DAX	Monthly	Gielen (1994)	
Japan	1948 - 2020	Nikkei 225	Daily	GFD (2020)	_N225D
	1914 - 1947	Nikkei 225	Monthly	GFD (2020)	_N225D

Table A.2: This table reports the used corporate bond yield indices, the available time period, the frequency, the source, and wherever available the ticker. Note, we use these indices in combination with the indices from Table A.3 to calculate the credit spreads.

Economic Area	**Time Period**	**Indicator**	**Frequency**	**Source**	**Ticker**
United States	1995 - 2000	YTM of S&P 500 10+ Year Investment Grade Corporate Bond Index	Daily	S&P (2020)	
	1919 - 1994	Moody's Seasoned Aaa Corporate Bond Yield	Monthly	Moody's (2020*a*)	AAA
	1919 - 1994	Moody's Seasoned Baa Corporate Bond Yield	Monthly	Moody's (2020*b*)	BAA
Europe	2000 - 2020	YTM of S&P Eurozone 10+ Year Investment Grade Corporate Bond Index	Daily	S&P (2020)	
	1978 - 1999	Germany Corporate Bond Yield	Daily	GFD (2020)	INDEUD
	1957 - 1978	Germany Corporate Bond Yield	Monthly	GFD (2020)	INDEUD
Japan	1998 - 2020	YTM of S&P Japan 10+ Year Investment Grade Corporate Bond Index	Daily	S&P (2020)	
	1934 - 1997	Japan Corporate Bond Yield	Quarterly	GFD (2020)	INJPNW

Table A.3: This table reports the used government bond yield indices, the available time period, the frequency, the source, and wherever available the ticker. Note, we use these indices in combination with the indices from Table A.2 to calculate the credit spreads.

Economic Area	**Time Period**	**Indicator**	**Frequency**	**Source**	**Ticker**
United States	1995 - 2000	YTM of S&P U.S. Treasury Bond 10+ Year Index	Daily	S&P (2020)	
	1960 - 1994	Long-Term Government Bond Yields: 10-year: Main (Including Benchmark) for the United States	Monthly	Organization for Economic Co-operation and Development (2020)	IRLTLT01USM156N
	1919 - 1944	Yield on Long-Term United States Bonds for United States	Monthly	National Bureau of Economic Research (2012)	M1333AUSM156NNBR
Europe	2000 - 2020	YTM of S&P Eurozone Sovereign Bond 10+ Years Index	Daily	S&P (2020)	
	1978 - 1999	Germany All Government Securities	Daily	GFD (2020)	BBKAD
	1957 - 1978	Germany All Government Securities	Monthly	GFD (2020)	BBKAD
Japan	1998 - 2020	YTM of S&P Current 10-Year Japan Sovereign Bond Index	Daily	S&P (2020)	
	1934 - 1997	Japan 10-year Government Bond Yield	Quarterly	GFD (2020)	IGJPN10D

Table A.4: This table reports the used real estate price indices, the available time period, the frequency, the source, and wherever available the ticker. Note that we use price indices and not sector performance indices.

Economic Area	**Time Period**	**Indicator**	**Frequency**	**Source**	**Ticker**
United States	1970 - 2020	Real Residential Property Prices for United States	Quarterly	Bank for International Settlements (2020*c*)	QUSN6 28BIS
	1953 - 1969	Case Shiller Price Index	Quarterly	Shiller & Standard and Poor's (2017)	
	1890-1952	Case Shiller Price Index	Annual	Shiller & Standard and Poor's (2017)	
Europe	1975 - 2020	Real Residential Property Prices for Euro Area	Quarterly	Bank for International Settlements (2020*a*)	QXMN6 28BIS
Japan	1955 - 2020	Real Residential Property Prices for Japan	Quarterly	Bank for International Settlements (2020*b*)	QJPN6 28BIS

Table A.5: This table reports the results of a Granger-causality test of Eurostoxx daily returns and EU Credit Spreads between 2000 and 2019. We find evidence that the EuroStoxx index Granger-caused EU Credit Spreads. Notably, this results contradicts with the findings for the US (Table A.6) and Japan (Table A.7). Thus no overall conclusion on the Granger causal influence between credit spreads and stock market daily returns can be drawn.

