Predicting and Assessing Economic Crises

Master Thesis I:

Estimating and Comparing Early Warning Models for Financial Crises

Submitted to Università Commerciale Luigi Bocconi (Milano, Italy) in June 2020

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Disclaimer:

Both theses have been written and submitted in accordance with the framework of the Double Degree Program in Finance between Stockholm School of Economics (Home School) and Università Commerciale Luigi Bocconi (Host School). Both theses can be read independently.

The former thesis was submitted as an independent piece of work in June 2020 to Università Commerciale Luigi Bocconi and was defended ibidem in July 2020. The thesis is in line with both universities standards and regulations and constitutes 18 ECTS.

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MASTER THESIS I

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Estimating and Comparing Early Warning Models for Financial Crises

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Abstract

After a long period of strong economic development, the global economy should according to its natural economic cycle be heading for a recession. While stock market prices were still booming and housing prices continuously growing in January 2020, experts started raising concerns about the economy approaching a new financial crisis.

Firstly, this paper discusses and evaluates some of the key triggers and key indicators to a potential financial crisis that professionals and authorities have shared with the public. Secondly, it estimates the probabilities of upcoming financial crises in selected OECD countries by further developing, validating and applying two existing early warning models. The models are constructed by a logit regression estimated on 32 and 15 countries respectively, using available data from 1980-2018 and 1970-2019 respectively.

Both the quantitative and qualitative results identify multiple vulnerable countries with high risk to enter a financial crisis state in case of another substantial market shock. The findings contribute to the existing literature by further developing and validating early warning models, applying them to predictions of the future economic state and comparing results across the models.

Keywords: early warning indicators, economic vulnerabilities, financial crisis forecasting, early warning models, macroeconomic imbalances

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Estimating and Comparing Early Warning Models for Financial Crises

1. Introduction

Financial crises are extremely costly and have occurred with a cyclical pattern. To limit the negative effects of financial crises on society and enterprises, it is of utmost importance for governments, central banks and market participants to regularly be updated on signals regarding an upcoming financial crisis. This study is devoted to the development, evaluation and comparison of models for predicting a financial crisis in the upcoming 5-12 quarters[1]. These models are furthermore applied to the global economic state as of January 2020.

The most recent global financial crisis (GFC), that occurred in 2007-2009, implied enormous costs for taxpayers, policymakers and the society (Beutel, List and Von Schweinitz, 2018), and some countries have still not fully recovered after it. Furthermore, the GFC has triggered a new wave of research on early warning models (EWMs) for financial crises. These models are used by central banks to monitor the stability of the financial system and to guide macroprudential policy (Drehmann and Juselius, 2014). The EWMs aim to recognize early warning signals, making it possible to activate macroprudential policy tools in time and to prevent the issuance of false alarms that might lead to costly over-regulation of the financial system.

During the past twelve months, in relation to the 10th anniversary of the GFC, multiple experts reported their concerns regarding an upcoming crisis to the press, predicting a new global financial crash in 2020 (see for example Stubley, 2018; and Mauldin, 2018).

[1] The current Covid-19 crisis is not considered as a financial crisis.

According to experts, a recession would have been a natural part of the economic cycle even without the Covid-19 pandemic outbreak. While experts now agree that a recession will occur in 2020 due to the Covid-19 outbreak, there is no clear consensus whether it will also trigger a financial crisis. Furthermore, a financial crisis might not occur in all countries, however, the larger and more important a country that fails is, the larger impact it will have on the global economy. A failure in one important country, might in turn force other countries to enter a financial crisis state.

This paper qualitatively analyzes current levels of selected early warning indicators (EWIs) for developed European countries and other selected large economies. EWIs are compared to previous pre-crisis levels and thresholds suggested by large authorities, such as the Bank of International Settlements (BIS) and the European Commission. Following the qualitative analysis, a quantitative approach using previously developed EWMs is applied. By combining the results from two different EWMs with the outcome from the qualitative analysis, the study evaluates whether there persists a high risk of an upcoming global or national financial crisis in the upcoming two years given the economic state in January 2020. Even though the Covid-19 crisis emerged in February 2020, it is not yet considered to lead to a global financial crisis. This study could therefore still contribute with valuable information for governments, central banks and market participants both in current times as well as for their future financial crisis evaluation procedures.

While this study mainly focuses on developed European countries, it is important to also include certain advanced global economies in the analysis, such as the US and Japan. These economies play a major role also for the European financial market due to the strong link and possible contingency effect they could have on the European economy. The background section is therefore presented both from a broader global perspective to mirror the current situation in the global developed economy, as well as from a European perspective.

The study is divided into six sections. Following the current introduction section, Section 2 gives a qualitative background to the rising concerns notable in media and compares the current economical state to previous pre-crisis levels. The section also gives an overview of previous relevant literature. Section 3 introduces the methodology and data underlying the qualitative and quantitative analysis and presents a summary of the qualitative analysis. Section 4 presents the main analysis and results from the quantitative approach based on the two EWMs. Section 5 discusses the implications of the findings and compares the results from the quantitative and qualitative approaches. Section 6 concludes the study and is then followed by references and appendices.

2. Background and Previous Literature

2.1. Background to the Rising Concerns

A natural economic cycle consists of four stages, namely expansion, peak, contraction and through, which can variate in length. The cycle can be identified as either a business cycle if mainly driven by GDP movements, or as a financial cycle if based on house prices and credit levels. Business cycles generally tend to last from two to eight years while a financial cycle, which typically makes the economy suffer more during contraction, around 15 to 20 years since the 1980s (Borio, C., Drehmann, M. and Xia, D., 2018). While a financial cycle tends to show little correlation with the business cycle, it is highly correlated to the medium-term GDP (longer than eight years). Also, it has been shown that major peaks and throughs of business cycles are aligned with those of financial cycles (Rünstler, G., 2016). A financial cycle tends to peak with banking crises or considerable financial distress. This happens as credit rapidly increases driving up property and asset prices. In turn, collateral values increase making it possible for the private sector to obtain even more credit. The spiral continues until an unexpected event occurs, disrupting the process and making it go into reverse.

Overall a financial crisis can be described as efficiency losses in the financial market and imbalances in the banking sector, such as sudden large changes in the pricing and quantities of financial instruments. It differs from a general recession by having a much faster and larger peak-to-through percentage decline in the GDP (Padhan and Prabheesh, 2019). Within the definition of a financial crisis, one can distinguish between banking crises, currency crises and sovereign debt crises, which can also occur at the same time. Neither type of crisis has a strict definition but is usually assessed both on quantitative and qualitative criteria. The most frequent type of financial crisis is the banking crisis, also known as a systemic crisis. A banking crisis is generally defined as significant distress or failure in one or multiple banks in the economy. It has a contagion effect on the national or even global economy and a mean duration of 15 quarters (Babecky, et. al., Oct 2012).

The last notable financial crisis that hit the whole global economy was the Great Financial Crisis (GFC) in 2007-2009. It had major consequences for all the largest world economies, such as major drops in GDP, a drastic increase in unemployment rates, huge amounts spent by governments on programs and bailouts, large losses of household wealth as house prices and stock prices dropped, and an unmeasurable amount of human suffering as the number of people in poverty increased (Childress, S., 2012). While the cycle reversed into an expansion phase, many economies have still not fully recovered from the dramatic downturn.

Until January 2020, the global economy witnessed a long period of expansion, exceeding eleven years in many European countries and other large economies. This naturally increases a countries credit levels, giving rise to concerns across experts, banks and authorities. While economies have tried to stay away from costly recessions, studies have shown that business cycles may not die of old age. Furthermore, when financial booms develop, the cycle becomes more fragile (Borio, C., Drehmann, M. and Xia, D., 2018). In the next section, an introduction of the main concerns emphasized by different experts, banks and authorities are presented.

2.1.1. Global Authorities, Banks and Experts are Forecasting a Depressing Year

In recent months debates in the media have been fueled with experts, global banks and large authorities warning for a new financial crisis. There are multiple potential triggers mentioned to cause this eruption. The underlying motivation is the rising debt levels among households and corporates in combination with the expected increase in interest rates by the European Central Bank (ECB) and Federal Reserve (FED) (International

Monetary Fund [IMF] 2019; World Bank, 2020). An increase in interest rates might create difficulties for debtholders to maintain their interest payments or repay their outstanding debts.

Global authorities such as the Organisation for Economic Cooperation and Development (OECD), the World Bank and the International Monetary Fund (IMF) have all in their most recently published semi-annual economic outlook reports, published before the Covid-19 global outbreak, revised forecasted GDP growth numbers lowering the numbers to a post-crisis low. Also, they all emphasize the currently high levels of debt as well as the importance of a well-functioning monetary policy (OECD, 2019; IMF, 2019; World Bank, 2020).

Large global banks, such as J.P. Morgan Chase, Morgan Stanley and UBS, presented major concerns about the global economic situation already before the pandemic outbreak (Anstey, 2018; Winck, 2019; UBS, 2019). In the most recent edition of "The future of Europe" (2019), UBS blames the Federal Reserve (FED) for tightening the yield curve increasing the recession risk. Furthermore, they presented a forecast of three different Eurozone growth scenarios based on the extent of the recession (see Figure 1 below). The expansion scenario includes a normalization of monetary policy and growth to migrate towards the growth according to the economic trend of -1 percent per annum in 2024-2025. The moderate recession scenario implies recession in the early 2020s in conjunction with the European Central Bank (ECB) lowering the deposit rate to the lower bound of -1 percent and proceeding with massive asset purchasing programs in the upcoming five years. The third scenario implies a severe recession that can be comparable to the size of the GFC, posing severe damage to the economy in terms of bail-in of banks and drastically increasing unemployment rates. In the last scenario, the inflation turns into modest deflation that doesn't turn to its prior peak until 2027-2028. With the Covid-19 crisis pushing the global economy into a recession, the last-mentioned scenario seems to be the most probable. This would thus imply another major global financial crisis.

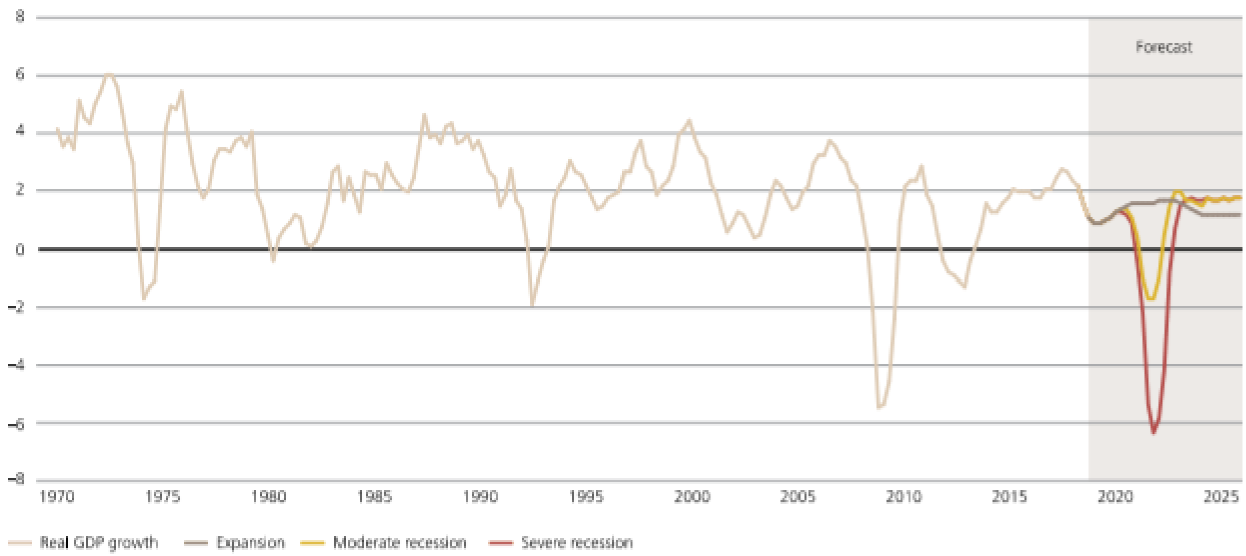

Figure 1. Eurozone Growth Scenarios according to UBS report, Real GDP growth, in percent year over year

Source: ECB, Haver Analytics, Oxford Economics, UBS

Famous economic newspapers keep raising awareness about the current unstable economic environment through different social media channels. Famous founder and author Ray Dalio and author Robert Kiyosaki have been debating in multiple television programs by among others CNBC, Bloomberg and Business Insider, explaining their view of the current economic environment. In the interviews they emphasize the high debt levels, the inefficient monetary policy and the overvalued stock markets, making cash less valuable and thereby suggesting diversifying investments into safe haven assets such as gold (CNBC, 2018, Sep 11 & 2020, Jan 21; Business Insider, 2018; Bloomberg Markets, 2019). Ray Dalio also argues that the market environments are very similar to the ones before the Great Depression in the 1930s, with low interest rates, high debt levels and asset purchasing programs initiated by the central bank.

As can be seen, there is no clear consensus among experts, institutes and authorities whether the economy is heading for a financial crisis or just a normal recession. However, there is a clear consensus about a decrease in economic growth and GDP growth, predicted to have occurred even without the Covid-19 pandemic. According to Diks', Hommes', and Wang's (2018) study, a critical slowing down in the economy, such as caused by the Covid-19 pandemic, has in multiple previous cases been shown to proceed with market collapses. To further discuss the potential risk factors highlighted by experts in the field, the following sub-section presents selected possible trigger events that could give rise to a new financial crisis.

2.1.2. Potential Triggers of a Financial Crisis

As previously described, a financial crisis can in a simplified way be explained as a process where there is a fast increase in an economy's debt levels which drives up asset prices, which in turn increases debt levels further, creating an upward going spiral, until the spiral breaks. The process typically seems stable until an unexpected event occurs triggering the reversion of the spiral. This event can trigger unexpected defaults in loans, which happens to be backed up with overvalued assets, which then triggers other defaults. While the Covid-19 pandemic can be seen as a trigger to such a process, this section aims to list a couple of other potential triggers that were identified by experts before the Covid-19 crisis outbreak and that can still be considered as relevant both in the current state of the economy as well as in the future.

- Worsening trade and geopolitical tensions, where increased trade barriers and higher trade and geopolitical tensions can worsen productivity growth. (Khan, 2019)
- Automated trading systems creating stock market imbalances (Stubley, 2018)
- No-deal Brexit withdrawal of the UK
- Contagion from a local credit crisis (Mauldin, 2018)
- Lack of measures that can rebuild macroeconomic policy space and undertake reforms to rekindle productivity growth (World Bank, 2020)
- Contagion from the manufacturing sector recessions in the US and Germany

The prevalence of such trigger events can only be speculated about and both the probability of them occurring as well as the consequences they would imply are extremely difficult to estimate. The underlying problem, i.e. credit booms driving up asset prices, can however still be analyzed using financial and economic EWIs. In the next section, an analysis of different categories of EWIs used in this study is carried out.

2.1.3. Categories of Indicators Used for Assessment of Financial Crisis

Multiple crises have been preceded by asset price booms, such as the GFC, and in Spain, Sweden, Norway, Finland and Japan between the 1970s and 1990s (Reinhart and Rogoff, 2008, 2009). Highly debt-leveraged assets when asset prices are high imposes a risk of financial indebtedness if asset prices decrease making borrowers unable to pay. This section presents three different categories of indicators that can be used for predicting an upcoming financial crisis:

i) credit development
ii) growth in asset prices
iii) monetary policy

For the first two categories, that will be in focus throughout this thesis, a comparison of current levels to pre-crisis levels is carried out. These are also the variables assessed in the qualitative analysis using thresholds proposed by the European Commission. Focus on the first two categories is put due to the possibility to analyze them on a cross-country basis. More vulnerable countries, i.e. countries that face a higher risk of crisis, can then be distinguished so that they can be monitored more closely.

The third category is related to monetary policy that could act as a stabilizing tool if responding efficiently to crisis signals, or if handled incorrectly, as a trigger of a financial crisis.

In addition to the three mentioned categories, also other variables related to internal and external imbalances will be assessed in the EWMs.

2.1.3.1. First indicator: Credit Development

Global debt is at all-time highs and many economies are running fiscal deficits already for many consecutive years (World Bank, 2019). Total debt of an economy can generally be divided into three categories: household debt, corporate debt and public sector/government debt. Furthermore, household debt and non-financial corporate debt, when summed up, are named as private sector debt. The current development of debt within each category will be analyzed separately in the following sub-sections.

Household debt is increasing in forms of credit card loans, auto loans, house loans and student loans. Globally, auto loans have reached record-high levels, especially in the US with seven million Americans being behind on their auto loans. Also, the US student loans have more than doubled since 2008 and impose a systemic risk due to their high default rate and uncertain payoffs (CNBC, 2018 Sep 22 and Warren, 2019). In the Euro Area, households' debt is at high levels and deleveraging has slowed down more markedly in recent years, specifically in the UK, Sweden, Belgium, and France (Alert Mechanism Report [AMR], 2019).

Corporate debt levels are high, mainly due to the low-interest rates, making it much more attractive for corporates to take up loans or issue bonds (Warren, 2019). Especially the bond market has plunged in the low-interest environment as investors are searching for yield by borrowing at low cost and investing in much riskier and illiquid securities through bond or equity investments (IFM, 2019 Oct).

Private sector debt to GDP (see Figure 2 below) has over the last years increased the most in the Euro Area. Since the GFC both Japan and the US have been able to keep the ratio stable or reduced it, while the Euro Areas private debt level has significantly risen. European Commission recommends keeping private debt levels below 133% of GDP, which has visibly not been achievable in the last 18 years. (BIS, 2019; MIP Scoreboard 2019).

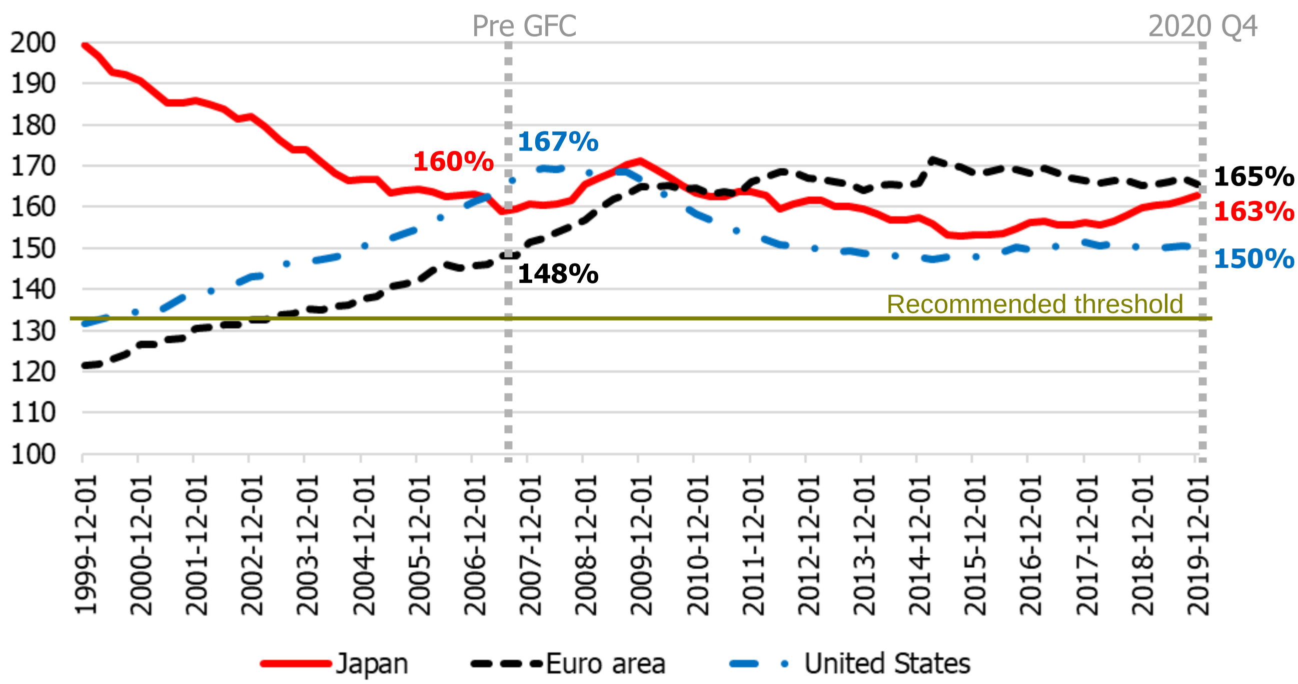

Figure 2. Quarterly Private Sector Debt of the Non-financial Sector as % of GDP, Adjusted for breaks (%)

Source: BIS

Note: The data displays borrowing activity of the private non-financial sector which consists of both non-financial corporations and households (including non-profit institutions serving households). The numbers illustrated for each respective country corresponds to the observations as of 2007-09-30 (just before the GFC) and 2019-12-31 (which is the last data available).

Public sector debt, i.e. government debt, is as of 2019, above $17 trillion in the US and has been growing at an extremely fast pace since the GFC, mainly driven by bond issuances. The sovereign bonds are trading at abnormally low levels with over $6.5 trillion in negative-yielding bonds impacting pensions and insurance companies. In the EU as of 2019, the government debt as % of GDP exceeded the European Commission's recommendation of a maximum of 60%, in 14 member states. Furthermore, some of the highest public debt ratios did not improve since 2018, remaining unchanged in France and increasing in Cyprus, Greece, and Italy (EU Commission, 2019).

Government debt levels in Europe, the US and Japan, as can be seen in Figure 3 below, are all significantly above the recommended thresholds of a maximum of 60% of GDP and have increased dramatically since the GFC.

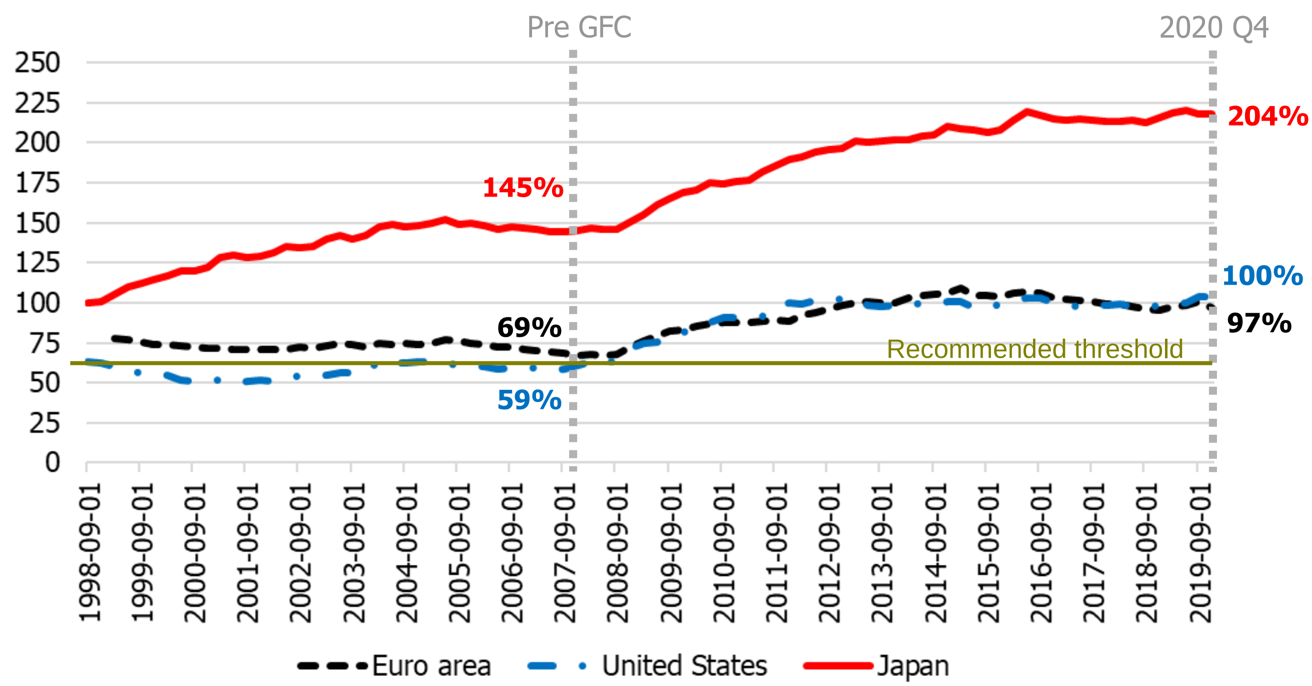

Figure 3. Quarterly Government Debt to the Non-financial Sector as % of GDP, Adjusted for breaks (%)

Source: BIS
Note: The graph displays the borrowing activity of the government sector from all sources of financing. The numbers illustrated for each respective country corresponds to the observations as of 2007-09-30 (just before the GFC) and 2019-12-31 (which is the last data available).

Total credit to GDP, including both the private debt and government debt, (see Figure 4 below) has increased drastically since the GFC in all areas assessed, most notably in the Euro Area and Japan. Currently, total debt is more than 2.5 times higher than GDP across all regions and almost 3.7 times higher in Japan.

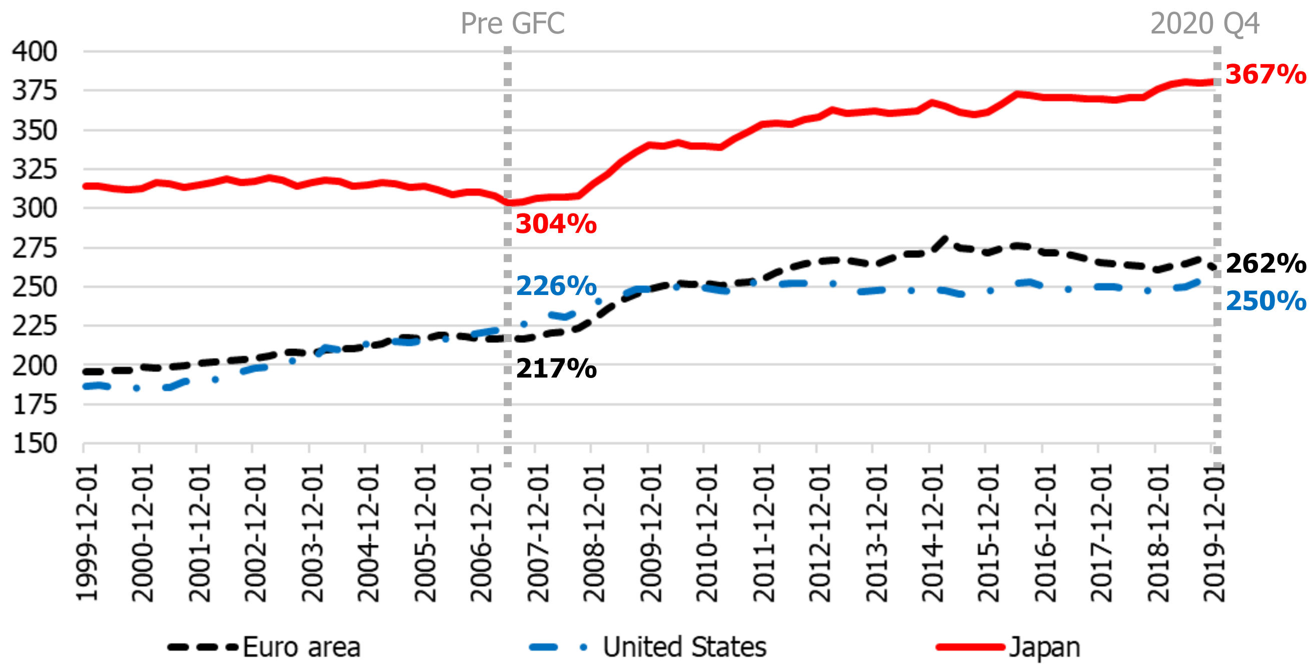

Figure 4. Quarterly Total Credit to GDP Ratio (%) – Including both the Private Non-Financial Sector and Government sector

Source: BIS
Note: The data displays borrowing activity of the non-financial sector including both the private non-financial sector and the government sector. The numbers illustrated for each respective country corresponds to the observations as of 2007-09-30 (just before the GFC) and 2019-12-31 (which is the last data available).