Lag	**EuroStoxx Granger-causes EU Credit Spread**		**EU Credit Spread Granger-causes EuroStoxx**	
	F-Value	Degree of freedom	F-Value	Degree of freedom
5	1.96	5147	0.70	5147
10	1.25	5132	0.84	5132
20	3.10***	5102	1.40	5102
50	2.53***	5012	1.27	5012
100	1.96***	4862	0.94	4862
150	1.55***	4712	0.91	4715
200	1.36***	4562	0.91	4562
250	1.25**	4412	1.01	4412
300	1.15*	4262	1.24**	4262
350	1.20	4112	1.57***	4112

Note: *p<0.05; **p<0.01; ***p<0.001;

Table A.6: This table reports the results of a Granger-causality test of S&P 500 daily returns and US Credit Spreads between 2000 and 2019. We find evidence that the S&P 500 index Granger-caused US Credit Spreads and that US Credit Spreads Granger-caused the S&P 500 index. These two results contradict each other and thus no conclusion on the Granger causal influence between US credit spreads and US stock market daily returns can be drawn.

Lag	**S&P 500 Granger-causes US Credit Spread**		**US Credit Spread Granger-causes S&P 500**	
	F-Value	Degree of freedom	F-Value	Degree of freedom
5	1.72	5049	25.78***	5049
10	3.65***	5034	15.46***	5034
20	3.41***	5004	8.30***	5004
50	4.60***	4914	3.67***	4914
100	3.26***	4764	2.27***	4764
150	2.66***	4614	1.94***	4614
200	2.24***	4464	1.75***	4464
250	2.04***	4314	1.54***	4314
300	1.89***	4164	1.41***	4164
350	1.77***	4014	1.42***	4014

Note: *p<0.05; **p<0.01; ***p<0.001;

Table A.7: This table reports the results of a Granger-causality test of Nikkei 225 daily returns and JP Credit Spreads between 2000 and 2019. We find no evidence of Granger causal influence.

Lag	**Nikkei 225 Granger-causes JP Credit Spread**		**JP Credit Spread Granger-causes Nikkei 225**	
	F-Value	Degree of freedom	F-Value	Degree of freedom
5	1.27	4927	1.11	4927
10	1.01	4912	1.16	4912
20	1.14	4882	1.10	4882
50	0.85	4792	1.20	4792
100	0.84	4642	1.17	4642
150	0.85	4492	1.10	4492
200	0.80	4342	1.06	4342
250	0.78	4192	0.93	4192
300	0.76	4042	0.90	4042
350	0.74	3892	1.02	3892

Note: *$p<0.05$; **$p<0.01$; ***$p<0.001$;

Appendix B

Explanation of Formula 4.4

The information presented in this appendix, is from a Swiss Re internal paper that derives Equation 4.4. Usually, price sensitivities are calculated using bump and revalue methods. However, this method is often not appropriate for fixed income assets, especially for large moves. This short appendix tries to show the derivation of Equation 4.4. We start with a zero price coupon bond formula:

$$\Delta P = e^{-rt} \tag{B.1}$$

where:

P = Price
r = interest rate
t = time to maturity in years

As this function is indefinitely differentiable at any real number a, we can use a Taylor series approximation

$$P(r_1) = \sum_{n=0}^{\infty} \frac{1}{n!} \frac{d^n P(r_0)}{dr^n} (r_1 - r_0)^n \tag{B.2}$$

The first order Taylor approximation is thus equal to:

$$P(r_1) = P(r_0) + \frac{dP(r_0)}{dr}(r_1 - r_0) = P(r_0) - P(r_0)t(r_1 - r_0) \tag{B.3}$$