The analyses of credit development indicate very high leverage across all types of debt, which especially in the Euro Area and Japan have constantly been increasing, currently being at levels above the ones during the GFC. Excessive levels of credit point towards an increased risk of the economy being in a credit bubble.

2.1.2.2. Second indicator: Asset Prices

The global stock market and house prices in many parts of the world have been growing rapidly since the financial crisis. In the American financial market, the price-to-earnings ratios are 50 percent above the historic average, private-equity valuations have become excessive, and government bonds are too expensive, given their low yields and negative term premia (Roubini and Rosa, 2018).

Commercial and residential real estate is said to be far too expensive in many parts of the world. With the housing prices increasing every year faster than the GDP and wages, also the household debt related to housing have increased at a radical pace. For example, the house prices have grown faster than income in half the EU Member states during 2018 (AMR, 2019).

According to the European Commission Alert Mechanism Report (AMR) 2020, house price valuations are in a growing number of EU Member States above peaks since the mid-2000s and likely to be overvalued. In some countries, new mortgage credit appears on the rise, which could lead to further house price accelerations going forward. The European Commission also reported that the recommended threshold (maximum 6% yearly growth in house prices) may be surpassed this year by several countries.

Comparing the real house prices in Figure 5 below, using 2010 as a base year index, it is notable that prices across all geographies have been consistently growing since 2013, most notably in the US. Moreover, current levels are similar to the levels just before the GFC.

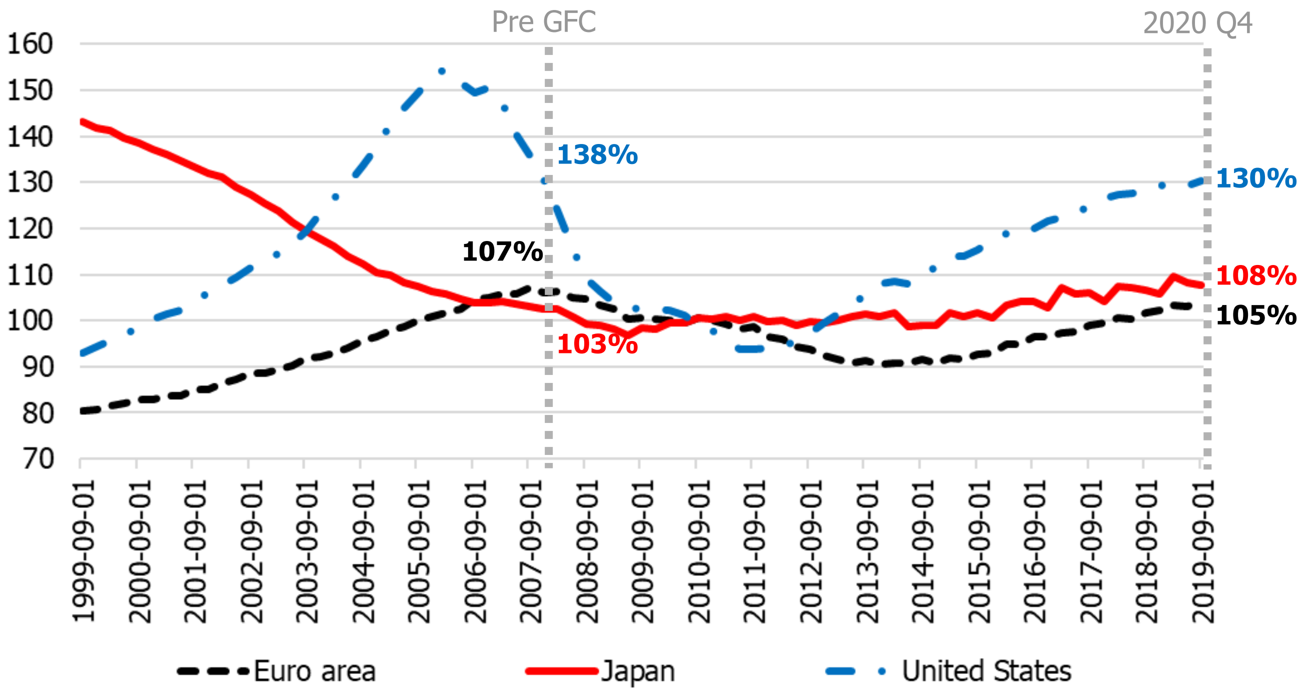

Figure 5. Quarterly House Price Index (Base year 2010) – Price Development in Euro Area, Japan and the US over the last 20 years

Note: The real house price index is based on 2010. The numbers illustrated for each respective country corresponds to the observations as of 2007-09-30 (just before the GFC) and 2019-09-30 (which is the last data available).

Following this, there could exist a house pricing bubble backed up by debt that in case a financial crisis is triggered, could burst and heavily harm the economy.

2.1.2.3. Third indicator: Monetary policy

The major central banks, FED and ECB, being the main monetary policy drivers, have for a long time communicated their intentions to increase the repo rate and implement a second round of quantitative easing (QE). While the economy is not able to catch up with this growth, there are major economic risks that these policies bring which can trigger a financial crisis.

The repo rate determined by the central banks is the interbank lending rate, which also affects the interest rates charged to corporates and households on their borrowings. Central banks have in recent months been determined to increase interest rates and thereby the borrowing costs, mainly to make it less affordable for households and corporates to take on loans and thus reduce the overall amount of debt outstanding. However, as the GDP growth is slowing down and the wages are not increasing, households, to meet their expenses, will either borrow more money or start saving more by consuming less. Borrowing will increase the leverage further imposing an even higher economic risk, while consuming less will slow down the economic growth further. When this happened during the GFC, collective bargaining and flexible contracts grew (Inman, 2019). When people are unable to bargain for a comparable salary in relation to their expenses, they will start failing on their loans. Lack of fixed working contracts and the inability of companies to pay high wages will further lead to increasing unemployment rates, further slowing down the economy.

QE, previously introduced by ECB in 2015, is a monetary policy tool where the central banks buy a large scale of assets, such as government bonds and financial assets according to a predetermined amount. This, in turn, increases the money supply, keeping the inflation up, while lowering the yield of the financial assets. Thus, working in the opposite direction of increased repo rate discussed above. FED lending money in the form of QE also poses a risk on the value of the US dollars, historically considered as a safe haven asset. A global rush to liquidate US dollars, other US debt and other dollar assets could generate a severe financial crisis (Focus Economics S.L.U., 2018).

Monetary policy can act as an efficient tool to stabilize the economy, but if used incorrectly it can instead harm it. Therefore, it is of great importance to carefully evaluate an economy's risk of a financial crisis so that the central banks can take appropriate action. Also, the development of the interest rate can be a valuable parameter to include in the modeling.

In summary, there are verifiable reasons for the raised concerns regarding a potential crisis. With these motivations, it makes sense to look back at previously developed EWMs to analyze the current economic state. In the following sections, a brief overview of previous models developed is given, as well as arguments for the choice of models used in this study.

2.2. Previous Literature on Early Warning Models

These sections aim to present different types of previously developed EWMs to better understand the tools available for crisis detection. The sections also serve the role of motivating the choice of methods used in this study.

2.2.1. Indicators and Corresponding Thresholds set by Authorities

Since the GFC, authorities, financial institutions and researchers have increased their focus on developing and utilizing qualitative and quantitative methods to detect financial crises. Authorities have proposed thresholds for multiple indicators related to economic imbalances, supposed to help to detect early warning signals of financial crises and to track the recovery process post crises. For example, the European Systemic Risk Board (ESRB) has developed a Dashboard with a set of quantitative and qualitative indicators monitored quarterly, while OECD has developed a set of 70 vulnerability indicators to detect risks (Röhn, et. al, 2015). In this study, the focus has been put on the MIP Scoreboard introduced by the European Commission in 2011.

The MIP Scoreboard is an oversight mechanism with 14 indicators related to the external position of the economy, private sector debt, house prices, the financial system and the labor market. The tool aims to support the early identification and monitoring of imbalances. Indicators are accessed annually in the AMR where the presence of risks is denoted if any indicator crosses its corresponding threshold. Kamps et al. (2014) have in their study showed that the MIP would have been able to give early warnings to the Great Recession. The crisis assessment method is very simple and typically compares single indicators to corresponding thresholds and counts the number of indicators crossing those thresholds for each given country.

2.2.2. The Scope of Early Warning Models

When setting up their macro-prudential policies, policymakers and large authorities can also use models as tools. In recent years academic interest in EWMs has increased considerably. Various papers have shown that there seem to be common patterns in the data that often precede financial crises (for example Borio and Lowe, 2004, or Reinhart and Rogoff, 2008). Some EWMs can be applied both on global and on country-specific levels and the preferred indicators vary depending on the width of geography.

Developing an EWM is a complex task and involves numerous assumptions regarding, for example, real-time information lags and model validation and calibration. Recent contributions to this literature employ different econometric methods, prediction horizons, evaluation approaches and datasets. It is also of importance to adjust the model after the size of the crisis. Macroprudential crises typically use longer prediction horizons of 5-16 quarters, while micro-prudential crises require shorter forecasting, up to eight quarters (Beutel, List and Von Schweinitz, 2018).

Various modeling techniques have been developed for EWMs. While the older models are generally based on traditional statistical approaches, more recent studies have focused on developing more flexible modeling techniques involving machine learning techniques. Holopainen, M. and Sarlin, P. (2016) developed a taxonomy for different predictive EWMs (see Figure 6 below) that covers the most common existing models and discusses their characteristics.

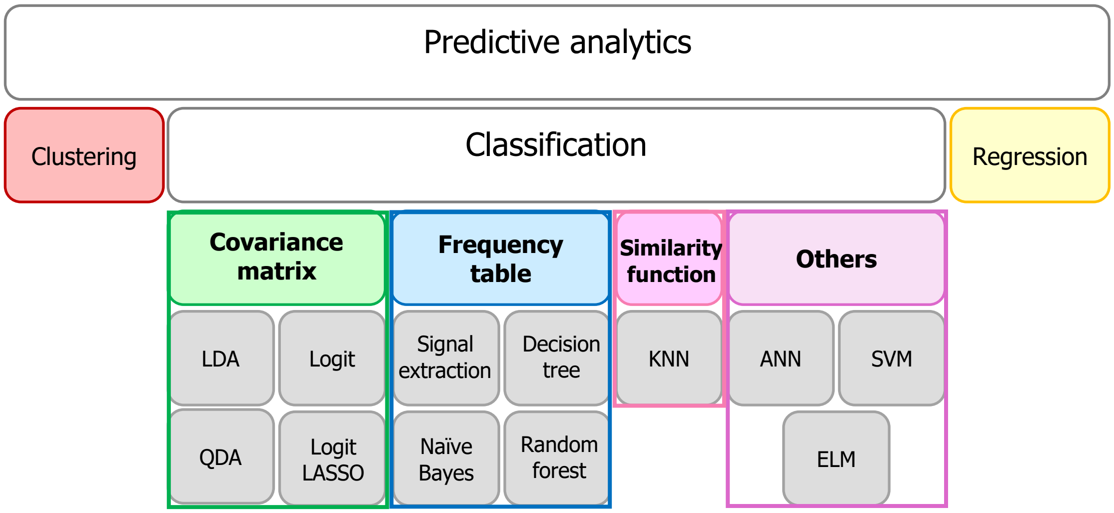

Figure 6. Methods used across different Early Warning Models

Note: The figure is based on the research by Holopainen, M. and Sarlin, P. (2016) but color-coded to mirror the different categories of models.
Abbreviations: Linear Discrimination Analysis (LDA), Quadratic Discriminant Analysis (QDA), k-nearest neighbors (KNN), Artificial Neural Networks (ANN), Extreme Learning Machines (ELM) and Support Vector Machines (SVM)

The grey boxes in Figure 6 above, include all different modeling techniques that were identified by the authors. They are classified into different evaluation methods.

Some of the models are relatively simple, such as the Signal extraction, Linear Discrimination Analysis (LDA) and Quadratic Discriminant Analysis (QDA). They are rather limited and have clear disadvantages in comparison to other models assessed here. The signal extraction method simply calculates a separate threshold for each indicator such that observations on one side of the threshold are seen as crisis signals while those on the other side are not (Sondermann and Zorell, 2019).

Logit analysis is a more common methodology for predicting financial crises and has been further extended to Logit Lasso. Beutel, List and Von Schweinitz (2018), comparing models for the case of banking crises, found the most robust results using a traditional multivariate logit model, as this model was able to issue relatively accurate warnings before the GFC for many countries.

Naïve Bayes, Decision tree, Random Forest, k-nearest neighbors (KNN), Artificial Neural Networks (ANN), Extreme Learning Machines (ELM) and Support Vector Machines (SVM) are all more advanced methods that apply machine learning techniques. Models using machine learning techniques are more flexible than the other models as they contain a much larger number of parameters. However, according to Beutel, List and Von Schweinitz (2018), they have been shown to perform worse in forecasting than the logit models mainly due to the high risk of overfitting sample data. Besides, machine learning methods are usually more difficult to interpret in terms of coefficients. Thus, the authors concluded that further enhancements to machine learning EWMs are needed before the models can offer a substantial value-added for predicting financial crises.

As the analysis this study aims to conduct focuses on predicting the future (ex-ante analysis), out-of-sample analyses must be conducted. From the comparison of out-of-sample performance made by Beutel, List and Von Schweinitz (2018), a clear benefit can be seen in using logit models. Thus, the next section looks further into the framework of logistic models.

2.2.3. The Logistic Regression

The logistic regression approach was first implemented in the early warning literature in 1996 by Frankel and Rose. They developed a logistic model using 16 explanatory variables. Over the years the approach has gained popularity due to its simplicity and flexibility. In the last decade, even though machine learning has been gaining popularity, researchers keep developing multivariate discrete choice models using logistic regressions (see for example Bussière and Fratzscher, 2006 and Lo Duca and Peltonen, 2013). The key advantage of a logit model is that it is based on straightforward statistical modelling which also considers uncertainty.

There are three main advantages identified with multivariate models in comparison with the signal extraction method used for example in the MIP Scoreboard analysis. While the MIP Scoreboard methodology compares every single variable to a certain threshold separately, the explanatory variables in a logit regression can be assessed jointly accounting for the correlation of the variables. Secondly, the models allow assessing the relative importance of individual indicators. Lastly, using the logit approach, tests can be performed to compare the statistical significance of individual variables and coefficients across countries and time (Sondermann and Zorell, 2019).

In summary, MIP Scoreboard, based on signal extraction, just comparing thresholds with actual values across different indicators, is the simplest method commonly used for detecting potential crises. Logit models, on the other hand, being one of the most studied groups of EWMs has proved to outperform other models in out-of-sample analysis.

The following section presents the selection of methods used in this study.

3. Qualitative and Quantitative Approaches for Crisis Estimation

3.1. Selection of Models for Detection of Early Warning Signs of Crises

To detect early warning signs of financial crises in current times, this study will implement three different methods. Firstly, it will apply a simple qualitative method by comparing EWIs to existing thresholds. Secondly, it will forecast probabilities of financial crises using two multivariate logit regression models. To limit the scope of this study, the focus has been put on assessing major developed economies in Europe, as well as the US and Japan across all three assessments. For the qualitative analysis, selected MIP Scoreboard thresholds and indicators are used, while specifications of the two following multivariate logit models, used for developing and validating the warning signs, are based on:

1. Beutel, List and Von Schweinitz (2018)
2. Sodermann and Zorell (2019)

The two logit models are based on different sets of vulnerability indicators related to the three underlying categories of key variables introduced in the background section (Credit development, Asset prices and Monetary policy & Imbalances). The first model is primarily based on gap variables, i.e. the deviations of actual values from the estimated trend in each country. The second model is instead mainly based on 3-year changes in values of each indicator.

In the remainder of this paper, the model, which is implemented analogously to the specification of Beutel, List and Von Schweinitz will be called "Model 1", while the model similar to Sodermann and Zorell's specification will be called "Model 2". When referring to a model's "benchmarking study", I refer to the corresponding benchmarking regression in the authors' published paper.

The next sub-section will present the assessment made using the qualitative approach.

3.2. The Qualitative Approach based on the MIP Scoreboard Analysis

The qualitative analysis focuses on selected indicators from the MIP Scoreboard introduced by the European Commission. Macro-economic imbalances are detected by simply counting the number of thresholds crossed by each country in a year. Not all the 14 indicators used in the MIP Scoreboard are directly related to the detection of a financial crisis. Thus, indicators are selected based on the key indicators identified in the background section, i.e. credit development and asset prices. The three indicators selected from the MIP Scoreboard, together with the corresponding thresholds are:

1. Government Debt to GDP
2. Private Sector Debt to GDP
3. One-year change in the House Price Index

While the first two indicators are identical to the ones assessed in the background section, they are now interpreted in 2019 for every selected country separately.

Table 1 below, summarizes the findings. Every indicator of a country that is above the given threshold is marked blue. In this analysis, countries assessed to be experiencing excessive credit risk are selected based on the criteria:

- At least two of the three indicators are exceeding the threshold.

For comparison purposes, column four also presents the total debt to GDP, with the yellow cells representing those countries whose total credit exceeds 193% of GDP (i.e. the sum of recommended thresholds for government and private sector debt).

Table 1. Results of Threshold Analysis based on three MIP Scoreboard indicators across relevant countries as of Q4 2019.

Indicators	Internal imbalances			Total debt (% of GDP) (=Private Debt + Gov. Debt)	No of thresholds crossed
	House price index (1 year % change)	Private sector debt (% of GDP)	General government debt (% of GDP)		
Thresholds	6%	133%	60%	N/A	
European countries					
Austria	4.1	139.4*	70.4	209.8	2
Belgium	2.6	185.7	98.6	284.3	2
Czech Republic	6.0	88.0*	30.8	118.8	1
Cyprus	2.0	282.6**	95.5	378.1	2
Denmark	1.2	219.0*	33.2	252.2	1
Estonia	4.4	101.5**	8.4	109.9	0
Finland	0.0	145.6	59.4	205.0	1
France	2.1	215.0*	98.1	313.1	2
Germany	3.9	113.9*	59.8	173.7	0
Greece	6.5	107.7	176.6	284.3	2
Hungary	10.8	67.4	66.3	133.7	2
Ireland	0.1	231.7*	58.8	290.5	1
Italy	-0.5	108.4*	134.8	243.2	1
Latvia	6.0	70.3**	36.9	107.2	1
Lithuania	4.8	56.4**	36.3	92.7	0
Luxembourg	8.1	392.4*	22.1	414.5	2
Malta	4.6	129.8**	44.1	173.9	0
Netherlands	4.7	258.0*	48.6	306.6	1
Poland	6.6	73.0	46.0	119.0	1
Portugal	8.6	150.1	117.7	267.8	3
Slovenia	5.0	69.3	66.1	135.4	1
Slovakia	6.2	92.4	48.0	140.4	1
Spain	3.9	129.7	95.5	225.2	1
Sweden	0.6	205.1	35.1	240.2	1
UK	-0.2	163.9*	85.4	249.3	2
Non-European countries					
Australia*	-5.3	191.2	37.1	228.3	1
Canada*	-1.2	215.4	78.9	294.3	2
Japan*	0.9	162.9	204.1	367.0	2
US*	1.6	150.3	100.1	250.4	2

Source: Eurostat for all European countries, for data not available for 2019 at Eurostat, Q4 2019 from BIS have been used(marked *), and if also that is not available, data from 2018 from Eurostat (marked **) *BIS statistics as of Q4 2019 used for non-European countries. For the second variable: Total credit to the private non-financial sector (core debt) as a percentage of GDP. For the third variable: Total credit to the government sector at nominal value (core debt) as a percentage of GDP.
Thresholds selected are identical to what is used by the European Commission in the MIP scoreboard.

Twelve out of the 29 countries crossed at least two of the three thresholds in 2019 (or 2018, if no data were available for 2019) and are marked orange in the table. These countries can according to the primary qualitative analysis be considered to have a higher risk of entering a crisis stage due to excessive leverage in one or both debt categories and/or whose house prices have been growing at a high rate.

To be noted is that the result differs significantly from the findings in the overall AMR which among the European countries identifies Cyprus, Greece and Italy as countries with excessive imbalances, and France, Germany, Ireland, the Netherlands, Portugal, Spain, and Sweden with imbalances. Thus, only four out of the ten countries identified with imbalances in the AMR report are captured in Table 1. However, as previously discussed, the AMR also aims to identify vulnerabilities not only related to financial crisis detection but also to post-crisis recovery and other imbalances. This analysis instead identifies Austria, Belgium, Luxembourg, Hungary and the UK as at risk. Out of the non-European countries, which have not been assessed in the AMR, Canada, Japan and the US are considered to have excessive leverage.

One reasonable explanation for the deviation, while not taking into consideration the remaining 11 indicators, could be that the government debt levels are considered more important by the European Commission. This would motivate why Greece and Italy are identified with excessive imbalances, having the highest government debt to GDP in Europe. An already high government debt level could make the EU Member States unwilling to give out additional new debt in case of a crisis, posing additional downside risk on the whole union.

Comparing the total debt to GDP to the combined threshold of the private and public debt (133%+60%), the majority of countries (19) exceed the suggested threshold (193%). Among the countries not identified at risk, the Netherlands stands out the most, reaching a debt to GDP ratio exceeding 300%.

In summary, multiple European countries and some of the largest developed economies in the world (Canada, Japan and the US) have in the MIP indicator analysis been identified with excessive credit levels and/or housing prices in 2019. This suggests an increased level of monitoring should be put in place for those countries.

It is, however, impossible to assess the overall situation of an economy just by using a snapshot of selected variables at the end of one year. While one might argue that the method is misleading, it can at least be used for identifying main deviations across countries. Furthermore, building up an effective EWM will make it possible to make a more accurate analysis over time and capture the correlation of the different variables over time in relation to pre-crisis periods, such as the increased risk of a crisis when both credit levels and house prices are low. The following section will present the EWM framework.

3.3. Methodology for the Quantitative Approach

This section introduces the main features of the two logit models used to detect financial crises. The first model is a gap model (Model 1) similar to Beutel, List and Von Schweinitz's (2018) approach and the second model is mainly based on three-year changes in variables (Model 2) as proposed by Sondermann and Zorell. Both models are estimated using a non-dynamic logit method, pooling observations both in the cross-section and the time dimension. As in most EWMs, the models used are based on an evaluation criteria framework for policymakers using a contingency matrix. The first part of the section hence introduces the multivariate discrete choice characteristics of the logistic models, while the second part focuses on the evaluation framework and assessing model performance.

3.3.1. The Multivariate Discrete Choice Characteristics of the Logistic Models

The multivariate logistic models are based on two main assumptions. First, the dependent binary variable, in our case – whether we are in a crisis state or not, is driven by a latent process y^*, which is linearly related to the employed explanatory variables: $y^* = X\beta + \varepsilon$. X is a vector of explanatory variables X_j, where $j \in J$ and β is the vector of coefficients to be estimated. The latent process is assumed to be linked to the binary variable by a logistic transformation, also implying the estimated errors ε follow a logistic distribution. Thus, the crisis probability is given by: $\Pr(Crisis = 1) = \frac{e^{X\beta}}{1+e^{X\beta}}$, based on a $JN * T$ matrix of observations, where N is the number of countries i = {1,2,..., N} and T is the number of years t = {1,2,..., T}. For any country-year observation, the model will produce a crisis probability ranging between zero and one which can then be evaluated against the evaluation criteria presented in the next sub-section. As the logit model is non-linear, the marginal effect of a change in the explanatory variables on the outcome is dependent on the precise state of *X*. The model can therefore also be rewritten as the ratio of the crisis probability to its complement: $\Omega(Crisis = 1) = \frac{P}{1-P} = e^{X\beta}$, meaning that an increase in the *j*:th regressor by one unit, while holding all other variables constant, will multiply the odds ratio by e^{β_j}.

3.3.2. Evaluation Criteria Framework used in Both Models

Every EWM requires evaluation criteria to determine the probability of a crisis. In line with previously introduced EWMs (for example Lang, Peltonen and Sarlin, 2018 and Alessi and Detken, 2014), the probability of a financial crisis starting between the next four to twelve quarters is estimated conditional on not already being in a crisis. For every country-year observation, a crisis probability between zero and one is produced. The estimated probability is then mapped into a binary signal using a threshold parameter *τ*, which will impact decision-making: if the probability exceeds *τ*, the signal is set to 1, implying a crisis warning, if it is less than *τ*, it is set to 0 and thus no signal is issued.

Ex-post the signal turns out either correct or false which can be illustrated in a contingency matrix (see Table 2 below). In other words, the outcomes are classified into true positives, false positives, true negatives and false negatives. The selection of the threshold involves a trade-off between maximizing the number of correct calls issued and minimizing the number of false alarms (FP).

Table 2. A contingency matrix for policymaking

		Actual Outcome, C_n	
		Crisis Occur	No Crisis Occur
Prediction Outcome, P_n	Signal Issued	Correct Call *True Positive (TP)*	False Alarm *False Positive (FP)*
	No Signal Issued	Missed Crisis *False Negative (FN)*	Correct silence *True Negative (TN)*

Source: This contingency matrix follows Holopainen and Sarlin (2017)

In the matrix presented above, there are two types of errors: issuing false alarms (FP) and missing pre-crisis periods (FN). The type I error rate (FN rate) represents the proportion of missed pre-crisis periods relative to the total number of pre-crisis periods in the sample $T_1(\tau) = FN/(TP + FN) \in [0,1])$, while the type II error rate (FP rate) represents the proportion of false alarms relative to the number of tranquil periods in the sample $T_2(\tau) = FP/(FP + TN) \in [0,1])$.

Following this, the loss of a policymaker is computed as a weighted average of T_1 and T_2 according to her relative preferences μ between missing crises and issuing false alarms. The loss function can hence be written as: $L = \mu\left(\frac{FN}{TP+FN}\right) + (1-\mu)\left(\frac{FP}{FP+TN}\right)$, where the loss – L varies between 0 and 1, and μ denotes the policymakers' preference of type I error against type II error. A μ higher than 0.5 reveals that the central banker cares more about missing a signal for a costly crisis than issuing a false alarm. While the choice of μ can be debated, in this study the relative preference parameter is assumed to be μ=0.5, implying the policymaker is indifferent between missing a crisis or issuing false alarms.

3.3.3. Assessing Performance of the Model

To make predictions using the model, data is typically split into training and testing data (out of sample), with training data being larger than testing. Regression is estimated on the training data to estimate the coefficients to be used in the model, and they are then applied to the whole dataset or for the testing data only. To assess the performance of a model, weighting correct classifications of crises against non-correct, four performance measures have been used; (1-FN rate), Relative Usefulness, AUROC and BPS.

1. ***(1-FN rate)*** is the simplest performance measure visualizing the share of crisis observations classified correctly.
2. ***Relative Usefulness*** is based on the loss function model, $L(\mu)$, and the loss of a naive decision rule, $min(\mu, 1-\mu)$ which is assumed to be 0.5:

$$RU = \frac{\min{[\mu, 1-\mu]} - L}{\min{[\mu; 1-\mu]}} = \frac{0.5 - L}{0.5} = 1 - \frac{L}{0.5}$$

   The maximum relative usefulness is therefore 1 when the model is perfectly informative, and 0 or negative if it is not useful.
3. ***Area Under the Receiver Operating Characteristics Curve (AUC or AUROC)*** operates on signals and has the advantage that it aggregates type I errors and type II errors over all possible classification thresholds τ, thus summarizing a model's goodness-of-fit. The AUC can take on values between 0 and 1, with 0 being a misleading, 0.5 an uninformative and 1 a perfect set of forecasts.
4. ***Briers Probability Score (BPS)*** - operates directly on probabilities instead of signals and is given by the mean of the squared differences between predicted probabilities and actual outcomes. The score measures the accuracy of probabilistic predictions between 0 and 1, where a score closer to 0 indicates that the predictions are calibrated well.

The model performance evaluation is carried out after the choice of threshold τ, which is selected so that the False Positive rate (type I error, $T_1(\tau)$) and False Negative rate (type II error, $T_2(\tau)$) combined are minimized, i.e. minimizing the loss function.

3.4. Data used for the Quantitative Approach

To perform the empirical analysis two datasets, similar to the benchmarking studies, have been organized. Even though the two EWMs are based on a similar approach, both the crisis dataset and the explanatory variables are significantly different across the two models. This sub-section thus gives an introduction of the data used in each of the two EWMs, highlighting the main differences across variables.

3.4.1. Key Differences Between the Two Quantitative Models

Even though the two EWMs used are based on the same framework, using logistic regression, the input and the output data will differ. The key differences and similarities across input variables are summarized in Table 3 below. As can be seen, while both the time periods, frequency and number of countries assessed differ, there are still some overlaps in geography, the crises identified and three of the ten explanatory variables being similar before the transformation. The explanatory variables are firstly compared before the transformation, and secondly, after transformation based on their corresponding category.

Table 3. Key parameters across the two different logit models.

Model Characteristic	**Model 1 – Gap based**	**Model 2 – based on 3-years change**
Time period	1971 Q1 – 2019 Q3	1980 2018
Frequency	Quarterly	Annually
Countries	15 OECD countries *13 European, JPN, USA*	32 OECD countries *26 European, JPN, USA*, KOR, CAN, AUS, NZL
No of crises	22	Definition 1: 17, Definition 2: 44
Definition of crisis	22 crises from the ECB and ESRB database	Definition 1: 17 crises using BBQ approach Definition 2: 17 from definition 1 and 27 from the ECB and ESRB database
Data used for explanatory variables	*House prices* *Real effective exchange rate (REER)* *Current account balance (% of GDP)*	
	Total credit (% of GDP) Gross fixed capital formation (GFCF) Equity prices Consumer price index (CPI) GDP (national currency) Three-month interbank rate Oil price	Government debt (% of GDP) Household debt (% of GDP) Non-financial corporate (NFC) debt (% of GDP) Credit growth Compensation per employee VIX Export market share
Transformed variables by category (EWI)		
Credit development indicators	Total credit-to-GDP gap, GFCF-to-GDP gap	Government debt, Household debt, Credit growth, NFC debt
Asset price indicators	Real house price gap, Real equity price gap	Real house prices growth
Macroeconomic environment indicators	CPI, Three-month interbank rate, Real GDP gap	Change in compensation per employee
External and global imbalance indicators	REER gap, Current account balance, Real oil price gap	Change in REER, Current account balance, Export market share growth, VIX

Due to limitations in historical data a shorter time period, 1980 - 2018, and annual instead of quarterly data are used in Model 2. To increase the number of observations, a larger number of countries are assessed.

Overall, the crisis database used for Model 1 and the second crisis definition in Model 2 covers all EU Member States and Norway for the period 1970-2016 and consists of a core set of 50 banking crises and a set of 43 residual periods of financial (market) stress. The residual periods are based on crises identified by previous researchers that have not been associated with a banking crisis and thus reported for transparency purposes. An additional classification of whether a crisis is relevant for a macroprudential policy setting has been done by the authors of the database. In this study, only banking crisis periods that are relevant for macroprudential policy have been used.

The indicators used in each model have been divided into four different categories of variables similar to what has been communicated in section 2.1.3: Credit development, Asset prices, Macroeconomic environment, External and global imbalance. Naturally, any list of potential indicators is incomplete, however, both benchmarking studies have shown substantial explanatory power for predicting crises. In the following sections, the data used in each model will be introduced in more detail.

3.4.2. Determinants of a Crisis in Model 1

3.4.2.1. Selection of Crisis Periods in Model 1

The crisis dataset used in Model 1 consists of 22 crisis periods from 1970 to 2016 for the 15 countries analyzed. 19 of these crises occurred in European countries, with eleven crises taking place before 2008. The remaining three crises occurred in the US and Japan, two of which took place before 2008. Table A1 in the Appendix gives a summary of the crisis dataset as well as the country coverage used in Model 1.

The crisis database used for crisis selection was developed by the Financial Stability Committee (FSC) in 2017 to serve as a tool for the ESRB and the ECB as a step to establish a common ground for macroprudential oversight and policymaking in the EU (Lo Duca et.

al. (2017)). All crisis periods have been identified by combining a quantitative approach based on a financial stress index as well as an expert judgment from national and European authorities (as described in previous section 3.4.1.).

3.4.2.2. Classification of Pre-crisis Periods

For each crisis, a pre-crisis period is identified between 5-12 quarters before the crisis starts. The choice of period follows previous EWMs developed for macroprudential crises, that use prediction horizons of 5-16 quarters. A binary variable taking the value of 1 for pre-crisis periods and 0 for tranquil periods is defined. Observations four quarters before the crisis and during the crisis are not included in the model.

The dependent term used in the regression is thus not a crisis period, but a pre-crisis period that lasts for eight quarters for every crisis. The fitted values from the model will consequently be an estimation of the probability of a financial crisis in each country in the upcoming five to twelve quarters.

3.4.2.3. Explanatory Variables used in Model 1

Data for ten variables have been retrieved for each country and year according to the representation in Table 3 above. Furthermore, the variables are transformed into relevant indicators and classified across the four different categories of indicators. The transformation of the variables can be explained in a five-step process as follows:

1. ***Collection of data***: Variables have been collected from BIS, OECD, IMF, Eurostat or World Bank based on the longest available data. Missing quarterly observations are estimated by linear approximation using yearly observations.
2. ***Adjusting for inflation***: To exclude the inflation factor from the variables, some variables have been inflation-adjusted, i.e. real house prices, real share prices, real oil prices, real GDP and real effective exchange rates.
3. ***Applying HP filter to create gap variables***: Many of the explanatory variables, before used, have been transformed with Hodrick-Prescott (HP) filter into gap variables. The HP filter function identifies a trend in the variables and smooths the

real outputs using a penalty parameter, λ. The gap variables are then calculated subtracting the trend from the actual values. The procedure is applied for real GDP, credit to GDP, gross fixed capital formation to GDP, real share prices, real oil prices, real house prices and real effective exchange rates. Table A2 in the Appendix gives more details on which λ has been used for each variable and whether the gap is calculated in relative or absolute terms.

4. ***Standardizing***: To make the variables united they are all standardized based on their unconditional mean and standard deviation.

5. ***Winsorizing***: To adjust for any extreme values, winsorizing is performed for top and bottom 1% of the observations across the variables.

3.4.2.5. Comparison of Variables in Different Periods

Descriptive statistics of the indicators and comparisons across pre-crisis, crisis and non-crisis periods are shown in Table 4 below. The table gives an overview of the explanatory variables and some hints on what to expect from the coefficients in the regression.

Table 4. Descriptive Statistics of Indicators in Model 1.

	Pre-crisis				**Crisis**				**Non-crisis**			
	Mean	St dev	Min	Max	Mean	St dev	Min	Max	Mean	St dev	Min	Max
Total credit-to-GDP gap	0.46	0.71	-1.75	2.89	0.85	0.96	-1.65	3.00	-0.26	0.72	-2.57	3.00
Real residential real estate price gap	0.85	0.76	-1.46	2.76	-0.07	0.92	-2.96	2.27	-0.07	0.92	-2.96	2.97
Current account as % of GDP	-0.62	0.93	-2.41	2.31	-0.23	0.87	-2.41	2.79	0.12	0.93	-2.41	2.97
Real equity price gap	0.50	0.98	-2.31	3.79	-0.39	0.85	-2.31	3.79	0.05	0.95	-2.31	3.79
GFCF-to-GDP gap	0.34	0.78	-2.09	2.31	-0.06	0.74	-2.09	2.31	-0.03	0.64	-2.09	2.31
Three-month interbank rate	0.28	0.96	-1.11	2.17	0.15	1.01	-1.19	2.40	-0.07	0.98	-1.20	2.40
Real effective exchange rate gap	0.11	0.79	-2.13	2.52	-0.12	0.69	-2.90	2.08	0.01	1.02	-2.90	2.52
Real GDP gap	0.05	0.83	-2.49	2.85	0.04	1.13	-2.57	2.85	-0.02	0.91	-2.57	2.85
Real oil price gap	-0.05	0.64	-2.51	1.21	0.09	1.06	-2.60	3.04	-0.02	0.95	-2.60	3.04
CPI (Inflation rate)	0.07	0.87	-1.10	3.66	-0.04	0.99	-1.18	3.66	0.00	0.96	-1.18	3.66

The main take-aways from each row are presented below.

1. ***Credit to GDP gap*** is on average highest during the crisis, but also high during pre-crisis periods, confirming that the indicator might capture growing credit bubbles also prior to the crisis. The gap indicator is measured as the absolute deviation between the actual value of total credit to GDP against the long-term trend. The measure is one of the most commonly used EWIs and implemented in the Basel III framework (Drehmann and Tsatsaronis, 2014)
2. ***House prices*** seem to be highly overvalued during pre-crisis periods, being much higher than the normal trend
3. ***Current account as % of GDP*** is on average most negative just before the crisis occurs, and generally positive during non-crisis periods
4. ***Share prices*** on the market tend to be overvalued in comparison to the trend in pre-crisis periods and quickly becomes undervalued when the crisis hit
5. ***Gross Fixed Capital Formation to GDP***, i.e. the net increase in fixed capital, is on average much higher during pre-crisis periods. In those periods the economy looks strong and growth is consistent. Meanwhile, during the crisis periods, the net investments are lowest in relation to the trend as the economy tries to lower expenses
6. ***The three-month interbank rate*** is on average highest during the pre-crisis periods and then significantly reduced during crisis periods
7. ***The real effective exchange rate*** relative to US Dollars seems to be negative in relation to the trend during crisis periods and positive in pre-crisis periods
8. ***Real GDP gap*** seems to be slightly higher during crisis periods and pre-crisis periods
9. ***Real oil prices*** are on average lower in pre-crisis periods and increase rapidly during the crisis as investors seek returns from tangible and necessary commodities.
10. ***CPI*** seems to be highest during the pre-crisis periods, i.e. as the economy is doing well the prices increase faster, while during the crisis, the prices remain low to attract people to keep spending

3.4.3. Determinants of a Crisis in Model 2

Model 2 aims to identify crisis periods by identifying significant slumps in GDP over a sample of 32 OECD economies from 1980 to 2017. In contrast to Model 1, the crisis periods are identified applying an algorithm on retrieved data. In the second definition of crisis periods, also periods retrieved from the database used in Model 1 are added.

3.4.3.1. Selection of Crisis Periods in Model 2

To identify crisis periods in Model 2, quarterly standard nominal GDP data for each country, retrieved from OECD's database, has been used. A crisis is defined as a recession with an average peak-to-trough decline in real GDP of at least 2.5% at a quarterly frequency.

A business cycle turning point is identified using the BBQ algorithm proposed by Harding and Pagan (2002), which identifies turning points as local minima and maxima of a time series within a window of k quarters. The distance between peak (maxima) and through (minima) must be at least p quarters and the cycle length (distance between successive peaks and throughs) at least c quarters. The standard choice of parameters: k=2, p=2, c=5 are used.

Once a turning point has been identified, all recessions with an average peak-to-through decline of at least 2.5% per quarter are selected and added to the set of crisis periods. The starting year of each crisis is converted to a country-year observation taking the value of 1. All other country-year observations take the value of 0. To deal with potential post-crisis bias, the year directly following the start of a crisis are removed. This is to prevent misleading trends in periods when macroeconomic variables undergo an abrupt adjustment process.

While this definition of crisis periods can also capture some crises irrelevant for macroprudential policy, the original authors argue that significant changes in GDP are the most encompassing definition and it is also implemented by IMF and OECD.

Using the BBQ algorithm this study identified 15 crisis periods from 1980-2017, evenly spread across countries assessed, with a maximum of one crisis per country.

To increase the number of crisis observations in the dataset, and thus improve the accuracy with which the model can estimate future crises, a second definition for crisis periods have been introduced.

In the second definition of crisis periods, observations from the ESRB and ECB crisis database (presented in section 3.4.1 and 3.4.2.1.) are added to the crisis periods identified by the BBQ approach. All additional crisis periods are according to the database classified as macroprudential. This increases the total number of crises to 44, with 16 of them occurring before 2008. While the crisis periods added from the database are often the same as the periods used in Model 1, it is not possible to solely use the database due to its country limitation.

In the remaining sections related to Model 2, both crisis period definitions are used for comparison (see Table A3 in Appendix for details about country coverage and crisis period definition).

3.4.3.2. Explanatory Variables used in Model 2

Similarly, to the process for Model 1, data for ten variables have been retrieved for each country and year according to the representation in Table 3 above (see section 3.4.1). The variables are thereafter transformed into relevant indicators and classified across the four different categories of indicators. The transformation is less complex than in Model 1 and follows the following three-step procedure:

1. ***Collection of data***: Variables have been collected from BIS, OECD, IMF, Eurostat or World Bank based on best availability from 1980 to 2018. For each country, the observations with the longest time horizon are taken. Thus, in some cases, a blend between data from OECD and Eurostat is required. For the seven of the eastern European countries included, only observations from 1999 are considered, to omit the impact from the reorganization after the Soviet Union breakup.
2. ***Converting to three-year change***: For most flow variables a three-year percentage change is applied to avoid false alarms driven by blips in the data. The

three-year percentage change calculation is applied to compensation per employee, total credit, real house price growth, export market share, and real effective exchange rate.

3. ***Multiplying indicators:*** Four variables were transformed by simple multiplication one on the other; multiplying house price growth with credit growth after the growth transformation, and government debt as % of GDP with VIX after lagging the first variable by one year.

3.4.3.3. Comparison of Variables in Different Periods

Descriptive statistics of the variables and comparison across crisis and non-crisis periods using the first crisis definition are shown in Table 5 below.

Table 5. Descriptive Statistics of Indicators in Model 2.

	Non-crisis				**Crisis**			
	Mean	St dev	Min	Max	Mean	St dev	Min	Max
Compensation per employee (3y change)	18.61	21.57	-48.90	148.25	27.91	31.37	-6.31	132.45
Government debt (% of GDP)	61.39	36.70	3.77	237.13	52.94	44.26	4.50	201.04
VIX	19.97	6.61	10.95	39.58	28.46	9.54	14.32	39.58
Current account balance (% of GDP)	-0.28	4.83	-20.89	14.66	-0.90	6.44	-13.61	10.37
Household debt (% of GDP)	55.43	28.90	1.50	135.30	68.10	35.50	20.90	139.40
Credit growth (3y change)	31.14	38.79	-34.95	252.33	51.16	41.31	-7.41	139.01
Real house price growth (3y change)	2.84	6.96	-19.44	47.76	-7.86	10.98	-37.04	13.80
NFC Debt (% of GDP)	81.53	45.94	0.00	274.50	105.77	58.38	0.00	274.00
Export market share (3y change)	2.05	13.70	-26.47	68.41	1.75	14.64	-23.94	36.44
Real effective exchange rate (REER), HICP-deflated (3y change)	0.93	9.09	-27.84	49.40	3.36	9.07	-26.41	20.15

From the descriptive statistics it is possible to draw the following conclusions:

1. ***Compensation per employee*** seems to have been increasing substantially during crisis periods. It could partly be explained by the lower hiring rate implying a larger share of senior people that require higher salaries

2. ***Government debt as % of GDP*** is on average slightly lower during crisis periods, which can be explained by the government trying to support the banks by paying back part of its debt
3. ***The VIX*** is on average a lot higher during crisis periods and fluctuates much more (standard deviation is higher) due to the high uncertainty in the market
4. ***Current Account as % of GDP*** is on average shown to be more negative during crisis periods, which can be explained by the decrease in GDP
5. ***Household debt as % of GDP*** is on average higher during crisis periods, which can be explained mainly by the decrease in GDP, but also households struggling as contagion from companies struggling
6. ***Credit growth*** is on average much higher during crisis periods due to many companies and households struggling to survive and need to take on more leverage
7. ***Real house price growth*** is on average negative during crisis periods while on average positive during tranquil periods. This could be explained by the overvalued asset prices heading back to normal levels during crisis periods
8. ***Non-financial corporate debt as % of GDP*** is on average higher during crisis periods as GDP decreases while corporates are struggling and need more financing
9. ***Export market share*** is on average lower during crisis periods as some exporting companies may go bankrupt
10. ***Real effective exchange rate to USD*** is on average much higher during crisis periods which can be explained by a high inflation rate in the country where the crisis occurs, while the USD is often seen to act as a safe haven asset

Comparing the finding from the descriptive statistics in Model 1 (Table 4 in section 3.4.2.5. above) with Model 2 (Table 5 above), it is possible to see multiple similarities in crisis periods versus tranquil periods. Most importantly, the debt as % of GDP and the asset prices seem to develop in similar ways.

3.5. The Seven-step Process for Developing, Validating and Applying the Two EWMs

In Figure 7 below, a presentation of the seven-step process conducted for each of the two models is depicted. Following the data collection and variable transformation (step 1) already presented in this section, the following "Results" section will cover step 2 to step 6 of the process for each model separately. The main findings (step 7) will then be discussed in the "Discussion" section of this study.

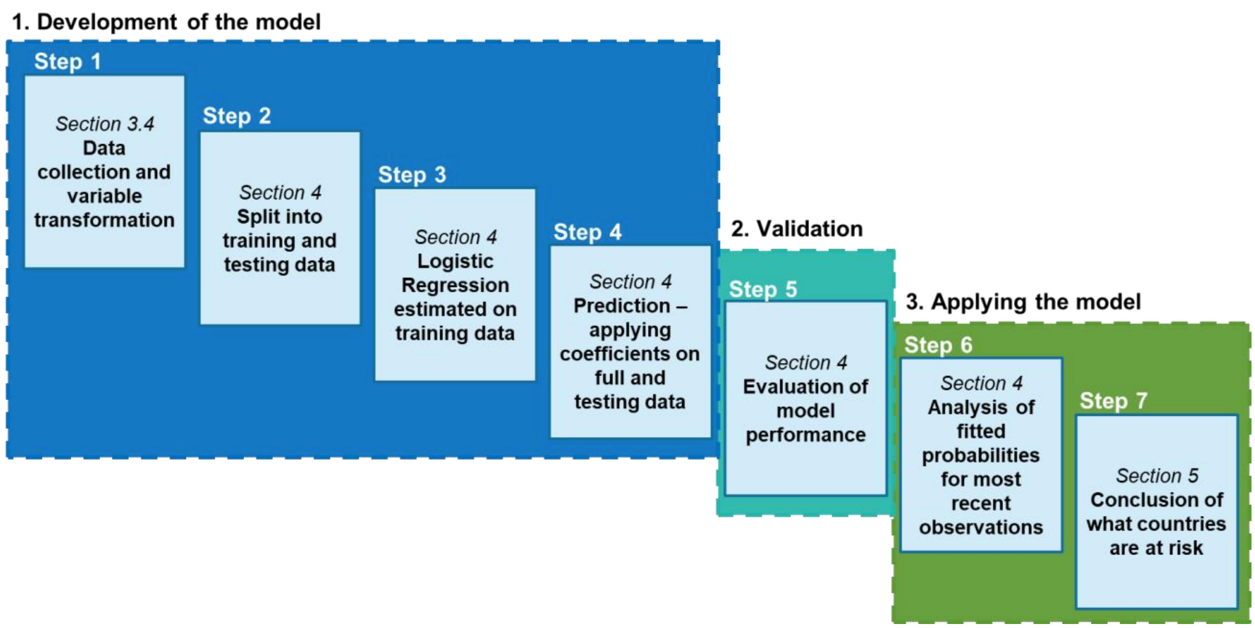

Figure 7. The seven-step process applied for the two EWMs

4. Results for the Quantitative Analysis

The results section is divided into two parts, one for each EWM. Each model will present step 2 to step 6, defined by the seven-step process presented above, in chronological order. The steps will thus be covered in the following way:

1. ***Step 2:*** Based on the transformed variables introduced in the data section (section 3.4), the data is divided into training and testing data.

2. ***Step 3:*** The logistic regression is estimated only on the training data and results of the regression are commented
3. ***Step 4&5:*** After applying the coefficients from the regression on either the full dataset or just the testing dataset, evaluation of model performance is done based on the measures presented in the methodology section (section 3.3.3).
4. ***Step 6:*** The most recent fitted values are analyzed across countries to determine what countries currently experience the highest probability of being in crisis.

4.1. Model 1 – The Gap Based Model

4.1.1. Step 2, Model 1: Dividing Data into Training and Testing Data

The data is split so that the training dataset consists of data from 1970 to 2007 Q2, while all observations from 2007 Q2 until 2019 Q3 are a part of the testing data. This implies around 80% of the observations being classified as training data and 20% as testing data. In the choice of the split, there is a trade-off between having the possibility to test that the model works as a good predictor on a significant amount of testing data and letting the regression capture as many crisis periods as possible to make it a better predictor for current times. 2007 Q2 is chosen as a break to catch the warnings of the GFC in some of the countries, but not all of them.[2]

Now that the data is split, a regression can be estimated on the training data, which is described in the following section.

[2] While the GFC affected many economies worldwide the timing of the major hit differed slightly across different countries, ranging anywhere from mid-2007 until early 2009 (Reserve Bank of Australia)

4.1.2. Step 3, Model 1: Interpretation of the Benchmarking Regression

Table 6 below, presents the regression results from the first benchmarking regression in Model 1 using the training dataset. Nine out of eleven coefficients are statistically significant with only the Real equity gap's and Real oil price gap's coefficients being insignificant.

Table 6. Model 1, Regression summary of benchmarking regression

	Coefficients	Estimate	Std. error	t value	Pr(> t)		Odds Ratio
1	Total credit-to-GDP gap	**1.71**	0.19	9.17	0.00	***	5.51
2	Real house price gap	**0.66**	0.12	5.40	0.00	***	1.93
3	Three-month interbank rate	**0.95**	0.17	5.69	0.00	***	2.59
4	CPI (Inflation rate)	**-0.81**	0.18	-4.62	0.00	***	0.45
5	REER gap	**0.58**	0.12	4.94	0.00	***	1.79
6	GFCF-to-GDP gap	**0.66**	0.16	4.17	0.00	***	1.93
7	Real GDP gap	**0.32**	0.14	2.29	0.02	**	1.37
8	CA as % of GDP	**-0.23**	0.13	-1.79	0.07	*	0.79
9	Real oil price gap	0.06	0.10	0.61	0.54		1.06
10	Real equity price gap	-0.11	0.14	-0.79	0.43		0.90
11	(Intercept)	**-2.87**	0.15	-19.75	0.00	***	0.06

Significance codes: 0.01 '***' 0.05 '**' 0.1 '*'
Log-Likelihood: -365.467,
Chi-squared test: X2 = 193.8, df = 9, P(> X2) = 0.0

Note: This table shows the regression result using the variables from Model 1. Nine out of eleven coefficients are statistically significant, with seven being statistically significant from 0 on a 99% level.

Coefficients are used to distinguish between the level of the indicators during pre-crisis periods in comparison to tranquil periods. From the regression results, a positive coefficient implies that the indicator tends to be higher during pre-crisis periods. For a positive coefficient, a higher value of the indicator in the prediction will lead to a higher probability of a financial crisis. The opposite applies for negative coefficients. Furthermore, some interpretations made from the regression results in Table 6 above, are described below.

The high value of the credit to GDP gap coefficient shows that a higher credit ratio in relation to the trend increases the probability of a crisis significantly. Also, high house prices and equity prices in relation to the trend, implying asset overvaluation, seem to increase the probability of a crisis. These three coefficients combined confirms that debt-financed asset price booms are strong drivers of crises.

The higher interest rates during pre-crisis periods motivate investors to keep investing in the overpriced market getting returns while inflation is low (negative coefficient). The real effective exchange rate is high during pre-crisis periods in relation to the USD. This is explained by the thriving economies, while during crisis periods people try to secure money in the safe haven USD currency. Also, the high level of gross fixed capital formation during pre-crisis periods indicates that the expectations are very optimistic which leads to problems when returns decrease heavily upon a crisis.

While during a pre-crisis period, the economy seems to still be growing in relation to the overall trend, it is notable that the real GDP gap coefficients are much lower than the ones for the GFCF-to-GDP gap, house price gap, credit to GDP gap. Also, notable is that the current account to GDP coefficient is negative, underlining that in these times, the current account might turn into a current deficit due to the high leverage. The decrease in oil prices can be seen either as a global shock leading to political uncertainty and tension between countries, or as a sign that commodities become undervalued as investors see more potential in other asset classes.

In addition to the regression presented above, a second regression has been estimated, including only the statistically significant variables from the first regression, i.e. the house price gap, credit to GDP gap, three-month interbank rate, consumer price index, real effective exchange rate gap, GFCF-to-GDP gap, real GDP gap as well as current account to GDP (see Table 3.A. for details). The reason for excluding the real oil price and the real equity price is to reduce the risk of overfitting the data. The more variables used, the higher risk of overfitting. The results, however, turn out very similar to the results in the first regression, with all coefficients now being statistically significant and all having the same signs as above.

Following the interpretations from the two regressions, predictions are made based on the coefficients obtained from both regressions. The prediction process is described in the following section.

4.1.3. Step 4&5, Model 1: Prediction and Evaluation of Model Performance

The sets of coefficients for each of the two regressions performed are saved and applied firstly on the whole dataset, and secondly only on the testing data, summing up to four different prediction outputs. The predictions on the whole dataset (named Fullpred1 for the prediction based on coefficients from the first regression and Fullpred2 for the predictions based on coefficients from the second regression) are based on both in-sample and out-of-sample estimations. The predictions applied only on the testing data (named Forecast1 and Forecast2, respectively) are on the other hand based only on out-of-sample estimations. While the fitted probabilities obtained in the predictions based on the same regression are identical for each country-year observation, the thresholds and the performance evaluation results will differ due to the different time lengths of the data.

As discussed in the Methodology section, a threshold τ, is chosen for each prediction, such that the Relative Usefulness is maximized, i.e. the number of signals issued fits the truth crisis classification as much as possible. In Table 7 below, the performance of the model is assessed using the previously introduced evaluation measures: FN rate, the Relative Usefulness, AUROC and BPS for each prediction.

Table 7. Model 1, Validating Model Performance

	Threshold	TP	FP	TN	FN	FP rate	FN rate	Usefulness	AUROC	BPS
Fullpred1	0.10	138	388	1596	34	0.20	0.20	0.61	0.88	0.06
Fullpred2	0.09	133	421	1563	39	0.21	0.23	0.56	0.86	0.06
Forecast1	0.10	14	94	451	0	0.17	0.00	0.83	0.98	0.02
Forecast2	0.08	14	132	413	0	0.24	0.00	0.76	0.98	0.02

Note: The first row (Fullpred1), shows the predicting result after applying the (10) coefficients from the first regression to the whole set of data, i.e. training + testing data. The second row (Fullpred2) illustrates the summary from applying the (8) coefficients from the second regression to the whole set of data, i.e. training + testing data. The third row (Forecast1) applies the (10) coefficients from the first regression only on the testing data, while the fourth row (Forecast2) shows the predicting power of the (8) coefficients from the second regression on the testing data.