This formula can be rearranged to tracking the price change $\Delta P = P(r_1) - P(r_0)$

$$\Delta P = -P(r_0)t(r_1 - r_0) = -P(r_0)t\Delta r \tag{B.4}$$

Formula B.4 can be used to approximate price changes of coupon paying bonds. Additionally, it can be used to approximate the impact of credit spreads. Swiss Re internal full revaluation tests, show that by separating spread and interest rates moves into separate formulas only small deviations are introduced.

$$\Delta P = -P(s_0)t\Delta s \tag{B.5}$$

where:

ΔP	= Change in bond values
$P(s_0)$	= Bond value with a credit spread of s_0
Δs	= increase in credit spread
t	= time to maturity in years
Δs	= credit spread increase

Note, all sensitives and tenor for a given currency can be summed. This simplifies any other method that is making use of bond prices and therefore needs to be evaluated individually per bond.

Appendix C

Figures

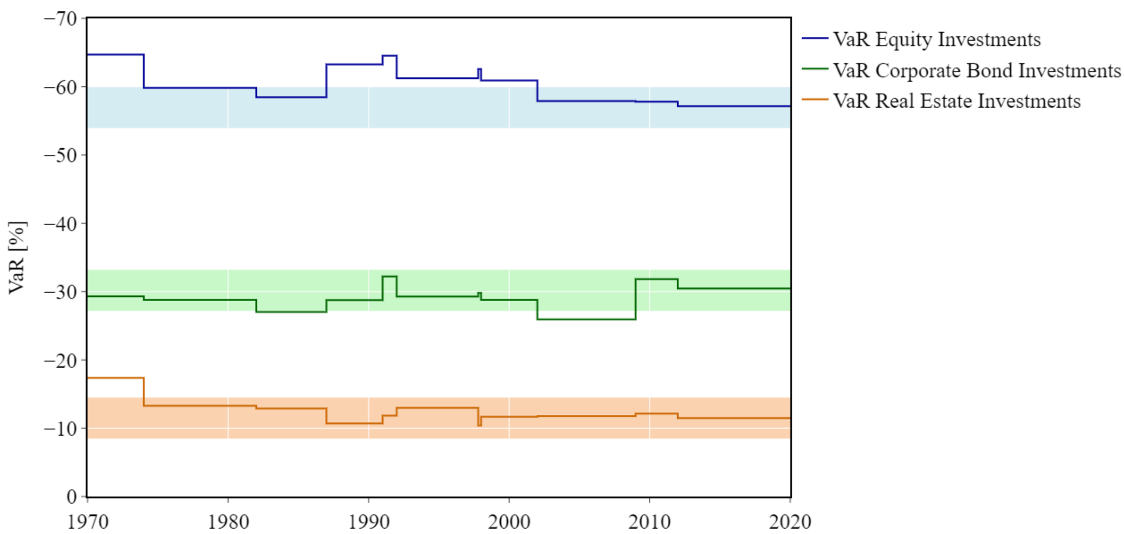

Figure C.1: This figure presents the changes in the value at risk ($VaR_{99.5\%}$) of our Monte Carlo simulation as we run through history. The lightly colored background represents a $\pm 3\%$ range of value at risks of our original model. We consider our model to be stable, as long as we stay within this defined range. We start in 1970 and add more crises as they occur. Generally, we note that the $VaR_{99.5\%}$ for the equity and real estate investments tend to slowly and gradually approach our final value. For corporate bond investments, we especially note the high increase in the $VaR_{99.5\%}$ after the 2008 crisis is added. However, the Great Financial Crisis has no substantial impact on the $VaR_{99.5\%}$ estimation of equity and real estate investments.