(1 – FN rate) shows that almost 80% of the actual pre-crisis periods are correctly classified for the predictions made on the full dataset (Fullpred1 and Fullpred2), and 100% of the actual pre-crisis periods are correctly classified for the forecasting (testing) dataset (Forecast1 and Forecast2). The relative usefulness is positive for all predictions implying that the model can indeed add value. The AUROC is well above 0.5 for all predictions. BPS score is close to 0 for all regression, being even lower for the two predictions on testing data.

In summary, the performance of the model is high and the results from the two regressions are quite similar. The coefficients from the first regression seem to estimate the pre-crisis periods slightly better, which can be explained by the additional two variables included in the estimation. Furthermore, the model has done a good job in predicting the historical crisis periods and can hence be considered to add valuable information in the assessment of the current economic environment. In the next section, a more detailed assessment of the model's predictions for the last four quarters is presented.

4.1.4. Step 6, Model 1: Application to Most Recent Data

Using the developed and validated model, a detailed analysis has been performed on the predictions for the last four quarters of the data (2018 Q4 to 2019 Q3). Based on the predicted probabilities generated by each set of regression coefficients, the aim is to check whether any crisis warning signals would arise across the last four quarters, and if so, for which countries. Table 8 below, presents the four countries found to have the highest probability of a financial crisis occurring in the upcoming years according to the fitted values of the last four quarters. For each country five rows are presented:

i. Counting the number of quarters exceeding the threshold, τ
ii. Indicating whether the probability has been increasing or decreasing during the year
iii. Estimating the average probability of being in a crisis across the four quarters
iv. Estimating the minimum and maximum probability estimated across the year
v. Estimating the 95% confidence interval for the whole year

Table 8. Model 1, Forecasting Results - Countries with Warning Signals Issued in the Last Four Quarters

Country		Regression 1	Regression 2
	Crisis Threshold, *T*	10%	8%
DEU	No. of quarters exceeding the threshold	4	4
	Increasing / Decreasing probability of a crisis	Increasing	Increasing
	Average crisis probability in the last four quarters	22.1%	23.0%
	Min-Max crisis prob. over the last four quarters	18-24%	18-25%
	95% confidence interval	7-51%	8-50%
JPN	No. of quarters exceeding the threshold	4	4
	Increasing / Decreasing probability of a crisis	Increasing	Increasing
	Average crisis probability in the last four quarters	24.3%	25.2%
	Min-Max crisis prob. over the last four quarters	20-30%	20-31%
	95% confidence interval	12-48%	15-45%
FRA	No. of quarters exceeding the threshold	1	3
	Increasing / Decreasing probability of a crisis	Increasing	Increasing
	Average crisis probability in the last four quarters	8.9%	9.7%
	Min-Max crisis prob. over the last four quarters	8-10%	8-10%
	95% confidence interval	7-10%	8-12%
USA	No. of quarters exceeding the threshold	0	0
	Increasing / Decreasing probability of a crisis	Stable	Decreasing
	Average crisis probability in the last four quarters	4.1%	4.4%
	Min-Max crisis prob. over the last four quarters	4-5%	4-5%
	95% confidence interval	3-5%	3-6%

Note: The table presents a summary of the fitted values obtained in the last four quarters for Germany, Japan, France and the US using the coefficients from the first and the second regression.

As can be seen in Table 8, in all predictions, warning signals for Germany, Japan and France occurred. The prediction using coefficients from the second regression estimated slightly higher probabilities of crisis for all countries. Japan and Germany are shown to be in a pre-crisis state during the whole period from 2018 Q4 to 2019 Q3, both when using the coefficients from the first and the second regression. The probabilities of the countries being in a crisis state are shown to be between 18% to 25% for Germany and 20% to 30% for Japan throughout the period. In France, the probability of a crisis is significantly lower but still exceeds 10% in some quarters. The fourth country on the list of highest probabilities is the US, but the probability of being in a pre-crisis state is much lower and is not exceeding thresholds and thus not considered to be abnormal. For all other countries, the probabilities of a crisis were estimated to be below 5% in the last four quarters.

In the following section, a detailed analysis of the fitted probabilities for the three countries exceeding the threshold in 2019 is carried out.

4.1.4.1. Illustrating Fitted Values Over Time

Following the results presented in the previous section, it is of interest to look closer at the fitted probabilities for Germany, Japan and France. Figure 7 below, illustrates the fitted values from the first prediction, Fullpred1. The graphs for Forecast1 (basically a zoom of the last 11 years of observations) and Fullpred2 are very similar and can be found in Appendix (Figure A1 and Figure A2). As can be seen, the probabilities of crisis for all three countries have been increasing with every quarter but are still far from historical peaks.

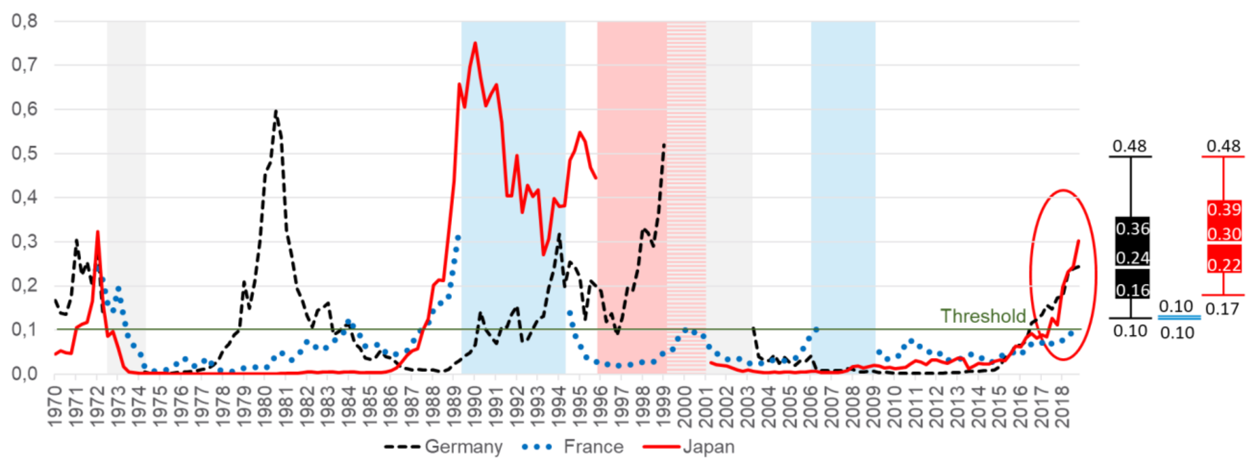

Figure 7. Model 1, Fitted Values for Countries Exceeding Thresholds in All Predictions - Fullpred1

Note: This figure shows the plotted fitted values for the three countries, Germany, France and Japan using the first prediction from Model 1 (based on the first set of regression coefficients). As noticed, only Germany and France exceed the threshold in the last four quarters. Breaks in the lines occur due to the start of a crisis period. The shaded areas are illustrations of previous crisis periods identified in the crisis dataset, with the color being linked to the country in crisis: grey for Germany, blue for France, red for Japan. The boxplots on the right-hand side of the graph are confidence intervals for the fitted values in the last observed quarter (2019 Q3). The numbers in the middle of the boxplots correspond to the actual fitted value, the top and bottom values in the boxplot accounts for the 68% confidence interval, while the numbers on the end of the lines indicate the 95% confidence interval.

In the graph above, the shaded areas represent identified crisis periods in the used crisis dataset. One can note that for all crisis period shaded, the fitted probabilities just before the crises, turn out to be quickly growing and exceeding the threshold. This is also what one can note in the development over the last three years. In addition to the true crisis peaks, there have been other peaks identified in the dataset. To assess them, a look back to the ECB and ESRB crisis dataset is done for each country separately on the following pages. A more detailed analysis of the crisis probability for Germany over time, together with the confidence interval of the fitted probabilities are presented in Figure 8 below.

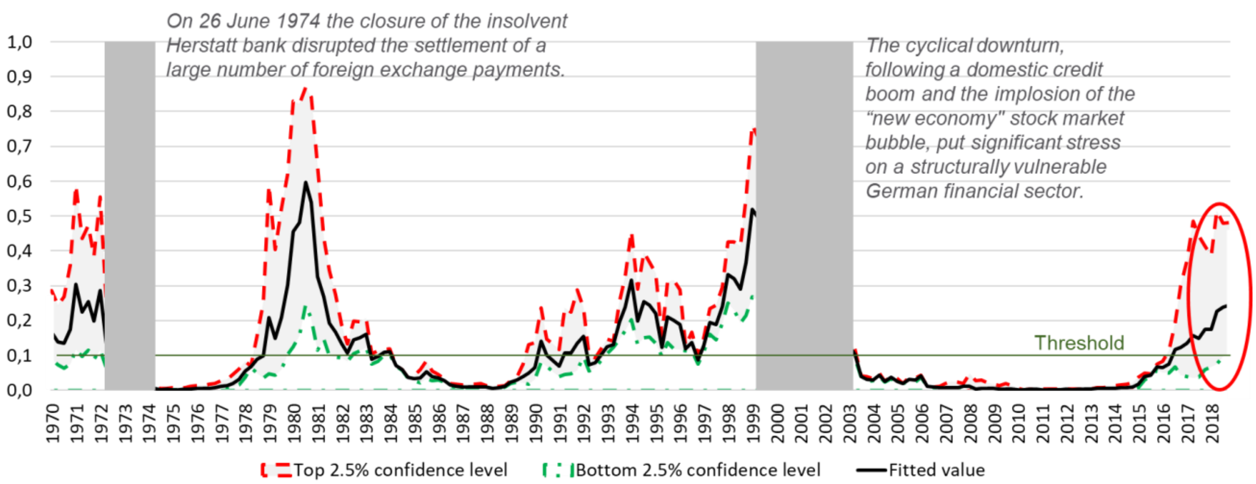

Figure 8. Model 1, Fitted Values for Germany with 95% Confidence level - Fullpred1

Note: This graph shows the plotted fitted values for Germany using the first prediction from Model 1 (based on the first set of regression coefficients). The black line depicts the fitted crisis probabilities over time, while the light grey shaded area between the red and green dotted lines shows the 95% confidence interval. Breaks in the lines are replaced with darker grey shades and occur due to the start of an identified pre-crisis period. A detailed overview of how the different variables included in the model varies over time for Germany is presented in two separate graphs in Appendix (Figure A3 and Figure A2).

Figure 8 shows that the selected threshold is significantly exceeded in the period of 1979 Q3 until 1983 Q4 for Germany. According to the ECB and ESRB dataset, a residual period in 1980 Q3 until 1982 Q4 described as "Limited financial stress emerged due to external factors" is identified. Another sequence of warning signals can be noted from 1991 Q1 to 1992 Q2 as well as 1992 Q3 to 1997 Q2. Once again, ECB and ESRB have determined a residual period between 1992 Q2 and 1994 Q4 described as "Limited financial stress emerged due to external factors (oil shock)" where significant asset price corrections appeared. According to the data, crisis management actions took place in forms of an interest rate increase and easing of fiscal spending. Furthermore, just three quarters later, in 1998 Q1, an actual pre-crisis period initiated. The crisis period, ending in 2003 Q4 had a significant impact on the whole German economy with the main accelerators being: exposure concentration, excessive credit growth and leverage, and misaligned incentives between stakeholders. No warning signals after this crisis have occurred until 2017 Q2.

To sum up, the model has performed well in terms of predicting past shocks in Germany and could thus be correctly predicting another crisis in Germany within the next 5-12 quarters. In fact, the German industrial sector has been said to witness a recession period already in 2019 which could potentially escalate also to other sectors.

A second detailed assessment is done for Japan (Figure 9), which is positioned in a similar state to Germany in current times.

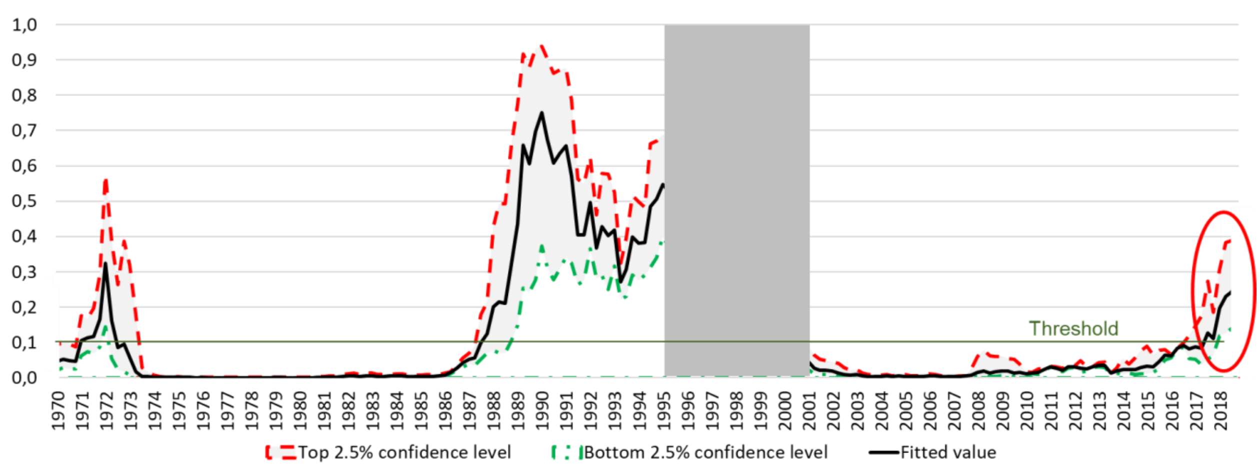

Figure 9. Model 1, Fitted Values for Japan with 95% Confidence level - Fullpred1

Note: This graph shows the plotted fitted values for Japan using the first prediction from Model 1 (based on the first set of regression coefficients). The black line depicts the fitted crisis probabilities over time, while the light grey shaded area between the red and green dotted lines shows the 95% confidence interval. Breaks in the lines are replaced with darker grey shades and occur due to the start of an identified pre-crisis period.

Due to the lack of data on previous crisis periods, a less detailed analysis of crisis periods is performed. However, according to the recent data, both the credit to GDP and the house price levels have been increasing dramatically in Japan. Furthermore, according to multiple sources, it seems like a recession has already started with GDP shrinking by 6.2% in the last quarter of 2019.

Overall, it is notable that for both Germany and Japan, the confidence interval for the fitted probabilities tends to widen just before the start of a crisis period. It has also widened in the last two years (2017-2019). Moreover, most of the identified peaks in the graphs are linked to a crisis period. While the crises selected for the definition of crisis periods referred mainly to systematic crises, the case of Germany shows that the model also captures other types of financial crises. Furthermore, the significantly smaller confidence interval for Japan compared to Germany in current times (with even the lower confidence bound above the thresholds) points towards a very high risk of Japan approaching a new financial crisis.

4.2. Model 2 – The Yearly Change Model

4.2.1. Step 2, Model 2: Dividing Data into Training and Testing Data

For Model 2 the training period is defined by all observations from 1980 to 2010, and the testing period as all observations starting from 2010 until 2018. The main reason for choosing a later date compared to 2007 Q2 chosen in Model 1, is that the large majority of crises identified occurred during the GFC. Moreover, the sample period in this model is significantly shorter than in Model 1, especially for the Eastern European countries with observations starting from 1999. Some crisis periods are, however, also identified in the 2010s, helping to assess the out-of-sample performance.

4.2.2. Step 3, Model 2: Interpretation of the Regression Results

Using the training data defined in the previous section, four different regressions are estimated, with results illustrated in Table 9 below. For all regressions, all variables are lagged by one year, except for the VIX that enters the model contemporaneously as it is assumed to be available at high frequency. This implies that the crisis probabilities in year *t* are mainly based on data up to year *t-1*. Furthermore, as most parameters are expressed as a three-year change, two quasi-automatic lags are included, i.e. data for 2015, 2016 and 2017 is used to project the probability of a crisis in 2018.

Table 9. Coefficients of the four different regressions – Model 2

	Regression 1	Regression 2	Regression 3	Regression 4
Crisis definition	Def. 1 (BBQ)	Def. 2 (Combined)	Def. 1 (BBQ)	Def. 2 (Combined)
Compensation per employee (3y change)	**0.0133** *	0.0033	**0.0131** *	
Government debt (% of GDP) x VIX	**0.0006** ***	**0.0003** ***	**0.0008** ***	**0.0004** ***
Current account balance (% of GDP)	**-0.0980** **	**-0.0523** **	-0.0480	**-0.0457** **
Household debt (% of GDP)	**0.0243** **	0.0030	**0.0224** ***	0.0047
Real house price growth x Credit growth (3y change)	0.0001	-0.0002		**0.0006** ***
NFC Debt (% of GDP)	0.0057	**0.0073** ***	**0.0094** **	**0.0078** ***
Export market share (3y change)	**0.0266** **	-0.0108		
Real effective exchange rate, HICP-deflated (3y change)	**0.0323** **	-0.0078		
Credit growth (3y change)			**0.0215** ***	
Real house price growth (3y change)				**-0.1256** ***
Intercept	**-6.3298** ***	**-2.5719** ***	**-7.5700** ***	**-2.5535** ***
Log-Likelihood	-101.12	-293.70	-94.83	-279.57
Chi-squared test	X2 = 31.0, P(> X2) = 1.4e-04	X2 = 30.6, P(> X2) = 1.6e-04	X2 = 38.9, P(> X2) = 7.4e-07	X2 = 52.8, P(> X2) = 1.3e-09

Significance codes: 0.01 '***' 0.05 '**' 0.1 '*'

Note: This table shows the summary of all regressions performed based on the Model 2 framework. Regressions 1 and 3 use the crisis definition 1 (based on BBQ approach), while 2 and 4 use the crisis definition 2 (the combined definition). Regressions 1 and 2 include all variables used in the benchmarking study and have seven and four out of eleven significant coefficients respectively. Regressions 3 and 4 have five and six out of seven significant coefficients respectively, introducing real house price growth and credit growth as separate variables. Detailed outputs from each separate regression can be found in Appendix (Table A5, A6, A7 and A8).

Regression 1 is the benchmarking regression, most similar to the benchmarking study, using similar variables and definition of crisis. Regressions 2 is based on the same variables as Regression 1 but uses the second definition of crisis. Notable is that for the same set of variables, using the second definition of crisis, a much lower number of significant coefficients is obtained. Also, the coefficient for "non-financial debt as % of GDP" was not significant in the first regression but turns out to be significant in the second. This indeed shows that additional crisis periods have a big impact on the estimated relations across variables.

In the subsequent two regressions (Regression 3 and Regression 4), different combinations of variables have been used to add explanatory power. As can be noted, all except for one variable is statistically significantly different from zero in these regressions. In addition, despite excluding two parameters, the log-likelihood score of the two later regressions are very similar to the score of the first two, being slightly closer to zero. Also, the Chi-square tests show values smaller than 0.000, implying that the model is meaningful.

Summarizing the main findings from these four regressions presented in Table 9, it is possible to conclude that higher government debt to GDP level seems to significantly increase a country's risk of crisis. Increases in household debt levels and wage growth seem to also play a large impact. A decrease in the current account balance and an increase in the non-financial corporate debt level in a country seem to have an impact on the crisis probability in most of the models. However, it is not possible to draw any conclusions from the asset price development in relation to crises.

4.2.3. Step 4&5, Model 2: Prediction and Evaluation of Model Performance

Based on the four different regressions performed, coefficients are (as in Model 1) saved and applied on the whole dataset (named Fullpred 1-4) and separately on the testing data only (named Forecast 1-4) to evaluate the predicting power. The thresholds chosen turns out to be significantly lower when using only the BBQ definition of crisis compared to when using the combined definitions of crisis. In Table 10 below, the performance of the model is assessed using the previously introduced evaluation measures (see section 3.3.3.).

Table 10. Model Performance – Model 2

	Threshold	TP	FP	TN	FN	FP rate	FN rate	Usefulness	AUROC	BPS
Fullpred1	0.08	18	160	754	14	0.175	0.438	0.387	0.722	0.034
Fullpred2	0.25	99	179	570	98	0.239	0.497	0.264	0.693	0.151
Fullpred3	0.08	18	124	790	14	0.136	0.438	0.427	0.753	0.031
Fullpred4	0.28	109	130	619	88	0.174	0.447	0.380	0.774	0.131
Forecast1	0.06	2	105	180	1	0.368	0.333	0.298	0.820	0.020
Forecast2	0.28	40	66	149	33	0.307	0.452	0.241	0.708	0.169
Forecast3	0.08	2	35	250	1	0.123	0.333	0.544	0.835	0.013
Forecast4	0.28	49	64	151	24	0.298	0.329	0.374	0.772	0.147

Note: Fullpred (1-4) predicts the whole set of data, i.e. training + testing data using the coefficients from the regression, respectively. Forecast (1-4) predicts only the testing data using the coefficients from the regressions, respectively.

(1 – FN rate) shows that on average about 50-55% of the crisis periods are correctly classified using the full data, while for the testing period (out-of-sample analysis), the ratio is slightly higher. The relative usefulness is strongly positive for all predictions, especially for the predictions using coefficients from the third regression. In all the predictions the AUC is above 0.5, with the second prediction having a value slightly lower than the others. The BPS is close to 0 for all predictions but slightly higher for the second and fourth prediction.

In summary, all four regressions seem to be adding value. Regressions 2 and 4 considers a much higher set of crisis periods than regressions 1 and 3, especially in the testing data. Thus, predictions 1 and 3, with fewer crisis periods occurring during the testing period, may seem to perform better than they actually do.

4.2.4. Step 6, Model 2: Application to Most Recent Data

Given the relatively good performance of Model 2, a closer assessment of the fitted crisis probabilities for the last two years is illustrated in Table 11 below. While the last available observations (2018) are the most relevant for the analysis, the penultimate observations (2017) are used to assess the development during the year. Countries assessed are those where the fitted probabilities were exceeding selected thresholds across all four predictions (using the thresholds selected in Fullpred 1-4 in Table 10).

Table 11. Forecasting Results - Countries with Warning Signals Issued in the Last Two Years

		Prediction 1	Prediction 2	Prediction 3	Prediction 4	Average
CYP	No. of years exceeding the threshold	2	2	2	2	2.00
	Average crisis probability when thresholds exceeded	43%	53%	18%	60%	43.5%
	Probability of crisis in 2018	53%	58%	25%	66%	50.5%
	Increasing /Decreasing	Increasing	Increasing	Increasing	Increasing	Increasing
GRC	No. of years exceeding the threshold	1	2	1	2	1.50
	Average crisis probability when thresholds exceeded	45%	3%	22%	42%	28.0%
	Probability of crisis in 2018	45%	50%	22%	52%	42.3%
	Increasing /Decreasing	Increasing	Increasing	Increasing	Increasing	Increasing
JPN	No. of years exceeding the threshold	1	2	1	1	1.25
	Average crisis probability when thresholds exceeded	50%	45%	55%	67%	54.3%
	Probability of crisis in 2018	50%	62%	55%	67%	58.5%
	Increasing /Decreasing	Increasing	Increasing	Increasing	Increasing	Increasing
CAN	No. of years exceeding the threshold	1	2	1	1	1.25
	Average crisis probability when thresholds exceeded	16%	38%	15%	45%	28.5%
	Probability of crisis in 2018	16%	43%	15%	45%	29.8%
	Increasing /Decreasing	Increasing	Increasing	Increasing	Increasing	Increasing
BEL	No. of years exceeding the threshold	1	2	1	2	1.50
	Average crisis probability when thresholds exceeded	17%	36%	11%	39%	25.8%
	Probability of crisis in 2018	17%	42%	11%	48%	29.5%
	Increasing /Decreasing	Increasing	Increasing	Increasing	Increasing	Increasing
FRA	No. of years exceeding the threshold	1	2	1	2	1.50
	Average crisis probability when thresholds exceeded	11%	36%	11%	37%	23.8%
	Probability of crisis in 2018	11%	42%	11%	46%	27.5%
	Increasing /Decreasing	Increasing	Increasing	Increasing	Increasing	Increasing

Note: This table presents a summary of the fitted values obtained in the last two years for Cyprus, Greece, Japan, Canada, Belgium and France using the coefficients from all four regressions analyzed. In the first row of each country, a count of the number of times across 2017 and 2018 that the selected threshold is exceeded. The second row illustrates the average probability of a crisis in the time when the threshold is exceeded, while the third row expresses the fitted probability for 2018. The fourth row explains whether the probability of crisis has been increasing or decreasing over the last two years. The last column in the table represents the average results of the four different predictions.

Summing results from all four predictions in the last column of Table 11 show that Cyprus, Greece and Japan have the highest probability of entering a crisis in 2020. To recall, the probability given in 2018 are based on data given in 2019 by the construction of the model, as all variables, except for the VIX, are lagged with one year. Thus, the crisis probability estimated in 2018 mirrors the chance of a country entering a crisis in 2020.

While Greece and Japan have mainly exceeded the thresholds during 2018, Cyprus has exceeded it also in 2017. Other countries with crisis probabilities exceeding thresholds are Belgium, Canada and France. The latter countries had a lower average probability in 2018 of almost 30%, compared to the previously mentioned countries whose probability of crisis estimated in 2018 exceeds 40% for Greece and 50% for Cyprus and Greece.

Countries with probabilities exceeding three out of four thresholds during at least one of the last two years (Australia, Finland, Italy and Luxembourg) might also be considered risky. They are however not assessed due to the lower number of years where thresholds were crossed across the predictions as well as the non-uniformed conclusion across the predictions.

In the following section fitted probabilities for the countries presented in Table 11 above, will be assessed over time.

4.2.4.1. Illustrating Fitted Values Over Time

In the following graphs (Figure 8-11 below), visualizations of fitted values over time using Prediction 1 and Prediction 4 are illustrated. The predictions chosen to visualize in this section are such that they capture the variety of the fitted probabilities achieved using diverse crisis definitions and indicators. Firstly, an overview of the fitted probabilities from the benchmarking regression (Prediction 1 in Figure 8 and 10) are presented, followed by the fitted probabilities from a revised set of indicators using the second crisis definition (Prediction 4 in Figure 9 and 11). The illustration of the fitted probabilities for Prediction 2 and Prediction 3 can be found in the Appendix.

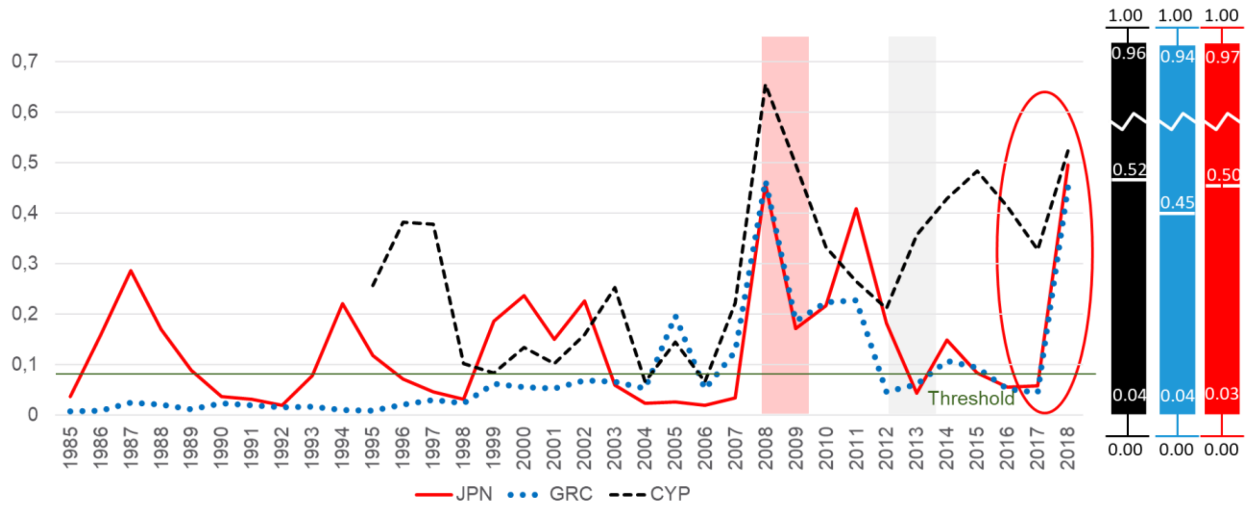

Figure 8. Fitted Values for Japan, Greece and Cyprus - Fullpred1

Note: This figure shows the plotted fitted values for Japan, Greece and Cyprus exceeding the threshold in the last two years in the first prediction (Fullpred1) using the benchmarking regression of Model 2. The shaded areas are illustrations of previous crisis periods identified, with the color being linked to the country in crisis: red for Japan and grey for Cyprus. The boxplots on the right-hand side of the graph are confidence intervals for the fitted values in 2018. The numbers in the middle of the boxplots correspond to the actual fitted value, the top and bottom values in the boxplots account for the 68% confidence interval, while the numbers on the end of the lines indicate the 95% confidence interval.

The probability of crisis has increased dramatically since 2017 for all countries in Figure 8, but more notably for Japan and Greece. As of 2018 Cyprus and Japan face the highest risk of crisis in 2020. As indicated by the model, Cyprus appears to already have been exposed to vulnerabilities for a couple of years, while Greece and Japan entered this face more recently.

Looking at the confidence intervals in 2018 for all the countries, it is important to note that the 95% confidence interval of the fitted values ranges from 0% to 100%, indicating that the estimates are very uncertain. No strong conclusion should thus be drawn from these results, but the model should preferably be combined with other qualitative and quantitative analyses for the selected countries.

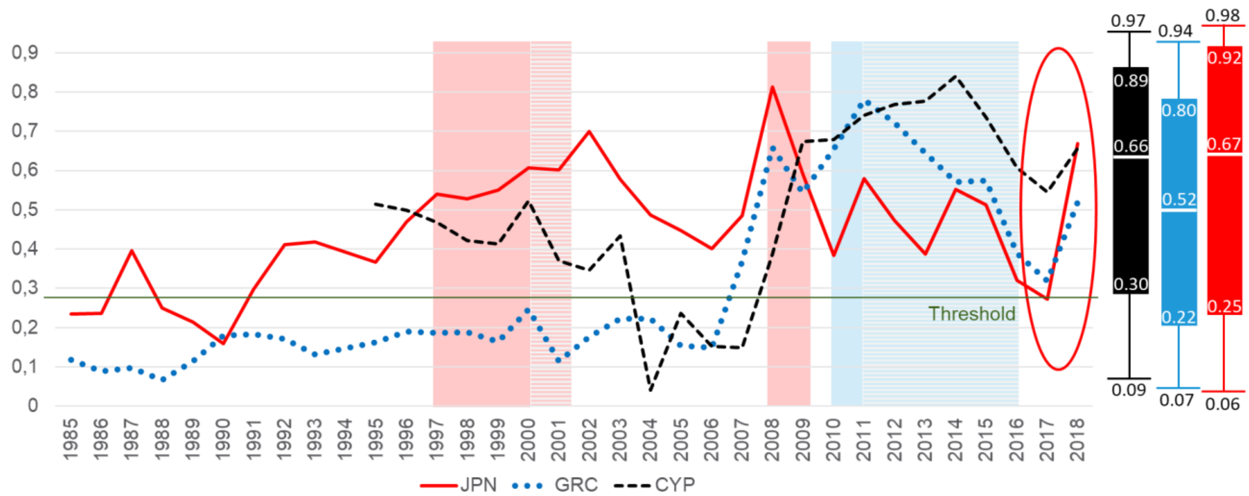

Figure 9. Fitted Values for Japan, Greece and Cyprus - Fullpred4

Note: This figure shows the plotted fitted values for Japan, Greece and Cyprus exceeding the threshold in the last two years in the fourth prediction (Fullpred4) of Model 2. The shaded areas are illustrations of previous crisis periods identified, with the color being linked to the country in crisis: red for Japan, blue for Greece and grey for Cyprus. The boxplots on the right-hand side of the graph are confidence intervals for the fitted values in 2018. The numbers in the middle of the boxplots correspond to the actual fitted value, the top and bottom values in the boxplots account for the 68% confidence interval, while the numbers on the end of the lines indicate the 95% confidence interval.

Also, in Figure 9 above, the probability of crisis has been increasing notably for Japan and Greece in recent years, while decreasing for Cyprus. The explanation is found in the definition of crisis, where Cyprus has been classified to be in a crisis state until 2016 (as can be seen in Table A3 in Appendix). As previously mentioned, according to the European Commission both Cyprus and Greece are currently experiencing excessive macroeconomic imbalances, supporting the results from this quantitative model.

In comparison to Figure 8 above, the confidence intervals are slightly tighter for the fitted values in Figure 9 above, indicating that the probabilities of crisis are estimated more correctly. The 95% confidence level shows that with 95% confidence the probability of a crisis occurring is between 9% and 97% for Cyprus, while with 68% confidence the probability is between 30% and 89%.

Figure 10 below, illustrates the fitted crisis probabilities for Belgium, France and Canada over time based on the first prediction, using the benchmarking regression of Model 2.

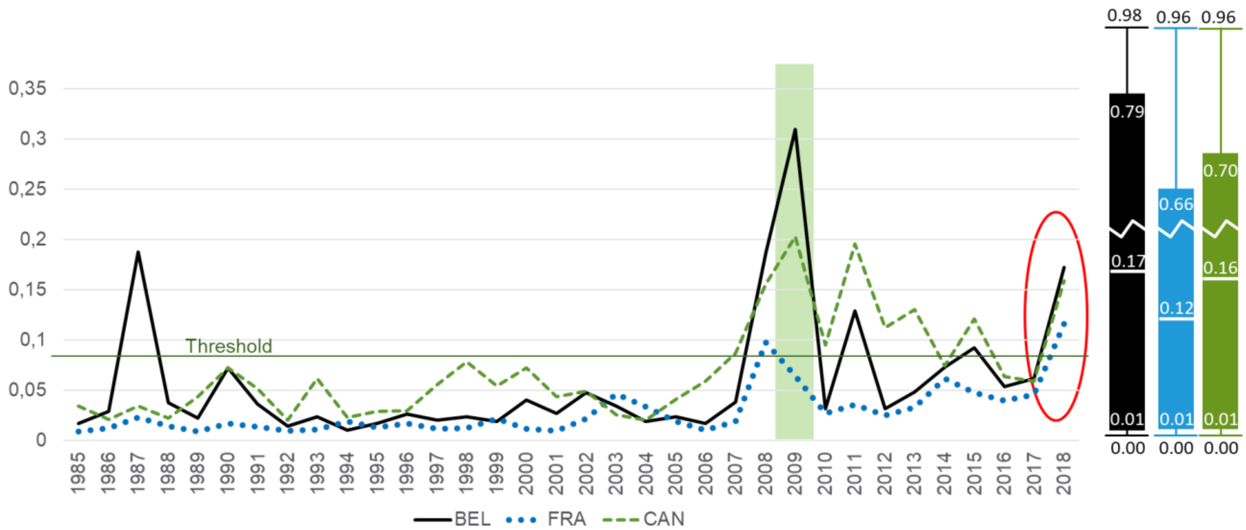

Figure 10. Fitted Values for Belgium, France and Canada - Fullpred1

Note: This figure shows the plotted fitted values for Belgium, France and Canada exceeding the threshold in the last two years in the first prediction (Fullpred1) using the benchmarking regression of Model 2. The shaded areas are illustrations of previous crisis periods identified, with the color being linked to the country in crisis: green for Canada. The boxplots on the right-hand side of the graph are confidence intervals for the fitted values in 2018. The numbers in the middle of the boxplots correspond to the actual fitted value, the top and bottom values in the boxplots account for the 68% confidence interval, while the numbers on the end of the lines indicate the 95% confidence interval.

From the graph, it can be noted that Belgium, France and Canada have been experiencing much fewer fluctuations in recent years compared to the countries analyzed in Figure 8. However, as of 2018, both Belgium and Canada are significantly exceeding the 8% threshold. The 68% confidence intervals estimated for these countries are significantly smaller than the ones estimated for Cyprus, Greece and Japan using the same prediction (see Figure 8 above).

Figure 11 illustrates the estimated probability over time for Belgium, Canada and France.

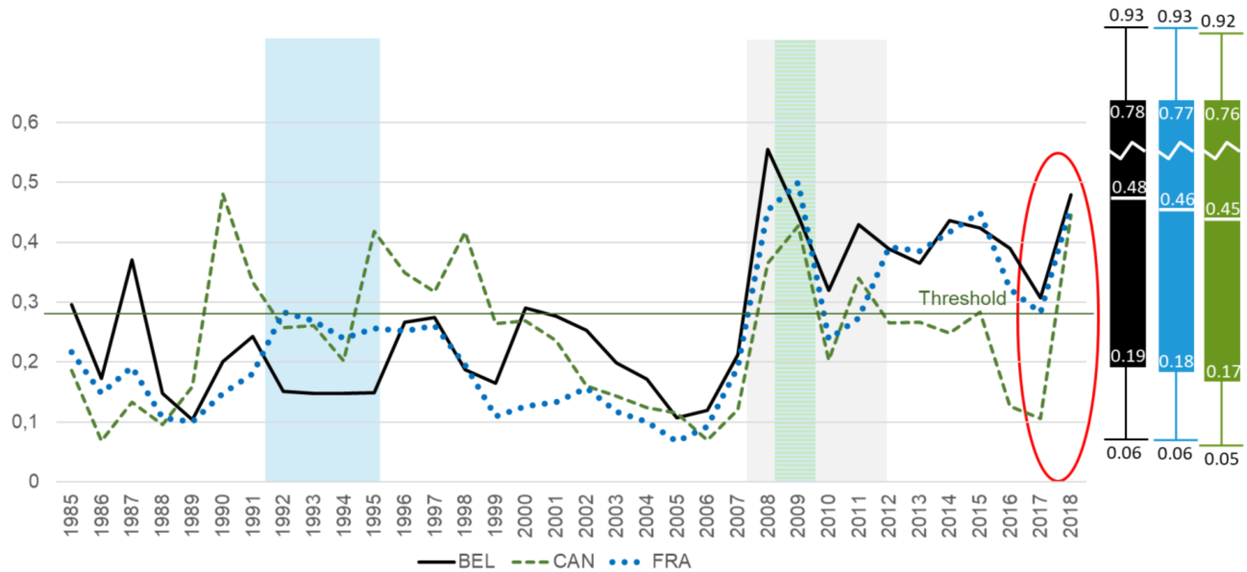

Figure 11. Fitted Values for Belgium, France and Canada - Fullpred4

Note: This figure shows the plotted fitted values for Belgium, France and Canada exceeding the threshold in the last two years in the fourth prediction (Fullpred4) of Model 2. The shaded areas are illustrations of previous crisis periods identified, with the color being linked to the country in crisis: grey for Belgium, green for Canada and blue for France. The boxplots on the right-hand side of the graph are confidence intervals for the fitted values in 2018. The numbers in the middle of the boxplots correspond to the actual fitted value, the top and bottom values in the boxplots account for the 68% confidence interval, while the numbers on the end of the lines indicate the 95% confidence interval.

Figure 11 above, compared with the previously assessed set of countries in Figure 9 has similar confidence intervals for the fitted probabilities. In 2018 Belgium, Canada and France are all positioned at similar levels, with Canada being the country that has increased the most since 2017.

In summary, while several countries have been identified with excessive risk, the confidence intervals for the fitted probabilities are considerably high for all predictions. The wide confidence intervals indicate a high risk of uncertainty in the estimates. While adding more crisis periods seems to improve the estimation, it is still not possible to assure that the threshold is exceeded, even with an 84% probability.

5. Discussion

Following the results visualized in the previous section, this section aims to discuss and compare the results across the different models.

5.1. Comparing the Quantitative Models with Benchmarking Studies

5.1.1. Model 1

Comparing the overall data used in this study with the benchmarking study by Beutel, List and Von Schweinitz (2018), the average relative values of the indicators during the pre-crisis and non-crisis periods seem consistent for all variables except for the Real oil price gap and CPI. An explanation to this deviation is that the data used in this study covers a longer period, 1970 - 2019 Q3, rather than 1970 - 2016 Q2 which influences the statistics. The long-term rates have been historically low in Europe in the last years having an impact on the overall CPI-rate in the data used. Also, the oil prices have during the last three years been lower than during 2009-2015 which could explain a more negative gap.

Due to the longer period of data used in this model, as well as the different aim (to evaluate crisis signals in current times), this study uses a longer training period - all observations from 1970 until 2007 Q2. The benchmarking study splits the training data as all observation from 1970 to 2005 Q2, and testing data as all observation after 2005 Q2, to evaluate predictions of the GFC. Thus, this study splits the data as 80% training data and 20% testing data, while the benchmarking study split is 76% to 24% respectively.

Despite the differences, the overall regression results and predictions are rather consistent with the benchmarking study. All statistically significant coefficients in the regressions have the same signs (+/-) as the model in the benchmarking study. Also, the thresholds τ, chosen are similar. While the thresholds look relatively low, they are consistent with similar previously developed models (for example Lang, Peltonen and Sarlin (2018)).

While the model was originally built for detecting banking crises, it has been shown to also detect other financial crises (see the example for Germany in section 4.1.4).

5.1.2. Model 2

This study has used a significantly different approach from the benchmarking study by Sondermann and Zorell (2019). While the first crisis definition is rather comparable to the benchmarking study, the second definition transforms the dependent variable significantly, making it more similar to the dependent variable used in Model 1. The input variables, however, are similar to the benchmarking study. The relations of the mean of the variables during the crisis and non-crisis periods seems rather consistent with the benchmarking study for all variables except for the four variables: credit growth, real house price, export market share and REER. This study shows lower export market share and real house price growth during crisis periods and higher credit growth and change in REER during crisis periods. A higher credit growth during crisis periods, however, makes sense, as the economy needs to finance their assets with debt as equity value decreases. With the same logic also the real house price growth should be negative during crisis periods. Export market share should reasonably be falling during crisis periods as companies go bankrupt and the GDP growth is reversed. Furthermore, crisis periods are often followed by higher inflation rates as the government needs to print money to help the economy which in turn makes the REER higher because the national currency loses value.

Another main difference between this study and the benchmarking study is the split of training and testing data for out-of-sample performance evaluation. While this study used a fixed training and testing dataset, the benchmarking study conducted a k-fold validation. That means that they split the data into three equal sizes and performed analysis on one at a time using the regression coefficients obtained from the other two parts.

Due to the large deviations both with regards to the data used and the evaluation method it is not relevant to compare the regression results, nor the thresholds used.

In summary, Model 2 has been significantly modified from the benchmarking study to obtain better model performance, accuracy in estimated probabilities, and make the two EWMs more comparable.

5.2. Assessing Key Relations and Usefulness of the Quantitative Models

The regression results from both models confirm the view that an excessive level of credit to GDP increases the probability of a crisis. Model 1 also confirms that excessive house price levels and equity price levels in relation to the trend (implying asset overvaluation) are shown to increase the probability of a crisis. This proves the assumption that excessive credit development and asset price growth increases the probability of a crisis occurring.

Model 1 has shown strong predictive power and according to the most recent predictions, Japan and Germany have been identified as countries with a high probability of entering a crisis in the upcoming 8 quarters. Also, the outlook for France looks somewhat unstable, with the fitted probability being close to the crisis threshold.

Model 2, while showing lower predictable power due to high uncertainty in estimates, have been stress-tested through the comparison of multiple different regressions and the use of two crisis definitions (i.e. developing four versions of the model). All predictions show that Cyprus, Greece and Japan have a very high probability of entering a crisis in 2020-2021, while Belgium, Canada and France are exposed to slightly lower risks, but still well above selected thresholds.

In summary, while Model 1 has performed well, the predictable power of Model 2 seems to be weaker. The lower performance of the last model might be because it doesn’t consider different countries having different overall trends for the same variables. A certain percentage change over three years may be normal for some countries and very unusual for others. The first logit model compensates for this by considering gaps between the trend and the actual value. Nevertheless, both models can still be considered to add value if combined with qualitative methods.

5.3. Comparing the Findings Across the Quantitative and Qualitative Approaches

The main findings from this study were covered in three different steps. Firstly, the assessment of selected MIP Scoreboard indicators (the qualitative approach) related to credit and asset value levels identified several potentially vulnerable countries, namely Austria, Belgium, Canada, Cyprus, France, Greece, Hungary, Japan, Luxembourg, Portugal, the UK and the US. In the second step, an EWM based on Beutel, List and Von Schweinitz's (2018) framework (Model 1), was developed, validated and applied, identifying Germany, Japan and France as countries facing an elevated risk of crisis. Finally, an EWM based on Sondermann and Zorell's (2019) framework (Model 2), was developed, validated and applied to a larger set of countries, identifying macroeconomic imbalances in Belgium, Canada, Cyprus, France, Greece and Japan. Table 12 below, illustrates a summary of identified vulnerable countries across different methods. The red shaded areas reflect countries not assessed by the specific model, while an "X" indicates that the country was exceeding the threshold(s) suggested by that method. Furthermore, several countries have been identified with "X" in all assessment methods conducted for these countries, namely Canada, Cyprus, France and Japan.

Table 12. Countries Showing Warning Signals across all Three Assessments

	Qualitative assessment	**Model 1 – Gap based**	**Model 2 – Yearly change**
No of EU countries assessed	25	13	26
No of non-EU countries assessed	4	2	6
No of countries exceeding thresholds	12	3	6
Belgium	**X**		**X**
Canada	**X**		**X**
Cyprus	**X**		**X**
France	**X**	**X**	**X**
Germany		X	
Greece	**X**		**X**
Japan	**X**	**X**	**X**
Austria	X		
Hungary	X		
Luxembourg	X		
Portugal	X		
UK	X		
US	X		

Note: The table presents a comparison across countries identified with excessive risk for a crisis across the three assessment methods. The cells marked with X specifies that a country in a given method exceeded the threshold in 2018 or 2019. The red shaded areas specify that a country was not assessed in that given analysis. Countries that are marked in bold are those where warnings were issued in at least two of the methods.

According to Table 12 above, France and Japan were the only two countries exceeding selected thresholds across all three assessments. Also, Cyprus and Canada, which were only assessed by two methods, were identified with elevated risk for a financial crisis in both. While Cyprus has recently exited a crisis state, the other three countries have not been said to enter a crisis state in the last couple of years.

For each of the two quantitative models, different signals are issued due to different time periods, geographical scope, management of crisis periods and types of variables used. The only two countries in common are France and Japan, where Japan was seen to experience a higher risk of crisis compared to most other countries in both models. Comparing Model 1 with the MIP Scoreboard analysis only France and Japan overlap, while Germany was not captured by any other method. Comparing Model 2 to the MIP indicators, all countries identified by the quantitative model were also captured by the qualitative. It confirms the benchmarking study's statement that the model can act as a quantitative complement to the MIP scoreboard as many of the 14 indicators used in the original MIP scoreboard are mirrored in the EWM.

The number of countries exceeding thresholds with the qualitative approach clearly outnumbers the other two methods. While the qualitative method might be seen as a potential selection criterion for the quantitative approach, it should not be recommended to use on a stand-alone basis. This due to its lack of evaluating the indicators over time and its incapability of assessing deviations from trends. For example, it assesses countries with a large established financial sector, such as the US, the UK and Luxembourg, that naturally have higher credit levels relative to economies with less developed financial sector, by the same thresholds. The EWMs, on the other hand, takes both trend and cross-country differences into account. Moreover, when using the quantitative models, there is no bias in the outcome, which can be the case for qualitative approaches where the issuer can have certain incentives and select biased thresholds or putting more emphasis on certain indicators.

Using different versions of each quantitative model to stress-test results and then combine them with the qualitative approach should give enough robustness to be considered realistic and thus help policymakers take action.

Because of the diverse results across the different methods in this evaluation, it is still hard to make precise conclusions of which countries are exposed to the highest risk of crisis in the upcoming years. According to the results from this study and some contributions from recently published market outlooks, Cyprus, Japan, Germany, Greece, Canada and France seem to be more exposed to macroeconomic vulnerabilities than other countries assessed in this study. Therefore, in the case of a large market shock due to any of the potential triggers previously discussed (section 2.1.2), these countries face a higher risk for financial distortion.

As demonstrated by previous studies, due to globalization, trade and financial integration, countries are more dependent on each other and in downturns more correlated to each other. The larger global importance a country that enters a downturn has, the bigger the impact on the rest of the global economy.

Research by Bondt, G. and Vermeulen, P. (2018) shows that expansions are duration dependent in the US and Germany, meaning that they are more likely to end as they grow older. Also, for all countries except for Canada and Japan, the monthly probability of recession roughly doubles for each extra G7 country in recession. This means that it is of utmost importance that the large economies, i.e. Germany, Japan, Canada, France, the UK and the US, which have important roles in the global economy, pay large attention to current warning signals and take measures to prevent unnecessary risks. To assess which measures to be taken is however not in the scope of this study.

6. Conclusion and Future Research

This paper has evaluated the risk of a new financial crisis in 2020-2021 as of January 2020 using three different assessment methods. The entire analysis was based on data available by the end of 2019 and therefore doesn't include the Covid-19 crisis impact on the economy. First, a qualitative approach, assessing selected MIP Scoreboard indicators across thresholds set by the European Commission identified 12 potentially vulnerable OECD countries out of the 29 assessed. Secondly, a quantitative approach was introduced through developing, validating and applying two EWMs with different time periods, geographical scope, types of variables used and management of crisis periods. A gap based EWM model was applied to current data for 15 OECD countries, identifying Germany, Japan and France as countries exposed to a high risk of crisis. Following, an EWM, mainly based on the three-year change in key indicators, identified six vulnerable OECD countries out of 32, namely Cyprus, Greece, Japan, France, Belgium and Canada.

While the different methods gave different results, several countries were identified with a high risk of crisis in multiple assessments. Combining results from both EWMs the countries identified in a vulnerable state are Belgium, Canada, Cyprus, France, Germany, Greece and Japan. Countries that were identified with a high probability of entering a crisis state in all assessments where they were present were Cyprus, Greece and Japan. However, a crisis in France, Germany or Japan would be more dangerous as it would have a larger impact on other countries.

6.1. Contribution to Society and Previous Literature

In current times, with high uncertainty about future economic development, this thesis helps to understand whether the rumors of a new financial crisis on its way in 2020 are reasonable. By combining qualitative and quantitative approaches as well as developing the logic behind what could trigger a financial crisis, this thesis is the only one of my knowledge that independently analyzes the current market conditions over such a broad scope of methods. Furthermore, it contributes to previous literature on EWMs by further developing, validating, applying and comparing two previously introduced EWMs.

Because crises are typically triggered by unexpected events such as political, environmental or market shocks, it is almost impossible to identify a crisis ahead of time. On the other hand, an underlying reason for a crisis, as confirmed by this study, is macroeconomic imbalances such as excessive leverage in combination with high asset prices. By identifying countries with such imbalances, this study can provide useful input to policymakers that can design strategies to prevent economic distortion.

Limitation and Future Studies

This research is limited to three different assessments of the current economic states across selected OECD countries. While a lot of work has been done on precious literature, present EWMs still have limited prediction power and need to be backed up with further research for each finding. For example, even though Model 1 showed high predicting power, correctly identifying 80% of all actual crises, it also issued many "false alarms" which can become very costly if policymakers act accordingly. Furthermore, the "False alarms" accounted for more than 70% of all alarms issued, indicating that the model either captured more crisis periods than the ones selected (as can be seen in the case of Germany), issued alarms even more ahead of the target forecast horizon, or just didn't perform well enough. Another argument could be that governments upon an "alarm" took actions in time and thus avoided the crisis. The selected quantitative models in this study, even though recently developed and proven to outperform machine learning models in out-of-sample analysis, still need further development to be used as stand-alone assessors.

Future research could extend the scope of the analysis by including other qualitative or quantitative methods or looking at a wider or different set of countries. Another important topic to investigate is the optimal strategy to be presented by each national monetary authority, to address the elevated financial crisis risk and prevent economic distortion in case of unexpected events.

As this study was based on data available by the end of 2019, i.e. before the Covid-19 virus spread globally, it does not capture the current Covid-19 crisis and the generalized GDP collapse in 2020. Furthermore, it would be valuable to assess how the model performs when including data from the Covid-19 crisis as it is a very unusual stress event that heavily impacted the economy in a way never observed before. While it is extremely difficult to predict a severe pandemic event, its impact on the economy could add valuable information in the case of future pandemics.

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Appendix

Table A1. Model 1, Country coverage and crisis dataset

	Crisis dates					
Country	Start	End	Start	End	Start	End
BEL	No crisis					
DEU	1974 Q2	1974 Q4	2001 Q1	2003 Q4		
DNK	1987 Q1	1995 Q1	2008 Q1	2013 Q4		
ESP	1978 Q1	1985 Q3	2009 Q1	2013 Q4		
FIN	1991 Q3	1996 Q4				
FRA	1991 Q2	1995 Q1	2008 Q2	2009 Q4		
GBR	1973 Q4	1975 Q4	1991 Q3	1994 Q2	2007 Q3	2010 Q1
IRL	2008 Q3	2013 Q1				
ITA	1991 Q3	1997 Q4	2011 Q3	2013 Q4		
JPN	1997 Q4	2001 Q4				
NLD	2008 Q1	2013 Q1				
NOR	1988 Q3	1992 Q4				
PRT	2008 Q1	2016 Q4				
SWE	1991 Q1	1997 Q2				
USA	1988 Q1	1995 Q4	2007 Q4	2010 Q4		

Note: The table illustrates all crisis periods identified in Model 1 across the 15 selected OECD countries over the period 1970-2017.

Table A2. Model 1, Gap transformation of explanatory variables

Variable	Lambda	Gap type
Real oil Price	1,600	Relative
Credit to GDP	400,000	Absolute
Real equity price	400,000	Relative
REER rate	400,000	Relative
Real GDP	1,600	Relative
GFCF-to-GDP	1,600	Absolute
Real house price	400,000	Relative

Note: The table illustrates the lambda parameter and type of gap computed for each transformed variable in Model 1.

Table A3. Model 2, Country coverage and crisis dataset

Country	Start	End	Start	End	Start	End	BBQ algorithm	Added from ECB and ESRB
AUS								
AUT	2007	2016						x
BEL	2007	2012						x
CAN	2008	2009					x	
CHE								
CYP	2000	2001	2011	2016			x	x
CZE	2007	2010						x
DEU	2001	2003	2007	2013			x	x
DNK	1987	1995	2008	2013			x	x
ESP	1993	1994	2009	2013				x
EST	2008	2010					x	
FIN	1991	1995	2008	2010			x	x
FRA	1991	1995	2008	2009				x
GBR	1991	1994	2007	2010				x
GRC	2010	2016						x
HUN	2008	2010						x
IRL	2008	2013					x	
ITA	1991	1997	2008	2013				x
JPN	1997	2001	2008	2009			x	x
KOR	1998	1998					x	
LTU	2008	2009					x	
LUX	2008	2010					x	
LVA	2008	2010					x	
MLT	2009	2012						x
NLD	2002	2004	2008	2013			x	x
NZL	1991	1991					x	
POL	2007	2009						x
PRT	2008	2016					x	x
SWE	1991	1997	2000	2001	2008	2010		x
SVK	1999	2002	2008	2010			x	x
SVN	2008	2014					x	x
USA	1988	1995	2007	2010				x

Note: The table illustrates all crisis periods identified across the 32 OECD countries according to the two crisis definitions in Model 2. Using the first definition (BBQ approach), only one crisis per country was identified, while most crises are identified with the additional dataset used in the second definition (the ECB and ESRB crisis dataset). The observation periods differ across countries with the Eastern European countries only including observations from 1999.