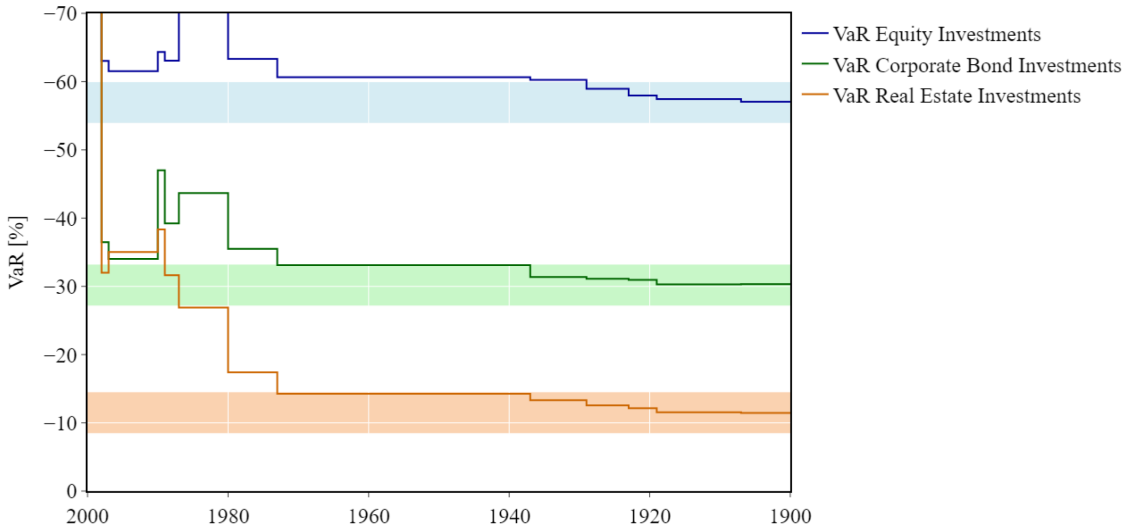

Figure C.2: This figure presents the changes in the value at risk ($VaR_{99.5\%}$) of our Monte Carlo simulation as we add more and more historical data. The lightly colored background represents a $\pm 3\%$ range of value at risk of our original model. We consider our model to be stable, as long as we stay within this defined range. Note if we only include data until 1998, our model becomes heavily unstable. However, as we add more historical data, our model starts to approach our desired stability range. After we include data until 1929, all our parameters have reached our stability condition, and the benefit of any prior data is marginal.