Table A4. Model 1, Regression 2 using only significant variables

	Coefficients	Estimate	Std. error	t value	Pr(> t)		Odds Ratio
1	Total credit-to-GDP gap	**1.72**	0.18	9.30	0.00	***	5.57
2	Real house price gap	**0.65**	0.12	5.36	0.00	***	1.91
3	Three-month interbank rate	**0.94**	0.17	5.68	0.00	***	2.57
4	CPI (Inflation rate)	**-0.82**	0.17	-4.74	0.00	***	0.44
5	REER gap	**0.60**	0.11	5.27	0.00	***	1.83
6	GFCF-to-GDP gap	**0.66**	0.15	4.36	0.00	***	1.94
7	Real GDP gap	**0.32**	0.14	2.31	0.02	**	1.38
8	CA as % of GDP	**-0.24**	0.13	-1.86	0.06	*	0.79
11	(Intercept)	**-2.85**	0.14	-19.96	0.00	***	0.06

Significance codes: 0.01 '***' 0.05 '**' 0.1 '*'
Log-Likelihood: -365.947
Chi-squared test: X2 = 178.2, df = 7, P(> X2) = 0.0

Note: The table shows the regression result using all variables that were significant in the first regression for Model 1. All nine coefficients are statistically significant, with seven being statistically significant from 0 on a 99% level. All coefficients have very similar values to the corresponding coefficients in Regression 1. The advantage of using fewer variables is the lower chance of overfitting in-sample data which can improve the models predicting potential.

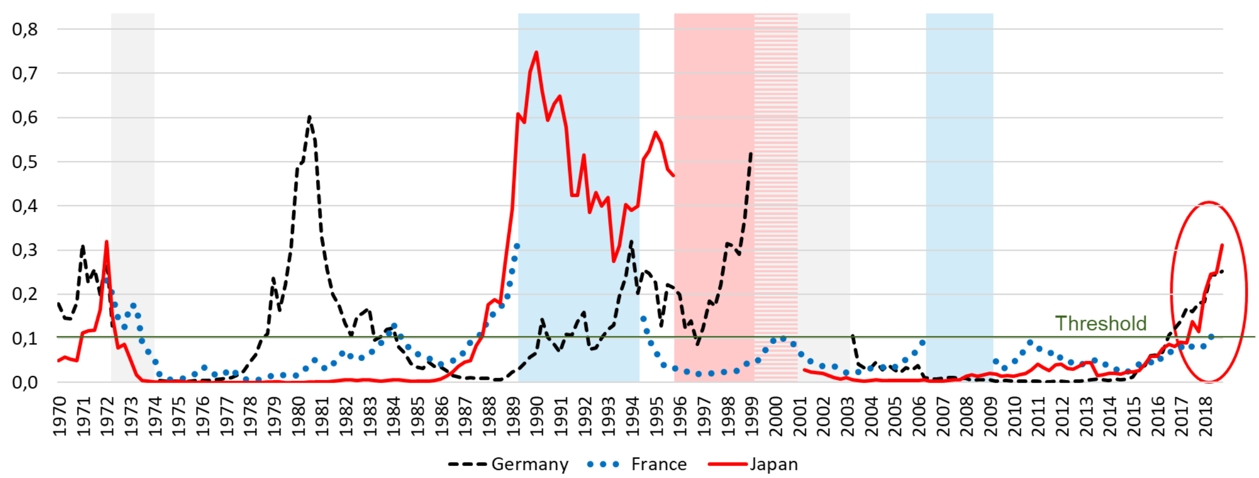

Figure A1. Model 1, Fitted Values for Countries Exceeding Thresholds in All Predictions - Fullpred2

Note: The graph shows the plotted fitted values for the three countries whose probability of crisis exceeded the selected threshold in the last four quarters in Model 1. Fitted probabilities are estimated using the (8) coefficients in Regression 2. Overall the fitted probabilities are developing very similar to what was seen in Fullpred1. Breaks in the lines occur due to the start of a crisis period. The shaded areas are illustrations of previous crisis periods with the color being linked to the country in crisis: grey for Germany, blue for France, red for Japan.

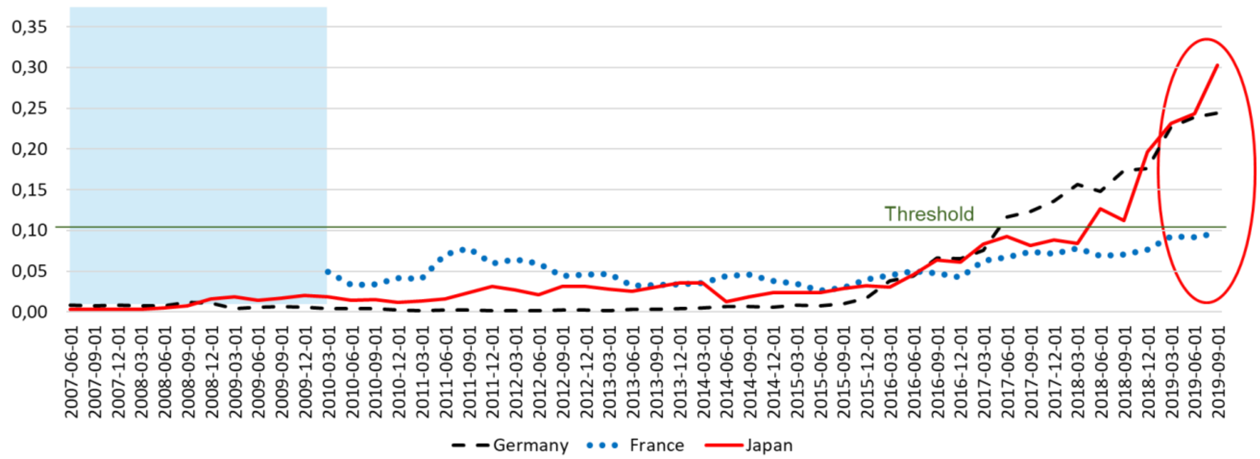

Figure A2. Model 1, Fitted Values for Countries Exceeding Thresholds in All Predictions - Forecast1

Note: The graph shows the plotted fitted values for the testing period for the three countries whose probability of crisis exceeded the selected threshold in the last four quarters in Model 1. The fitted probabilities are estimated using the (10) coefficients estimated in the first, benchmarking regression. The fitted probabilities are identical to the graph in the result section (Fullpred1) but show a more zoomed picture over the last twelve years. Breaks in the lines occur due to the start of a crisis period. The blue shaded area is an illustration of a previous crisis period in France.

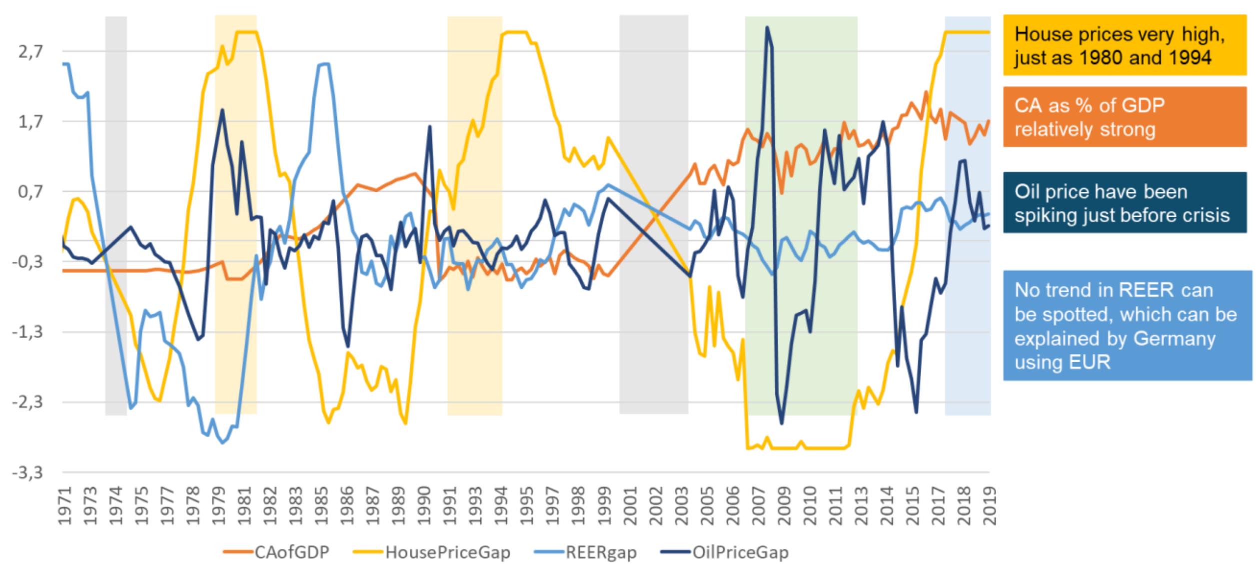

Figure A3. Model 1, A Detailed Overview of Germany (1/2) using historical data

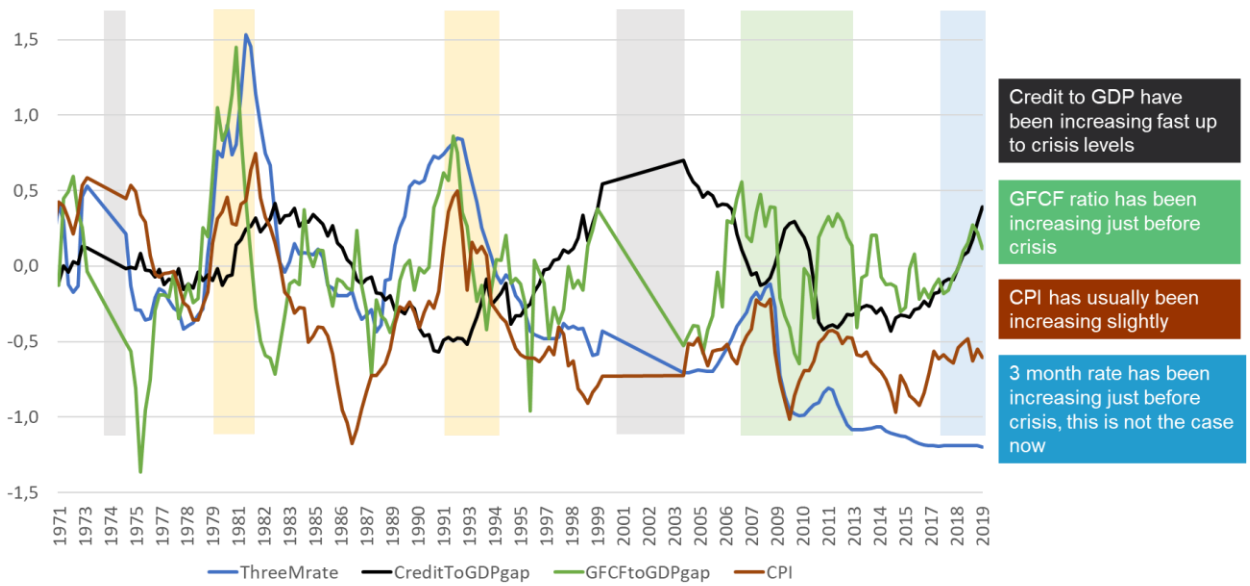

Figure A4. Model 1, A Detailed Overview of Germany (2/2) using historical data

Table A5. Model 2, Regression 1: Benchmarking Regression

	Coefficients	Estimate	Std. error	t value	Pr(> t)	
1	Compensation per employee (3y change)	**0.013**	0.008	1.707	0.099	*
2	Government debt (% of GDP) x VIX	**0.001**	0.000	3.089	0.002	***
3	Current account balance (% of GDP)	**-0.098**	0.038	-2.575	0.010	**
4	Household debt (% of GDP)	**0.024**	0.010	2.504	0.012	**
5	Real house price growth x Credit growth (3y change)	0.000	0.000	0.416	0.678	
6	NFC Debt (% of GDP)	0.006	0.005	1.211	0.226	
7	Export market share (3y change)	**0.027**	0.015	1.778	0.075	**
8	Real effective exchange rate, HICP-deflated (3y change)	**0.032**	0.018	1.790	0.073	**
9	(Intercept)	**-6.330**	0.761	-8.317	0.000	***

Significance codes: 0.01 '***' 0.05 '**' 0.1 '*',
Log-Likelihood: -99.54616,
Chi-squared test: X2 = 35.5, df = 8, P(> X2) = 2.2e-05

Note: The table shows the regression results from the benchmarking regression in Model 2, i.e. the most similar analysis compared to the benchmarking study. Seven out of nine coefficients are statistically significant, with two being statistically significant from 0 on a 99% level and four only on a 95% level. All statistically significant coefficients have the same sign (+/-) as the results in the benchmarking study showing that the results are consistent. The dependent variable is based on the first definition of crisis data (using the BBQ algorithm).

Table A6. Model 2, Regression 2: Benchmarking Regression Using Different Crisis Data

	Coefficients	Estimate	Std. error	t value	Pr(> t)	
1	Compensation per employee (3y change)	0.003	0.005	0.629	0.529	
2	Government debt (% of GDP) x VIX	**0.000**	0.000	2.789	0.005	***
3	Current account balance (% of GDP)	**-0.052**	0.022	-2.353	0.019	**
4	Household debt (% of GDP)	0.003	0.005	0.601	0.548	
5	Real house price growth x Credit growth (3y change)	0.000	0.000	-1.157	0.247	
6	NFC Debt (% of GDP)	0.007	0.003	2.706	0.007	
7	Export market share (3y change)	**-0.011**	0.009	-1.230	0.219	***
8	Real effective exchange rate, HICP-deflated (3y change)	-0.008	0.011	-0.699	0.484	
9	(Intercept)	**-2.572**	0.348	-7.391	0.000	***

Significance codes: 0.01 '***' 0.05 '**' 0.1 '*',
Log-Likelihood: -101.117,
Chi-squared test: X2 = 31.0, df = 8, P(> X2) = 0.00014

Note: The table shows the regression results from Regression 2 in Model 2, using the same explanatory variables as in the benchmarking regression but the second definition of crisis as the dependent variable (based on both the BBQ algorithm and ECB and ESRB classification). Four out of nine coefficients are statistically significant, with three being statistically significant from 0 on a 99% level, one only on a 95% level and only on a 90% level.

Table A7. Model 2, Regression 3: Adjusted for Higher Explanatory Power

	Coefficients	Estimate	Std. error	t value	Pr(> t)	
1	Compensation per employee (3y change)	**0.013**	0.008	1.723	0.085	*
2	Government debt (% of GDP) x VIX	**0.001**	0.000	3.746	0.000	***
3	NFC Debt (% of GDP)	**0.009**	0.005	2.022	0.043	**
4	Household debt (% of GDP)	**0.022**	0.009	2.576	0.010	***
5	Credit growth (3y change)	**0.022**	0.005	4.459	0.000	***
6	Current account balance (% of GDP)	-0.048	0.035	-1.371	0.170	
7	(Intercept)	**-7.570**	0.898	-8.432	0.000	***

Significance codes: 0.01 '***' 0.05 '**' 0.1 '*',
Log-Likelihood: -94.83383,
Chi-squared test: X2 = 38.9, df = 6, P(> X2) = 7.4e-07

Note: The table shows the regression results from Regression 3 in Model 2, using the first definition of crisis (the BBQ algorithm), but different explanatory variables from the benchmarking regression. Six out of seven coefficients are statistically significant, with four being statistically significant from 0 on a 99% level and one coefficient only on a 95% level. The separate variable "Credit growth" is introduced and is shown to be positive, meaning growth in credit increases the probability of a crisis.

Table A8. Model 2, Regression 4: Adjusted for Higher Explanatory Power

	Coefficients	Estimate	Std. error	t value	Pr(> t)	
1	Compensation per employee (3y change)	**0.001**	0.000	3.044	0.002	***
2	Government debt (% of GDP) x VIX	**0.000**	0.000	3.096	0.002	***
3	NFC Debt (% of GDP)	**0.008**	0.003	2.889	0.004	***
4	Household debt (% of GDP)	0.005	0.005	0.971	0.331	
5	Real house price growth (3y change)	**-0.126**	0.024	-5.294	0.000	***
6	Current account balance (% of GDP)	**-0.046**	0.022	-2.045	0.041	**
7	(Intercept)	**-2.553**	0.325	-7.864	0.000	***

Significance codes: 0.01 '***' 0.05 '**' 0.1 '*',
Log-Likelihood: -279.5657,
Chi-squared test: X2 = 52.8, df = 6, P(> X2) = 1.3e-09

Note: The table shows the regression results from Regression 4 in Model 2, using the different combinations of the explanatory variables than in the benchmarking regression and the second definition of crisis, based on both the BBQ algorithm and ECB and ESRB classification. Six out of seven coefficients are statistically significant, with five being statistically significant from 0 on a 99% level and one coefficient only on a 95% level. The separate variable "Real house price growth" is introduced and is shown to be positive, meaning growth in credit increases the probability of a crisis.

Table A8: Table of Acronyms

Acronym	Meaning
ANN	Artificial Neural Networks
BBQ algorithm	BBQ - Boshan Quarterly algorithm (by Harding-Pagan)
BIS	Bank of International Settlement
CPI	Consumer Price Index
ECB	European Central Bank
ELM	Extreme Learning Machines
ESRB	European Systemic Risk Board
EWM	Early Warning Model
EWI	Early Warning Indicator
FED	Federal Reserve
FN rate	False Negative rate
FP rate	False Positive rate
FSC	Financial Stability Committee
GFC	Great Financial Crisis (2007-2009)
HP filter	Hodrick-Prescott filter
IMF	International Monetary Fund
KNN	k-nearest neighbors
LDA	Linear Discrimination Analysis
MIP Scoreboard	Macroeconomic Imbalance Procedure Scoreboard
OECD	Organization for Economic Cooperation and Development
QDA	Quadratic Discriminant Analysis
QE	Quantitative Easing
SVM	Support Vector Machines
TN-rate	True Negative rate
TP-rate	True Positive rate

END OF MASTER THESIS I

MASTER THESIS II

Stockholm School of Economics
Department of Finance
Master's Thesis (M.Sc. Finance)
Fall 2020

COVID-19's Impact on the European Stock Market

October 2020

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Student ID: 23233

Abstract

In light of the COVID-19 pandemic outbreak, the global stock market has experienced high volatility in the first two quarters of 2020. This study aims to identify key patterns in the developed Europe stock market during the crash in March 2020 and the following recovery. It further compares the performance of developed Europe national benchmarking indices and sector indices to the US stock market and to the performance during the last global financial crisis 2007-2010. The findings suggest that even though both the US and the European indices dropped by up to 35% during the "Black days", the US indices recovered faster than the European indices. Italy, Spain and Belgium with the highest number of deaths per capita at that time were also hit the most, with their national stock market indices dropping by more than 30%. The stock market crash during March 2020 is shown to be of similar size to the crash during the Global Financial Crisis, but with larger single-day drops, suggesting that it has been more concentrated in time and that increased market activity and globalization can have triggered greater stock market movements. In terms of sector performance, quite similar to the US stock market, Technology, Healthcare and Utilities have been recovering the fastest, while Oil & Gas, Travel & Leisure and Banks have been suffering the most. Comparing the sector performance across different sizes of companies, surprisingly, small and mid-sized Basic Resource and Food & Beverage companies have outperformed larger companies, suggesting that large companies in those sectors might be undervalued. The findings can help investors in setting up investment strategies during pandemic turmoil.

Keywords: COVID-19, stock market crash, sector performance

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Table of Contents

COVID-19’s Impact on the European Stock Market

1. Introduction

The stock market crash in March 2020 was one of the most dramatic crashes witnessed in history, with the US stock market dropping by more than 35% in a couple of days. The COVID-19 global outbreak together with falling oil prices and a trade war between the US and China were the main drivers to the crash.

2020 has so far been an extraordinary year, impossible to predict by any expert. With the COVID-19 pandemic starting as a local outbreak in Wuhan at the end of 2019, it quickly spread globally and was declared as a pandemic by World Health Organisation (WHO) on the 11th of March 2020. Before that time China had already regulated strict quarantine for almost two months, Italy had imposed strict quarantine three days earlier and most countries had imposed travel restrictions. By the 13th of March, President Trump declared a national emergency on behalf of the US and on the 17th of March at least 26 European countries closed off for all visitors for at least 20 days. As more countries enforced quarantine regulations during the end of March, the economy was forced to make a halt. A large number of people were fired, and the unemployment rate drastically rallied. (Secon, Woodward and Dave, Business Insider, 2020 and Al Jazeera, 2020)

While the COVID-19 shock forced the world to adapt and find completely different ways of living, some sectors could still benefit from people staying at home. The most evident sectors that have benefitted during the restriction period are health care, food and beverage, and technology. On the other end, sectors that seem to have been suffering the most include oil companies, travel and leisure companies, and restaurants.

While there is still evident distortion in the market environment, the stock market prices have recovered the majority of the losses witnessed during the middle of March. This seems somewhat irrational as the economy is still taking major losses with the unemployment rate rocketing and many enterprises forced to go into bankruptcy. While multiple vaccines are under development, some of them already in the stage of human trials, final approval and large-scale production will most likely not start before 2021 (Corum et. al, The New York Times, 2020). Meanwhile, many countries are still dealing with large epidemics and a widespread fear for a second wave arriving in the fall have arisen as restrictions are eased (Gallagher, BBC, 2020).

Since the COVID-19 global outbreak, the global stock market has witnessed increased volatility with the VIX volatility index increasing by more than five times from the levels at the beginning of 2020 (CBOE Volatility Index, 2020). Nevertheless, the stock market has still performed much better than experts' estimates and in comparison, to the overall expected loss in GDP growth presented by the International Monetary Fund's (IMF), The Organisation for Economic Co-operation and Development's (OECD) and the World Bank's forecasts. According to a study developed by Junttila (2020), this can mainly be explained by the European Central Bank (ECB) and the Federal Reserve (FED) taking extensive, unconventional monetary policy actions to stabilize the economy.

This study aims to compare the drop and the following recovery of major European and US indices during the COVID-19 crisis to the major drops witnessed during the Great Financial Crisis (GFC) in 2007-2010. It also analyses the performance across different European Sector Indices and their recovery by the end of June 2020, comparing the results for only large companies with the total market. The findings help to understand if investment strategies developed for the US stock markets could also be applied to the European market.

The paper is divided into six sections. After this introduction section, Section 2 presents previous literature that has been published in recent months about the COVID-19's impact on the global stock market. Section 3 outlines the data used for this study. Section 4, presenting the main results of this study is split into three parts: the main drops witnessed during the middle of March 2020, the comparison of market drops and recovery in the light of the COVID-19 crisis compared to the GFC, and the performance and recovery of different sector indices during the first half of 2020. The fifth section discusses the main findings of the analyses and the sixth section concludes and provides suggestions for future research. The remaining pages present a list of references and appendices for details.

2. Previous Literature

In recent months a lot of literature has been published about the impact of COVID-19 on the stock market, analyzing the market's response to the pandemic, the role of policy intervention on markets as well as possible investment strategies.

Multiple studies have found significant negative correlations between the number of COVID-19 cases or deaths and the stock market returns and volatilities in numerous countries (Alber 2020, Alfaro et. al. 2020, Ashraf 2020, Onali 2020, Wang and Enilov 2020). While results differ significantly across countries, they also differ across different subperiods across the outbreak (Alber 2020). Overall the studies find that the stock market returns have a stronger relationship with the number of infections rather than the number of deaths. Also, the stock markets reacted much stronger at the beginning of the outbreak. Shanev et. al. (2020) in addition to the number of infections, pointed out irrational panic surrounding COVID-19 and national lockdown policies as the main drivers of the stock market drops.

As the stock market witnessed a quick recovery after the March 2020 drop, several studies have focused on explaining the rationale behind the renaissance despite negative GDP growth expectations. Junttila (2020) and Shanev et. al. (2020) have found that unconventional monetary policy actions have played a key role in stabilizing the stock market. Moreover, to keep the financial markets at current levels the central banks must continue to support the economies.

Mazur et. al. (2020), in addition to investigating the overall US stock market performance during the crash in March, analyzed and compared US stock market performance across sectors. They found that natural gas, food, healthcare and software stocks earned higher positive returns, whereas petroleum, real estate, entertainment and hospitality sectors fell dramatically. Also, Ramelli and Wagner (2020) investigated industry performance across North American companies, splitting the analysis into three periods: Incubation period, Outbreak period and Fever period. They concluded that Telecom, Pharma & Biotech and Semiconductors had the highest performance during the whole period, while Energy, Consumer Services and Real Estate suffered the most. Utilities gained only in the beginning, while Food and Staples retailing suffered in the beginning but surged in the Fever period. Other studies have further extended such analysis, investigating a smaller number of the best performing US and global stock market sector indices and developing strategies for investors to use during similar market conditions (Feng et. al. 2020, Wang et. al. 2020, Yan et. al. 2020). Albuerque et. al. (2020) showed that highly rated environmental and social (ES) stocks outperformed other stocks during the first quarter of 2020 in terms of higher returns, lower return volatility and higher operating profit margins.

While the literature on the US stock market concerning sector performance and investment strategies during the COVID-19 crisis has grown fast, little has been said about the European sector performance. This study aims to fill this gap by comparing the overall development of 19 supersectors in Europe during the COVID-19 crisis. The findings can then be further applied to investment strategies similar to the one identified by Wang et. al. (2020).

The following section presents the data used in this study.

3. Stock Market Data

The analyses conducted in this study are based on stock market data collected from publicly available sources such as the Wall Street Journal, Yahoo Finance and Investing.com based on the longest available data.

For 17 national benchmarking stock market indices, daily closing prices and trading volumes have been retrieved from 2007-01-01 until 2020-07-01. Two of the indices (DJI and S&P500) are mirroring the US stock market and one is approximating the Japanese market (N225). The EURO STOXX 50 is a blue-chip index developed by STOXX, covering 50 stocks from 8 Eurozone countries. The remaining 13 indices cover different developed European countries. For full details on the national benchmarking indices and their corresponding countries, see Table A2 in Appendix.

To compare developed Europe sector performance, supersector indices developed by STOXX Ltd are used. 19 STOXX Europe 600 Supersector indices are used to proxy the total market return of each supersector. Each STOXX Europe 600 Supersector index consist of a fixed number of 600 components representing large, medium and small size companies across 17 developed European countries. The stocks are weighted according to free-float market capitalization with the largest constituent being capped at 30% and the second largest at 15% (STOXX Qontigo, 2020 and STOXX "STOXX Europe 600", 2020). Also, 19 EURO STOXX Supersector indices are used to cover the 50 largest and most liquid stocks in 11 Eurozone countries across each supersector (STOXX "EURO STOXX 50", 2020). In this way, while STOXX Europe 600 mirrors the total market return, covering approximately 90% of the free-float market capitalization of the developed European stock market, the EURO STOXX covers only the largest companies in the Eurozone (considered to have the largest impact on the European market) with approximately a 60% free-float market capitalization. Full details on the sector indices used are provided in Table A3 and Table 4 in the Appendix.

Once retrieved, all closing price data have been transformed into daily returns using discrete compounding:

$$Return_t = \frac{Closing\ Price_t}{Closing\ Price_{t-1}} - 1$$

Also, total index returns during 2020 and returns after the worst drops in middle March have been computed to assess the overall market performance and recovery.

The following section will present the main results obtained using the stock market data.

4. Results for the Quantitative Analysis

The results section is divided into three parts. The first part measures the largest stock market drops during March 2020. The second part compares the stock market drops and the recovery during March 2020 with the downturns during the GFC. The third part of this section analyses sector performance across 19 European sector indices and compares COVID-19's impact on all companies against the impact on only large companies.

4.1. Main Market Drops amid COVID-19

During a period of slightly more than one week in March 2020, the global stock markets witnessed extreme negative returns. Afterwards, three dates where the global stock market decreased the most were named:

1. ***"Black Monday I"*** on the 9th of March was the first trading day after Italy imposed a strict quarantine in the whole country on the 8th of March.
2. ***"Black Thursday"*** on the 12th of March witnessed investors reactions after Wednesday when WHO declared the COVID-19 as a pandemic and the US blocked all visitors besides British to enter the country.
3. ***"Black Monday II"*** on the 16th of March was a response to Presidents Trump declaring "National emergency" on Friday, the 13th of March, and limiting gathering to maximum 50 people on the 15th of March.

A classification of a stock market crash can be done when there is at least a 20% decline in the main index (Mishkin and White, 2002). During these three days, almost all European and US national stock indices witnessed extreme drops in stock returns exceeding 20%. Table 1 below presents a summary of the total drop in each national benchmarking index analyzed during the black days as well as during the whole week.

Table 1. Stock Market Crash across National Benchmarking Indices in March 2020

Index	Country	9th March	12th March	16th March	Total drop Black days	From 6th to 16th March
BEL20	Belgium	-8.1%	-14.2%	-7.1%	-29.4%	-31.7%
OMXC20	Denmark	-4.9%	-7.5%	-1.6%	-14.0%	-19.4%
EURO Stoxx50	Europe	-8.5%	-12.4%	-5.3%	-26.1%	-30.2%
OMXH25	Finland	-7.3%	-10.1%	-5.2%	-22.6%	-30.5%
CAC40	France	-8.4%	-12.3%	-5.8%	-26.4%	-30.8%
DAX	Germany	-7.9%	-12.2%	-5.3%	-25.5%	-29.8%
ISEQ20	Ireland	-6.4%	-9.9%	-7.9%	-24.3%	-29.6%
FTSE MIB	Italy	-11.2%	-16.9%	-6.1%	-34.2%	-33.5%
N225	Japan	-5.1%	-4.4%	-2.5%	-11.9%	-22.2%
AEX	Netherlands	-7.7%	-10.8%	-3.7%	-22.1%	-27.1%
OBX20	Norway	-8.6%	-8.5%	-3.9%	-20.9%	-24.4%
PSI20	Portugal	-8.7%	-9.8%	-4.4%	-22.8%	-27.0%
IBEX35	Spain	-8.0%	-14.1%	-7.9%	-29.9%	-33.3%
OMX30	Sweden	-5.3%	-10.6%	-3.4%	-19.3%	-22.7%
FTSE100	UK	-7.7%	-10.9%	-4.0%	-22.6%	-25.2%
S&P500	US	-7.6%	-9.5%	-12.0%	-29.1%	-21.5%
DJI	US	-7.8%	-10.0%	-12.9%	-30.7%	-23.3%

Overall, the countries suffering the most during the three "black" days where Belgium (-29%), Spain (-30%), US (S&P500: -29%, DJI: -31%) and Italy (-34%). However, summing the drops across the whole 1.5 weeks: from 6th of March until 16th of March the European stock market indices seem to have suffered much more than the US that recovered almost 8% from the drop. The BEL20, CAC40, DAX, ISEQ, Spain, EURO Stoxx, OMXH25 and FTSE MIB all dropped by at least 30% while the total drop of S&P500 and DJI was 21% and 23% respectively. Notably, the American Indices dropped by 29% and 30% respectively during the black days, but the drop on each black day followed by a much stronger recovery than for most European indices. For example, the day after Black Thursday the US markets recovered by more than 9% (after dropping by 10%), while the average recovery across the European indices were just 2%. The same applies for Black Monday I and II, where the US indices on average recovered by 5% and 6% respectively, while the European indices on average dropped by 2% on the 10th of March and recovered only by 2% on the 17th of March. The explanation could be that during this period the virus was spreading quickly across southern Europe with Italy, Spain and Belgium being the countries suffering the most. Also, restrictions where much stricter in the European countries than in the US during that time. Thus, investor strategies based on the major drops caused by the sudden shutdowns and investors panic-selling could be more effective in the European market than in the US market during these times.

Notable is that, while European countries suffered the most during the Black Thursday, the US indices dropped the most during Black Monday II which seems rational with regards to the news. The Asian market was not affected as much, with the Japanese index dropping only by a total of 12% during these three days.

4.2. Market Drops and Recovery during COVID-19 compared to the Great Financial Crisis

It is of interest to put the COVID-19 crisis in perspective to the GFC as it also triggered major drops in national stock indices. This section thus provides a comparison of the daily returns and trading volumes during the most negatively impacted days of the national benchmarking stock market during the COVID-19 crisis and the GFC. Further, the volatility during both crises is assessed and a 25 trading days period is selected to further understand the crises evolution. Finally, the cumulative returns of the indices are compared over a longer period to capture the immediate recovery of the stock markets following the market crashes. This is done by looking at a 6-month period for both crises both on an index by index basis, and on a regional basis, by constructing an equally weighted European and an equally weighted US return index, linking all indices previously assessed to the corresponding region.

Table 2 below, presents a comparison of the worst-performing trading day in each national index during the COVID-19 versus the GFC.

Table 2. Comparison of Daily Returns during the GFC and the COVID-19 Crisis across National Benchmarking Indices

	COVID-19 Crisis			Global Financial Crisis		
Index	**Date**	**Max negative return**	**Volume**	**Date**	**Max negative return**	**Volume**
FTSE MIB	2020-03-12	**-16.92%**	**1 540.00M**	2008-10-06	-8.24%	n.a.
BEL20	2020-03-12	**-14.21%**	n.a.	2008-09-29	-7.98%	74.76M
IBEX35	2020-03-12	**-14.06%**	**723.61M**	2008-10-10	-9.14%	0.60M
DJI	2020-03-16	**-12.93%**	770.13M	2008-10-15	-7.87%	374.35M
EURO Stoxx50	2020-03-12	**-12.40%**	167.33M	2008-10-10	-7.88%	n.a.
CAC40	2020-03-12	**-12.28%**	371.40M	2008-10-06	-9.04%	277.66M
DAX	2020-03-12	**-12.24%**	390.48M	2008-10-06	-7.07%	304.49M
S&P500	2020-03-16	**-11.98%**	7 781.54M	2008-10-15	-9.03%	6 542.33M
FTSE100	2020-03-12	**-10.87%**	2 210.00M	2008-10-10	-8.85%	n.a.
AEX	2020-03-12	**-10.75%**	n.a.	2008-10-06	-9.14%	188.52M
OMX30	2020-03-12	**-10.57%**	305.01M	2008-10-06	-7.24%	n.a.
OMXH25	2020-03-12	**-10.13%**	149.37M	2008-10-06	-8.52%	n.a.
ISEQ20	2020-03-12	-9.94%	75.19M	2008-09-29	**-13.03%**	44.36M
PSI20	2020-03-12	**-9.76%**	200.14M	n.a.	n.a.	n.a.
OBX20	2020-03-12	-8.48%	172.28M	2008-11-06	**-10.66%**	n.a.
OMXC20	2020-03-12	-7.52%	35.68M	2008-10-06	**-11.06%**	n.a.
N225	2020-03-13	-6.08%	0.17M	2008-10-16	**-11.41%**	0.19M

Note: Data that is not publicly available for the whole period is marked "n.a." in the table.

Out of the 17 indices analyzed, 11 performed worse during the COVID-19 crisis than during GFC, while 5 performed slightly better. As previously discussed, the common date for the largest relative loss during the COVID-19 crisis across Europe was the 12th of March, where many European benchmarking indices experienced the largest drops in their history. The US indices dropped the most on the 16th after President Trump declared a national emergency and banned gathering of more than 50 people. The Japanese index experienced its largest drop on the 13th of March which was the smallest drop of all indices assessed.

During the GFC, the drops were much more split across different dates than during the COVID-19 crisis as the crises occurred during different times across countries. This can partly be explained by the different natures of the two crises, but possibly also by the increased globalization and integration across economies in recent years.

When comparing the trading volumes for the same indices across the two crises it is evident that the volumes were significantly higher during the COVID-19 crisis across the majority of indices. This once again points towards the recent economic integration with investors being able to diversify their holdings across different geographies, but also towards the increased popularity of trading. The higher number of trades also explain the larger drops.

To get a broader view of how the market evolved during the two crises, Figure 1 below, compares the rolling 25 trading days volatility across different regions during the GFC and the COVID-19 crisis.

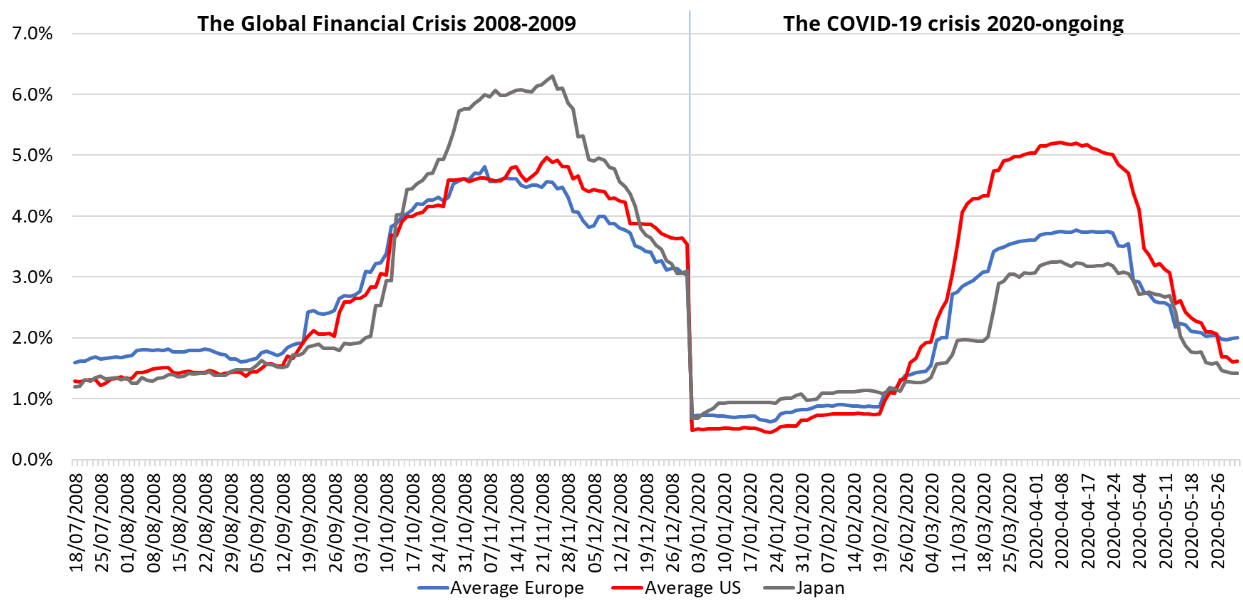

Figure 1: Comparison of rolling 25 trading days volatility during the GFC and the COVID-19 crisis

Note: The rolling 25 trading day volatility windows are computed as 25 trading days backwards-looking standard deviation of index returns. The indices used are the same as listed in Table 1 and Table 2 and have been equally weighted within each region.

As can be noted from Figure 1, the average volatility in the European and Japanese markets have been significantly lower during the COVID-19 crisis compared to the GFC, while the volatility in the US has been higher during the COVID-19 crisis. During the GFC the volatility started to rise in the middle of September, most notably in Japan, reaching its peak in November. For the COVID-19 crisis, the volatility started rising in the middle of February, most notably in the US market, reaching its peak at the beginning of April. With this background analysis, it is of interest to look closer into the period where the volatility started increasing dramatically. For this purpose a 25 trading days period for each crisis has been brought into attention in the following Table 3: 2008-09-01 to 2008-10-06 for the GFC and 2020-02-21 to 2020-03-27 for the COVID-19 crisis.

Table 3: Comparison of daily returns during the GFC and the COVID-19 crisis over 25 trading days

	COVID-19 crisis				Global financial crisis 2008-2009				COVID-19 crisis - GFC			
Index	**Mean**	**St.Dev**	**Min**	**Max**	**Mean**	**St.Dev**	**Min**	**Max**	**Diff Mean**	**Diff St. Dev**	**Diff Min**	**Diff Max**
BEL20	-0.88%	3.78%	**-14.21%**	**7.64%**	-1.33%	3.73%	-7.98%	6.56%	0.45%	0.05%	-6.23%	1.08%
ISEQ20	-0.77%	3.32%	-9.94%	6.94%	-0.94%	5.06%	**-13.03%**	**9.36%**	0.17%	-1.74%	3.10%	-2.42%
DAX	-0.58%	3.46%	**-12.24%**	10.98%	-1.07%	3.96%	-7.07%	**11.28%**	0.49%	-0.50%	-5.17%	-0.30%
CAC40	-0.56%	3.48%	**-12.28%**	8.39%	-1.02%	4.14%	-9.04%	**9.23%**	0.46%	-0.66%	-3.24%	-0.85%
IBEX35	-0.55%	3.79%	**-14.06%**	7.82%	-1.03%	4.09%	-9.14%	**9.42%**	0.47%	-0.31%	-4.92%	-1.60%
PSI20	-0.54%	2.89%	**-9.76%**	**7.82%**	n.a.	n.a.	n.a.	n.a.				
EURO Stoxx50	-0.53%	3.47%	**-12.40%**	**9.24%**	-1.07%	3.95%	-7.88%	5.61%	0.53%	-0.48%	-4.52%	3.63%
OMXH25	-0.53%	2.98%	**-10.13%**	**6.89%**	-1.02%	3.50%	-8.52%	5.82%	0.49%	-0.53%	-1.61%	1.07%
FTSE100	-0.47%	3.27%	**-10.87%**	**9.05%**	-0.81%	4.00%	-8.85%	8.05%	0.35%	-0.73%	-2.03%	1.00%
OBX20	-0.45%	2.91%	-8.48%	5.38%	-1.54%	5.90%	**-10.66%**	**8.68%**	1.09%	-2.98%	2.18%	-3.30%
FTSE MIB	-0.44%	3.99%	**-16.92%**	8.93%	-1.13%	4.09%	-8.24%	**9.87%**	0.69%	-0.10%	-8.68%	-0.94%
AEX	-0.38%	3.19%	**-10.75%**	8.97%	-1.39%	4.58%	-9.14%	**9.09%**	1.01%	-1.39%	-1.61%	-0.12%
OMX30	-0.32%	3.01%	**-10.57%**	**7.09%**	-1.09%	3.68%	-7.24%	6.86%	0.78%	-0.67%	-3.33%	0.23%
N225	-0.31%	2.85%	-6.08%	8.04%	-0.73%	5.82%	**-11.41%**	**14.15%**	0.43%	-2.97%	5.33%	-6.11%
OMXC20	-0.19%	2.21%	-7.52%	3.50%	-1.28%	4.34%	**-11.06%**	**8.55%**	1.10%	-2.13%	3.54%	-5.05%
DJI	-0.18%	4.82%	**-12.93%**	**11.37%**	-1.08%	4.01%	-7.87%	10.88%	0.90%	0.81%	-5.06%	0.49%
S&P500	-0.14%	4.46%	**-11.98%**	9.38%	-1.27%	4.30%	-9.03%	**10.79%**	1.13%	0.17%	-2.95%	-1.41%

Note: Both datasets are based on the same number of data points (25 trading days). The period used for the COVID-19 crisis is 2020-02-21 to 2020-03-27, while the period used for the GFC is 2008-09-01 to 2008-10-06. St. Dev stands for standard deviation and proxies the daily volatility of the indices during the assessed period. The value "Min" corresponds to the most negative daily returns witnessed during the period assessed. The value "Max" refers to the highest returns observed after the first drop.

Both these periods captured the largest single-day stock market drops during each crisis. While the COVID-19 crisis had larger single-day drops in prices, the overall single-day increases have been of similar size. Still, both the average decline during this period and the volatility seem to have been higher during the GFC. This can be explained by fewer larger drops during the COVID-19 crisis.

In the following graphs (Figure 2-4) the two crises are compared over a longer period of 6 months (125 trading days) by region. The period used for the COVID-19 Crisis includes 2020-01-02 to 2020-07-01, while the period used for the GFC is 2008-08-01 to 2009-02-01. The most volatile 25 trading day period previously assessed is thus presented from day 37 to day 62 in the graphs.

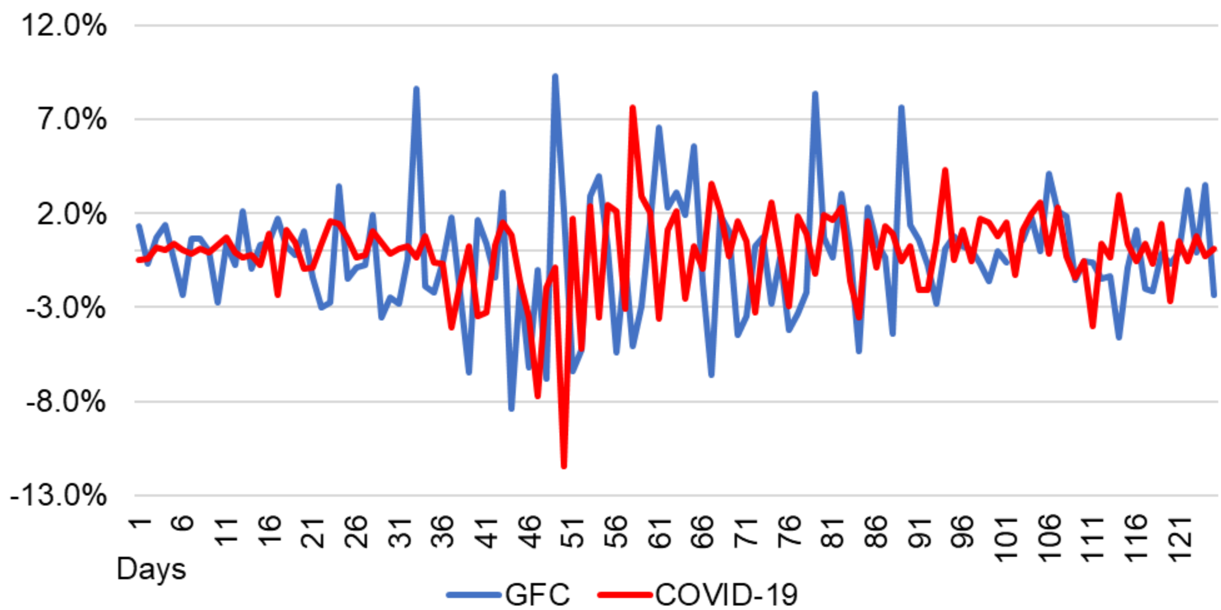

Figure 2: Comparison of equally weighted index returns for major European Indices over 125 trading days during the GFC and the COVID-19 crisis

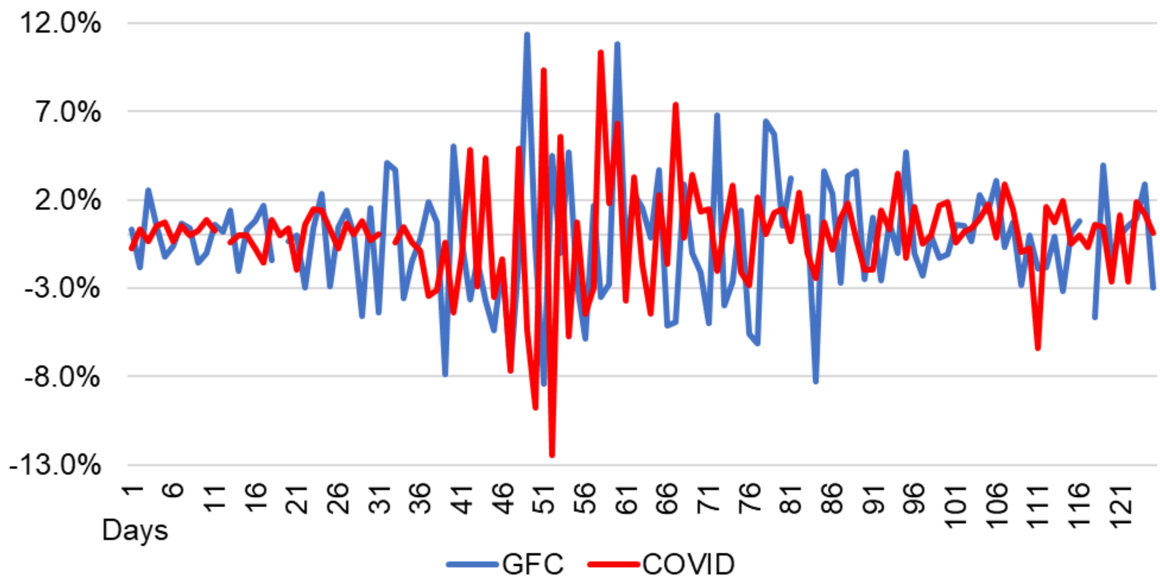

Figure 3: Comparison of equally weighted index returns for major American Indices over 125 trading days during the GFC and the COVID-19 crisis

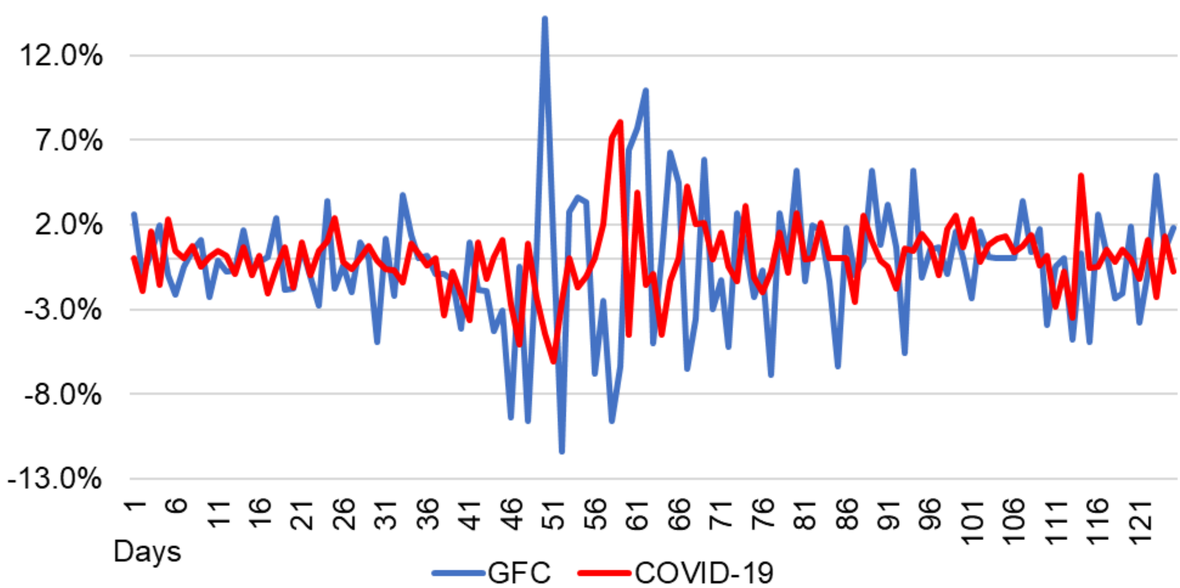

Figure 4: Comparison of returns for the Japanese index over 125 trading days during the GFC and the COVID-19 crisis

As can be seen from the graphs above, the COVID-19 crisis experienced major drops exceeding the GFC in both Europe and the US, while the drops in the stock market returns in Japan has been substantially smaller.

Table 4 below, presents a summary of the returns by index, comparing the overall market impact over the 6 months during the COVID-19 crisis with the GFC.

Table 4: Comparison of overall market impact for 125 trading days during the GFC and the COVID-19 crisis using cumulative returns

	COVID-19 Crisis			**Global Financial Crisis**		
Index	Diff from Max	Largest drop	Recovery	Diff from Max	Largest drop	Recovery
	Max-Last date	*Max-Min*	*Min-Last date*	*Max-Last date*	*Max-Min*	*Min-Last date*
FTSE MIB	-12.02%	-44.40%	18.61%	-31.17%	-43.63%	2.31%
BEL20	-12.49%	-41.57%	20.00%	-28.67%	-47.86%	3.90%
IBEX35	-21.37%	-41.03%	11.56%	-22.83%	-35.80%	4.71%
ISEQ20	-18.09%	-40.31%	22.22%	-28.81%	-61.07%	2.92%
DAX	-5.40%	-39.95%	28.53%	-28.84%	-38.81%	3.30%
EURO Stoxx50	-11.44%	-39.21%	22.90%	-27.24%	-39.46%	2.71%
OMXH25	-1.04%	-39.11%	24.23%	-31.09%	-44.30%	2.39%
CAC40	-17.29%	-39.00%	19.40%	-25.86%	-39.17%	2.89%
DJI	-8.49%	-37.96%	24.74%	-25.33%	-37.35%	3.96%
AEX	-5.52%	-36.73%	25.87%	-31.66%	-48.83%	6.51%
S&P500	-0.42%	-35.26%	26.96%	-30.90%	-43.87%	5.83%
FTSE100	-18.10%	-35.25%	15.31%	-17.24%	-34.65%	6.88%
OMX30	-2.32%	-33.62%	21.16%	-22.43%	-38.92%	5.82%
N225	-2.70%	-32.45%	22.18%	-36.38%	-47.87%	6.35%
OBX20	-14.58%	-31.84%	16.01%	-40.68%	-59.07%	10.53%
OMXC20	23.05%	-29.93%	27.71%	-32.54%	-46.86%	6.77%
PSI20	-14.14%	-34.94%	14.34%	n.a.	n.a.	n.a.
Average Europe	-9.34%	-37.63%	20.56%	-28.39%	-44.49%	4.74%
Average US	-4.46%	-36.61%	25.85%	-28.12%	-40.61%	4.89%

Note: The period used for the COVID-19 Crisis includes 2020-01-02 to 2020-07-01, while the period used for the GFC is 2008-08-01 to 2009-02-01. The value "Min" corresponds to the lowest index price during the period. The Max-Min mirrors the total drop of the index from the highest price observed in the weeks before the stock market crash until the lowest price. The last date refers to the price on the last day of the period assessed.

The difference between maximum and minimum for 125 trading days have been higher for the COVID-19 crisis than for the GFC for most of the European countries. Italy, Spain, Germany, the US (through DJI) and the UK, have all experienced more decline during COVID-19 in comparison to the GFC over the half-year period.

The average decline from max to min across all markets has been 37.6% during 2020, compared to 44.5% during the GFC. Italy has declined the most, 44.4% and Denmark the least, 29.9%. Based on the data, the stock market recovery of COVID-19 crisis has been faster than during the GFC with almost all indices having increased by at least 15% since the lowest point as of 1st July 2020. This is also seen in the graphs below (Figure 5 - 7), where the COVID-19 crisis and GFC are compared over the respective 125-days periods.