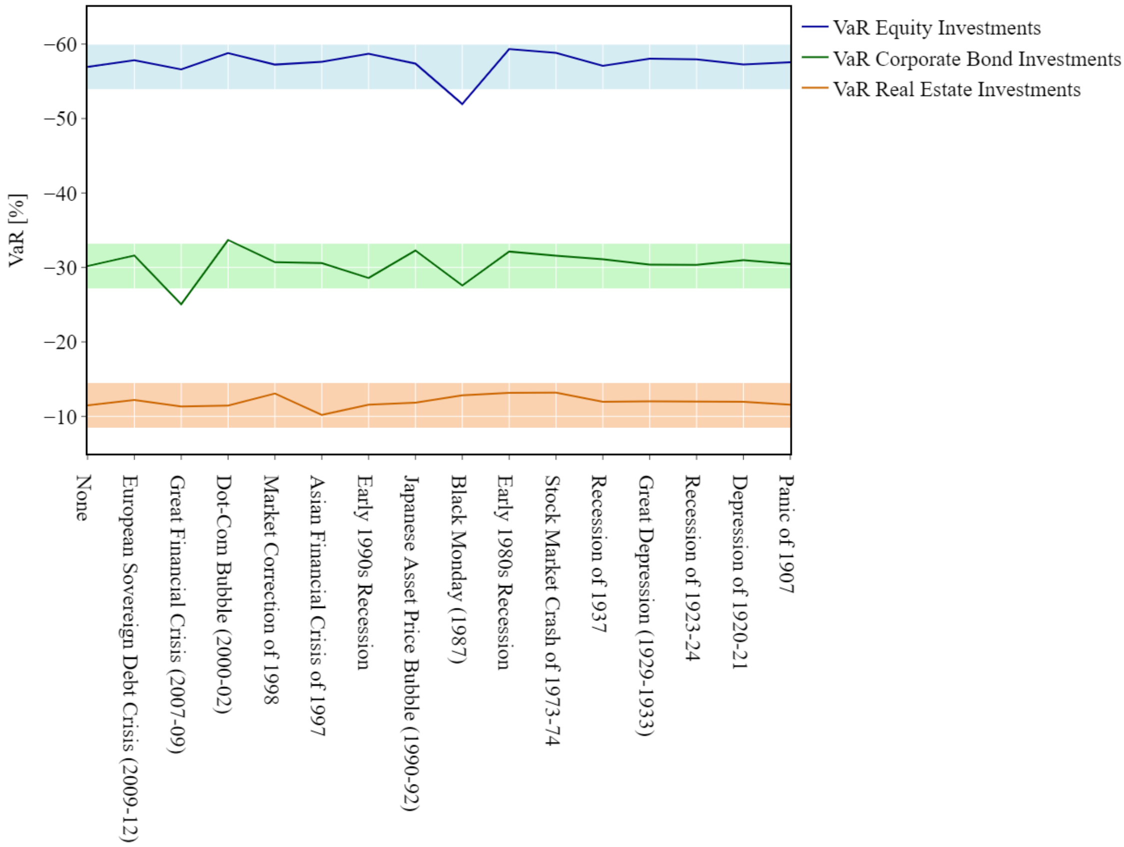

Figure C.3: This figure presents the changes in the value at risk ($VaR_{99.5\%}$) as a single crisis is removed. The x-axis states the name of the removed crisis. The lightly colored background represents a $\pm 3\%$ range of value at risk of our original model. We consider our model to be stable, as long as we stay within this defined range. Note, if we remove the Dot-Com Bubble or the Global Financial Crisis, our stability condition cannot be upheld for the value at risk due to the widening of the credit spread. Furthermore, if we remove the Black Monday crash, our model does not uphold our stability condition for the value at risk of equities.

Appendix D

Errata

In a first version of this thesis, average daily performance (ADP) from Equation 3.2 was referred to as volatility (v). This terminology was wrong, as volatility measures the dispersion of returns for a given security. This is different from Equation 3.2, which measures the daily performance of an equity index and averages it out over a given period. However, while the used terminology was incorrect, the thesis never treated the measure as a volatility measure. This can be seen from Equations 4.1 and 4.3. These calculations would not be possible with a normal volatility measure, as volatility has no directional input. Therefore, we would not know if the equity increases or decreases in value. Thus, to avoid any potential confusion, the thesis was updated and the variable was renamed to average daily performance (ADP).

In finance, volatility is usually measured as the standard deviation of return or the square root of the variance. However, by taking the absolute value of the percentage changes of Equation 3.2, the equation can be transformed to approximate a measure of volatility.

$$v = \frac{1}{N} \sum_{n} \left| \frac{I_n^c - I_{n-1}^c}{I_{n-1}^c} \right| \tag{D.1}$$

where:

v = Average volatility
I_n^c = Index closing value on day n
n = A trading day of the crises
N = Number of trading days between observation start and end

By using Equation D.1, we could then identify the following volatility for each crisis (see Table D.1).

Table D.1: This Table reports the equity volatility of each crisis as defined in Equation D.1. Blank spaces mean that the region was unaffected by a crisis. Note, these values were never used by the model defined in this thesis.

Crisis	**United States**	**Europe**	**Japan**
European Sovereign Debt Crisis (2009-12)		1.07E-02	
Global Financial Crisis (2007-09)	1.63E-02	1.49E-02	1.84E-02
Dot-Com Bubble (2000-02)	1.09E-02	1.21E-02	1.30E-02
Market Correction of 1998	1.28E-02	1.40E-02	
Asian Financial Crisis of 1997			1.33E-02
Early 1990s Recession	9.16E-03	9.45E-03	1.92E-02
Japanese Asset Price Bubble (1990-92)			1.30E-02
Black Monday (1987)	2.57E-02	1.99E-02	1.83E-02
Early 1980s Recession	6.77E-03	9.45E-04	4.84E-03
Stock Market Crash of 1973-74	8.85E-03	1.39E-03	7.93E-03
Recession of 1937	1.52E-02		
Great Depression (1929-1933)	1.85E-02	1.92E-03	1.86E-03
Recession of 1923-24	6.82E-03		
Depression of 1920-21	9.56E-03		3.16E-03
Panic of 1907	1.12E-02		

While we already stated that these values could not be used in our model because of Equations 4.1 and 4.3, it would still be interesting to see if we can identify a regression relationship between v and crisis duration. This would then present a similar regression relationship as we identified between ADP and crisis duration.

As can be seen from Figure D.1, a similar regression relationship would be possible. However, the quadratic relationship between volatility and crisis duration is insignificant. Thus we used a linear relationship. Furthermore, we note that R^2 would become much smaller than the R^2 we found for the relationship between ADP and crisis duration. This means that less of the variance for a dependent variable is explained by an independent variable. Even though we were able to find a statistical relationship, the fundamental issue would remain. We would be unable to convert our volatility into peak to trough values and annual equity losses without any directional input. In consequence, a new model with new mathematical relationships would need to be defined to incorporate a volatility measures into this thesis.

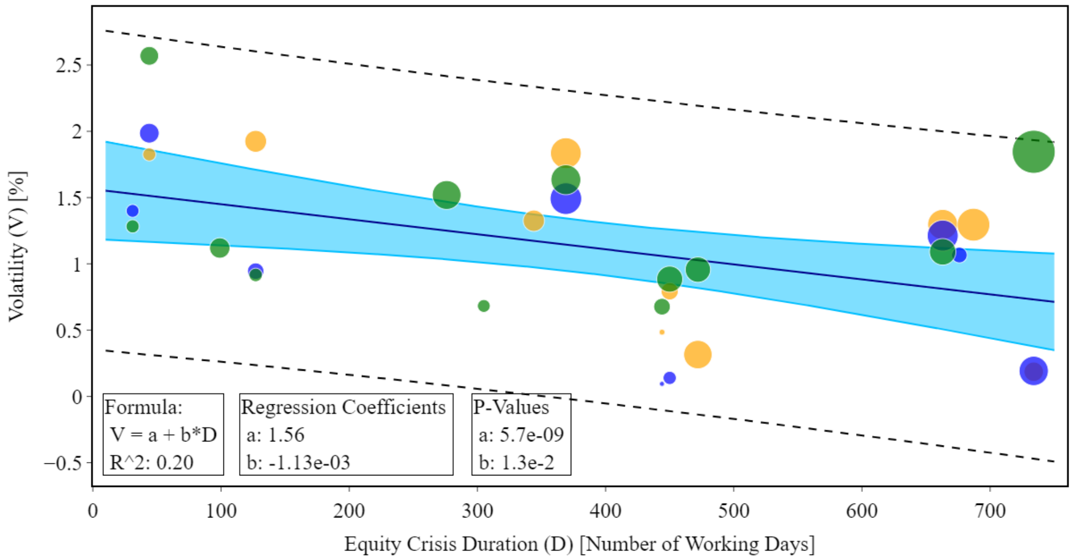

Figure D.1: This figure presents the linear regression between equity crisis duration in working days and average volatility. The diameter of the data points is proportional to the peak to trough value of the equity index and colored according to their economic region (US - green, Europe - blue, Japan - yellow). The blue line represents the regression line, the light blue area the 95% confidence interval, and the area between the two dashed lines the 95% prediction interval.

To conclude this Errata, it can be stated that even though we called the variable volatility in the first version of this theses, we never treated it as such. This can be seen from the fact that our approximations of peak to trough values and annual equity losses (see Equations 4.1 and 4.3) would not be possible if we used a volatility measure. In consequence, this also explains why we were able to fix this error by renaming the variable average daily performance (ADP) instead of volatility.

Courtesy goes to Prof. Dr. Didier Sornette for pointing out this error.

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