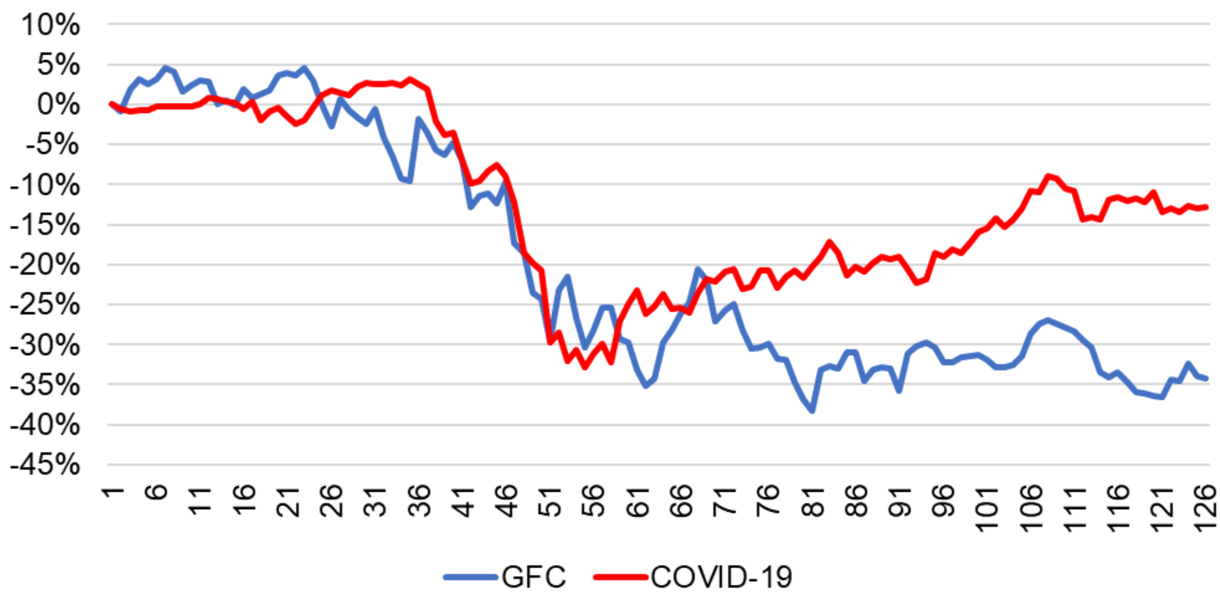

Figure 5: Comparison of equally weighted cumulative index returns for major European Indices over 125 trading days during the GFC and the COVID-19 crisis

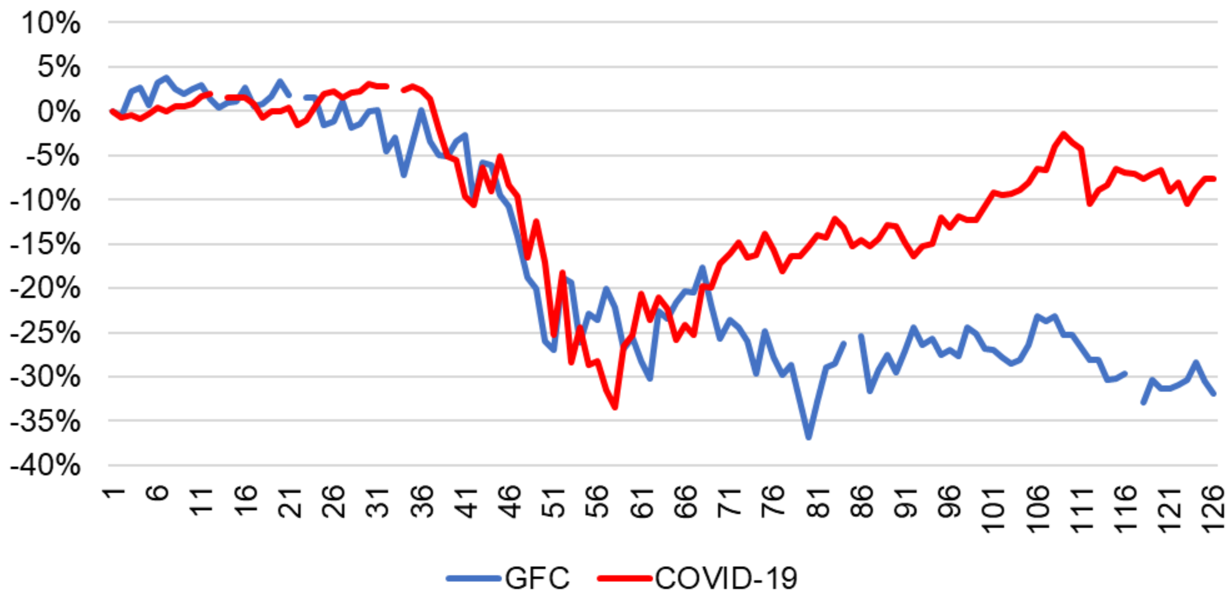

Figure 6: Comparison of equally weighted cumulative index returns for major American Indices over 125 trading days during the GFC and the COVID-19 crisis

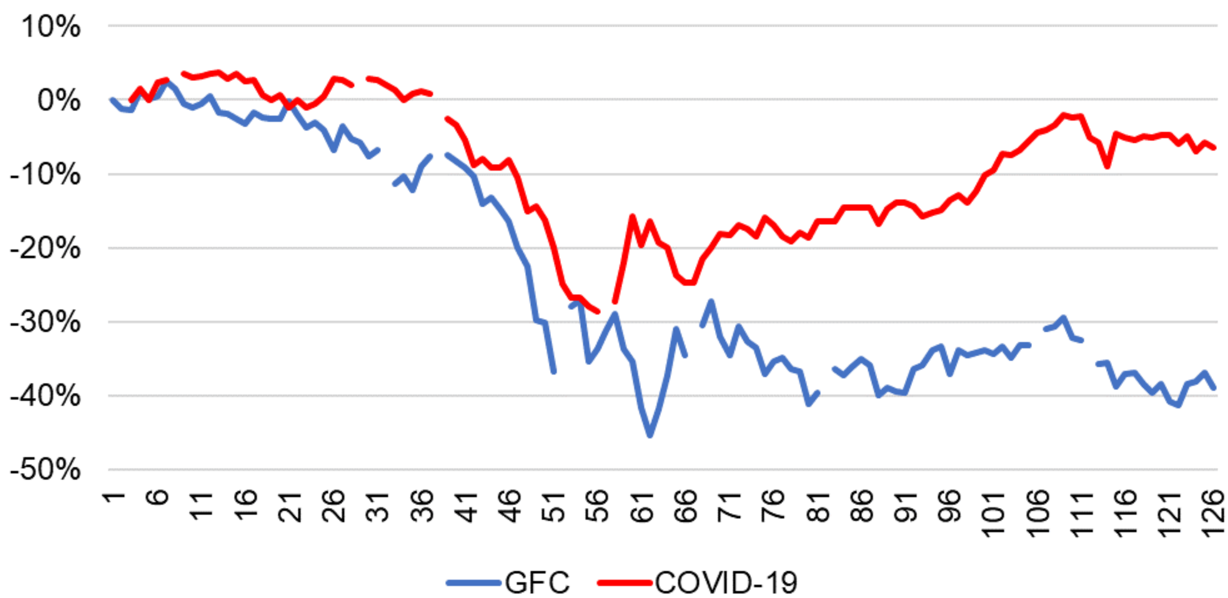

Figure 7: Comparison of cumulative returns for the Japanese index over 125 trading days during the GFC and the COVID-19 crisis

In summary, the stock market drops during the COVID-19 outbreak had similar patterns to the GFC, with the stock market dropping by around 30% in the first weeks. During the COVID-19 crisis, the stock markets, however, experienced slightly larger single-day drops. This can partly be explained by the united hit on the whole global economy. Over a longer period, the stock markets during the COVID-19 crisis have recovered much faster than during the GFC.

4.3. Performance and Recovery Across European Sectors

This section studies the COVID-19 crisis impact on 19 different Supersectors in Europe and compares their recovery up until July 2020.

Out of the 19 analyzed sectors, Figure 8 below, presents the six best-performing (Technology, Health care, Utilities, Personal & Household Goods, Retail and Food & Beverage) and the five worst-performing European sector indices (Travel & Leisure, Banks, Oil & Gas, Automobiles & Parts and Insurance) since the start of 2020 until the 1st of July 2020. For details on the performance of all 19 sector indices as of 1st July, see Table A5 and Table A6 in Appendix.

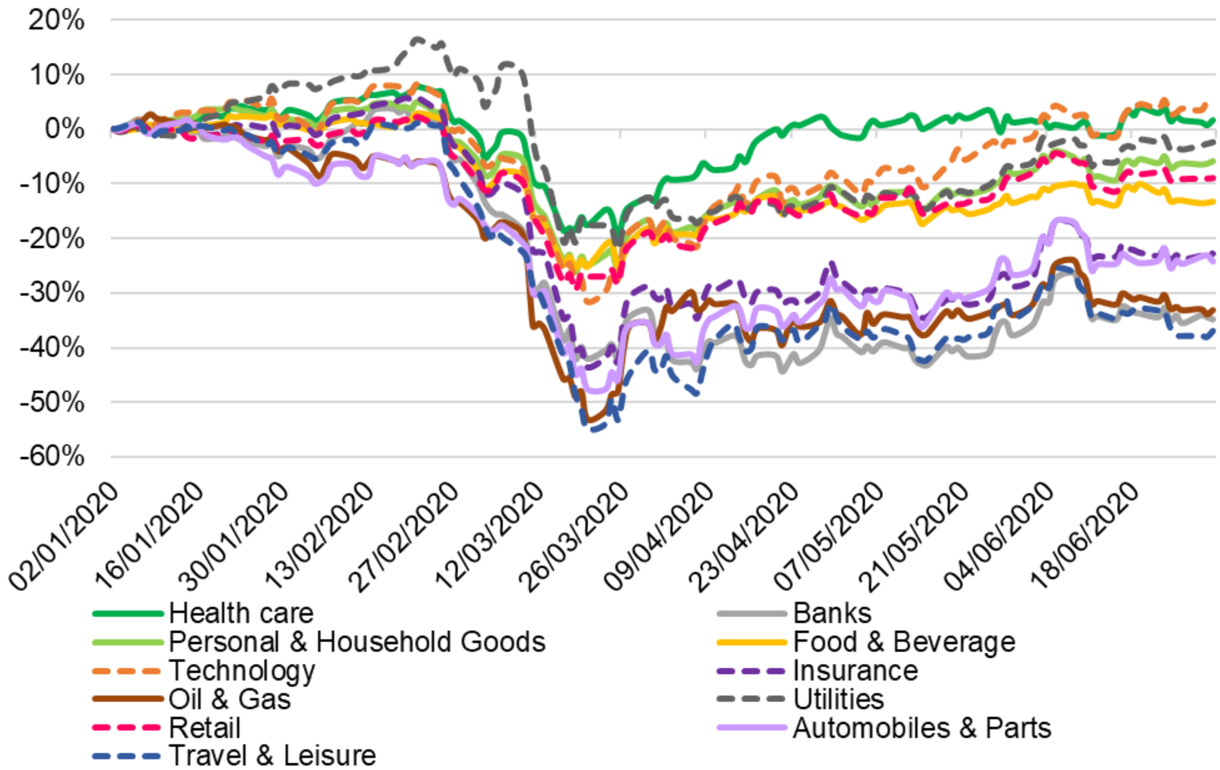

Figure 8. Performance of corporates per sector using STOXX Europe 600

As can be seen from Figure 8, Travel & Leisure, Oil & Gas and Automobiles & Parts were hit the most during the drops (-55%, -53% and -48% in total returns respectively [see Table A6 in Appendix for details]). The hit on the Travel & Leisure sector is a natural reaction to the lockdown of societies and the closing of borders. The drop in Oil & Gas and Automobiles & Parts indices, on the contrary, can be partly explained by the decreased demand for fuel and travel, and partly by the OPEC price war, with countries increasing their oil supply forcing weaker oil companies to enter bankruptcy.

While all indices reached their lowest levels around the 20th of March, banks reached their lowest marks one month later and have as of today recovered the least (only 10%), totaling in a -35% loss since the start of 2020 (see Table A6 in Appendix for details). This could be explained through the domino effect that follows as banks get hit once significant companies start failing.

The best performing European sectors during the COVID-19 outbreak were Technology, Health care and Utilities. While Health care experienced the quickest recovery, Technology has recovered the most: 37% since the largest drop. Technology and Health care (+5% and +2% since the start of the year respectively) are the only two sectors with positive returns despite the COVID-19 outbreak. With regards to recovery, Financial Services, Basic Resources, Industrial Goods & Services and Construction & Materials have been recovering the most (together with Technology) since the major drops (+28%, +27%, +25% and +26% respectively). These are all services that would be needed even if a lockdown would take place under a longer period.

Interestingly, while in the US the Food and Beverage sector was identified as a high performing sector during the COVID-19 in comparison to other sectors, in Europe it has not been as successful. While the index didn’t drop as much (-26%) as the worst-hit sectors, it only recovered 12%, yielding a -13% return since the start of 2020. On the other hand, Retail and Personal & Household goods have performed rather well, recovering by 20% each with a return of -9% and -6% respectively, since the start of the year. This seems rather unintuitive as retailers (except for food and beverage suppliers) should under imposed restrictions suffer more as the supply decrease and certain stores might need to close down.

In terms of volatility (see Table A5 in Appendix for details), the most volatile sectors in Europe during the period of March and April were Oil & Gas, Travel & Leisure, Automobiles & Parts and Basic Resources, while the least volatile were Health Care, Food & Beverage, Personal & Household Goods and Retail.

Figure 9 below, illustrates the sectors with the largest differences across the accumulated returns for large versus small/midcap companies since the start of 2020. The delta is computed taking the difference in accumulated returns since the start of 2020 of all corporates (STOXX Europe 600) and large corporates (EURO STOXX 50) across each sector at each point in time. A line below zero, therefore means that small/midcap companies performed worse than large corporates and vice versa.

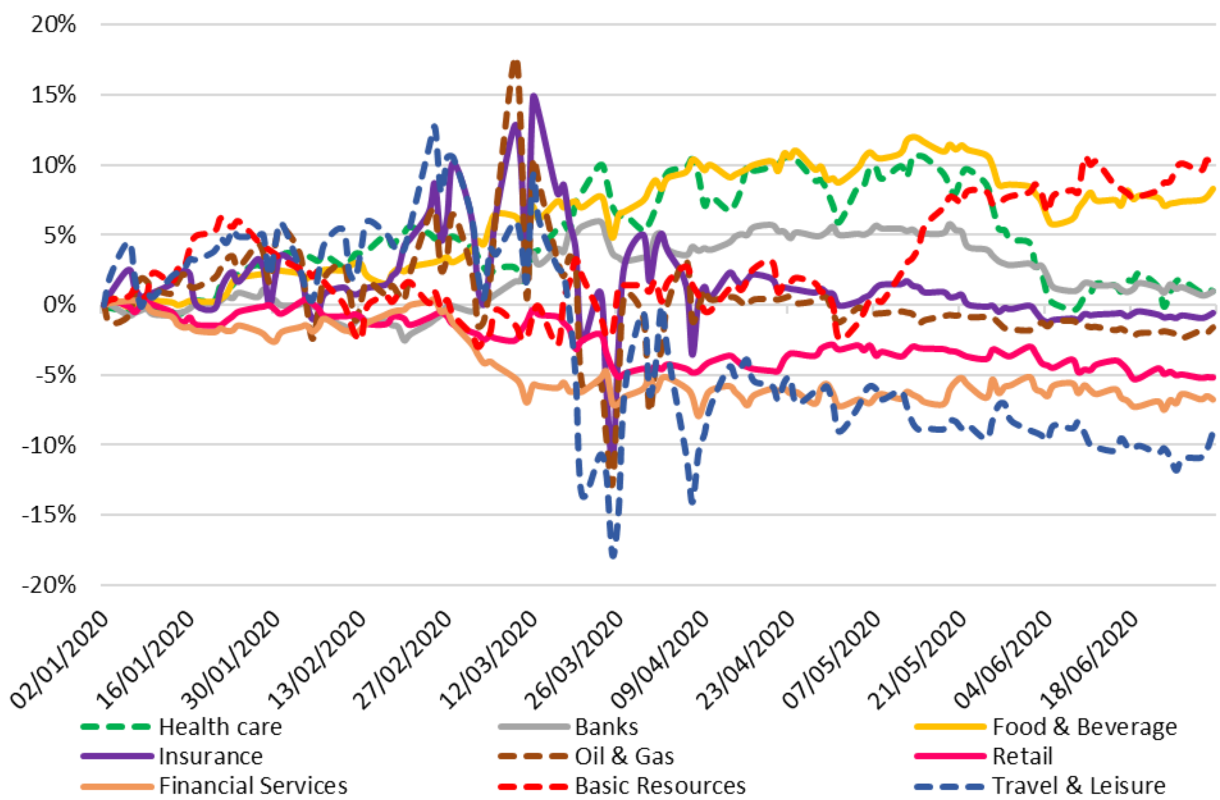

Figure 9. Delta per sector: Performance of All corporates – Performance of Large corporates

As can be seen from Figure 9, during the middle of March 2020 the difference between the performance of large and small/midcap companies (delta) started increasing. Three of the sectors experienced large changes in the delta during the end of March: Travel & Leisure, Oil & Gas and Insurance, which were also some of the sectors suffering the most. While the Oil & Gas and Insurance deltas have been stabilizing around 0% since April, Travel & Leisure delta has increased toward 10%. This can be expected as large and important travel companies will most likely be rescued by the governments, while smaller companies might be forced to go bankrupt due to the lockdown restrictions put in place. Besides Travel & Leisure corporates, as of today, also large Retail, Media and Financial Services companies have outperformed small and medium-size companies (see Table A7 in Appendix for details).

On the contrary, small and mid-sized corporates seem to have outperformed large corporates mainly within Food & Beverage, Basic Resources and until June also in Health care. As of July 1, small and mid-sized Basic Resource and Food & Beverage companies have performed 10% and 8% better than large companies respectively. This seems rather unintuitive as the earnings pattern for all sizes of corporates should be rather similar in times of COVID-19 in these sectors. We can thus expect large corporates within Basic Resources and Food & Beverage to recover in the short term.

5. Discussion

Following the results from the European sector indices visualized in the previous section, this section aims to discuss and compare the results with previous findings from the US stock market. Following the comparison, it tries to identify potential investment opportunities across different sectors in current times.

According to Mazur et al. (mentioned in section 2), the worst-performing sectors in the US market included Crude petroleum and Oil, Real Estate and Hospitality and Entertainment which all decreased by more than 70% during March 2020. On the contrary, Health care, Natural Gas, Food and Beverage and Technology were identified as the winners.

The study of sector performance in Europe found similar trends with Oil & Gas and Travel & Leisure being the sectors suffering the most, while Health care and Technology sectors being the once performing well. Interestingly, Real Estate seems to have performed significantly better in Europe than in the US, reaching a -36% low since the start of the year and recovering by 16% until July. Moreover, while the Food and Beverage sector saw a relatively small drop in March 2020 compared to other sectors (-29% from the yearly "Max" to "Min" in 3.5 weeks [see Table A6 in Appendix for details]), it has still not recovered as much as other sectors, trading at a -13% return since the start of the year. Also, as large Food & Beverage corporates seem to have performed worse than small and mid-sized corporates, there are indications that large Food & Beverage companies can be undervalued.

Table 5 below, presents a summary of sector performance across the European and the US market. Only sectors that were covered in both Mazur et. al.'s and this study have been included. "Winner" refers to the top-performing sectors (for Europe the ones that yield positive returns since the start of the year). "Loser" refers to the sectors suffering the most (for Europe the two most affected sectors). "Neutral" refers to companies that performed somewhere in between (for Europe – not among the top or bottom five sectors).

Table 5: Comparison of Sector Performance across Europe and the US

Sector	Europe	The US
Health care	Winner	Winner
Technology	Winner	Winner
Food & Beverage	Neutral	Winner
Real Estate	Neutral	Loser
Travel & Leisure	Loser	Loser
Oil	Loser	Loser

Note: The classifications are based on the overall performance during March 2020 as this is the period considered by Mazur et. al.

A sector that hasn't been mentioned as much in previous literature is Basic Resources, that was heavily hit during March 2020 (-43% since the start of the year at its lowest point) but recovered substantially (+27% since lowest value until 1st of July 2020). However, the results show that the large corporates have been recovering much slower than small and mid-sized corporates. This suggests that investing in Large Basic Resource companies could be another effective investment strategy.

Overall, while two of the worst-performing and two of the best-performing sectors across the US and Europe are the same, there are clear differences in the performance of other sectors. The different development could be explained by the different timing of the outbreak and corresponding political actions in the US and Europe, by the different sector focus across the two regions, and by the irrationality of investors. With the unexpected economic downturn, investors started panic-selling their holdings (see section 2 for references) and then searched returns from the most evident sectors such as Health care and Technology. While certain sectors, such as Basic Resources and Food & Beverage should also remain stable in times of economic turmoil, especially across large companies, it seems that they have not been priced fairly in the European stock market.

While there is a clear fear of the second wave of COVID-19 outbreaks occurring in Europe during fall 2020, it will most likely result in less negative market reactions compared to the first wave. First of all, societies have adapted to extreme circumstances and are now more prepared. Secondly, the second wave is most likely already priced in the market which explains the slower recovery in recent weeks and the generally lower performance of small and mid-sized companies across the most affected sectors.

6. Conclusion and Future Research

Firstly, this study compares the largest national benchmarking stock market index drops across developed European countries, US and Japan during the March 2020 crash. The findings suggest that even though both the US and European indices dropped by up to 35% during the black days, the US indices recovered substantial amounts within a few days, while European indices didn't. Over 10 days, Italy, Spain and Belgium suffered the most with the national stock indices dropping by more than 30%.

Secondly, the study compares the worst national benchmarking stock market drops and their immediate recoveries after the crash in March 2020 with the worst drops during the Global Financial Crisis 2007-2010 across the developed European region, the US and Japan. It finds that the single-day drops during March 2020 were larger than during the Global Financial Crisis in Europe and the US, but the overall recovery in the following months were much faster during the COVID-19 stock market crash in comparison to the GFC.

Thirdly, this study investigates the drops and recoveries in 2020 across different European sectors using the STOXX indices and compares the performance of the US stock market documented by previous research. While the Technology and the Healthcare sectors are identified as winners and the Oil and the Travel & Leisure sectors are identified as the worst-hit sectors across both regions, there is some divergence in the performance of other sectors.

Moreover, the study compares the performance of the STOXX Europe 600 sector indices based on 600 companies per sector, with the EURO STOXX sector indices based on 50 companies, to identify any differences across the performance of large and small/mid-sized corporates. Results suggest that small and mid-sized companies within Travel & Leisure, Retail and Financial Services have suffered more than large companies in those sectors. This was an expected outcome from the lockdown forcing many small corporates into bankruptcy. The more surprising findings concerned the small and mid-sized companies outperforming the large companies within Food & Beverage and Basic Resources by 10% and 8% respectively. These are sectors that are expected to remain robust during downturns. With large corporates naturally being considered as more stable, these findings suggest that they may be underpriced. Thus, investing in large corporates within Basic Resources and Food & Beverages could yield significant positive returns in the short and medium term.

6.1. Contribution to Society and Research

This paper extends the literature on stock market crashes by investigating national stock market and sector performance across the European stock market amid the COVID-19 crisis. It is important to emphasize that this stock market crash is unique in its kind due to its underlying nature. Identifying the stock market development in Europe across countries and sectors during this exceptional downturn as well as comparing the development to the US market offers a great understanding of the market dynamics during a pandemic. This could be used by market participants when searching for investment opportunities in the current time, in the case of the second wave of COVID-19 outbreak or in the case of any other future pandemic outbreak.

6.2 Limitation and Future Studies

Because this unique stock market crash is having a huge impact on the economy there is plenty of interesting research that could be done in the field. Future research could extend the scope of this analysis by comparing it to the SARS and MERS outbreaks. It would also be of interest to analyze the most relevant Supersectors in detail by looking into the respective sector and subsector performance. In the event of a second major COVID-19 outbreak, it would also be interesting to redo the analysis to evaluate whether the patterns in the European stock markets will be similar.

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Appendix

Table A1: Timeline over selected news since WHO was informed about the virus

From the time that WHO gets an alert	
2019-12-31	China alerts WHO about unusual pneumonia in Wuhan
2020-01-01	Wuhan market shut down
2020-01-07	Officials announced virus belonged to corona family
2020-01-11	Announcement of First death China
2020-01-13	First case outside China - Thailand
2020-01-16	Second case outside China - Thailand
2020-01-21	The US confirmed case
2020-01-22	Many European airports stepped checks from Wuhan
2020-01-23	Closing of Wuhan - quarantine
2020-01-24	China expands closure to major events and nearby cities
2020-01-25	Lunar New Year events cancelled
2020-01-30	WHO declares global health emergency
2020-01-31	Trump restricts travels from China
2020-01-31	Russia, Spain, Sweden and the UK confirmed cases
2020-02-01	New cases in Australia, Canada, Germany, Japan, US, UAE, Singapore, Vietnam
2020-02-02	First Corona death outside China
2020-02-05	Japanese cruise ship in quarantine
2020-02-07	Alarming Chinese doctor dies
2020-02-11	WHO announces the name COVID-19
2020-02-13	More than 14,000 new cases in Hubei (14840)
2020-02-14	France announce first corona death
2020-02-18	China infection figures dropped the first time
2020-02-19	Hundreds leave the quarantine cruise ship
2020-02-19	Two deaths in Iran
First cases discovered in Italy	
2020-02-21	Italy reports the first transmission of the virus: 3 to 6 cases
2020-02-22	Italy reports first death
2020-02-23	Italy suspends sport events
2020-02-23	Italy close down schools and universities
2020-02-24	Trump administration asks Congress for 1.35 billion ISD for corona response
2020-02-26	Latin America reports corona case
2020-02-26	The first case in Norway and Greece
2020-02-27	The first case in Denmark, Ireland, Netherlands and Estonia
2020-02-28	Sub-Saharan Africa records its first infection
2020-02-28	The first death in the US
2020-02-29	The US - Highest level warning travel restrictions to Italy and South Korea and Iran
2020-03-08	Italy imposes strict quarantine in Lombardy and 14 other areas
2020-03-08	Italy imposes a strict quarantine on the whole country
2020-03-09	Germany reports first death
2020-03-11	**US - blocks all visitors besides the UK**
2020-03-11	**WHO declares Corona a pandemic**
2020-03-12	**Lowest infection number from China since the start**
2020-03-13	**Trump declares a national emergency**
2020-03-15	**US - no gathering of 50 or more**
2020-03-17	France imposed lockdown
2020-03-17	Europe closed off at least 26 countries for all visitors for at least 30 days
2020-03-19	Italy overtook China in no of deaths
2020-03-19	China reports 0 local infections
2020-03-23	The UK imposes lockdown
2020-03-24	Tokyo Olympics delayed until 2021
2020-03-24	India imposes 21-day lockdown
2020-03-27	Trump signs 3 USD trillions measure

Note: The table tries to highlight the main events occurring in relation to the COVID-19 outbreak to use for understanding what affected investors behavior on the stock market.

Table A2: List of National Benchmarking Indices used in the Study.

Index	Country
BEL20	Belgium
OMXC20	Denmark
EURO Stoxx50	Europe
OMXH25	Finland
CAC40	France
DAX	Germany
ISEQ20	Ireland
FTSE MIB	Italy
N225	Japan
AEX	Netherlands
OBX20	Norway
PSI20	Portugal
IBEX35	Spain
OMX30	Sweden
FTSE100	UK
S&P500	US
DJI	US

Table A3: List of STOXX 600 Supersector Indices Used to mirror the European stock market performance

Index	Sector
STOXX Europe 600 Automobiles & Parts	Automobiles & Parts
STOXX Europe 600 Banks	Banks
STOXX Europe 600 Basic Resources	Basic Resources
STOXX Europe 600 Chemicals	Chemicals
STOXX Europe 600 Construction & Materials	Construction & Materials
STOXX Europe 600 Financial Services	Financial Services
STOXX Europe 600 Food & Beverage	Food & Beverage
STOXX Europe 600 Health care	Health care
STOXX Europe 600 Industrial Goods & Services	Industrial Goods & Services
STOXX Europe 600 Insurance	Insurance
STOXX Europe 600 Media	Media
STOXX Europe 600 Oil & Gas	Oil & Gas
STOXX Europe 600 Personal & Household Goods	Personal & Household Goods
STOXX Europe 600 Real Estate	Real Estate
STOXX Europe 600 Retail	Retail
STOXX Europe 600 Technology	Technology
STOXX Europe 600 Telecommunications	Telecommunications
STOXX Europe 600 Travel & Leisure	Travel & Leisure
STOXX Europe 600 Utilities	Utilities

Note: The 17 countries included in the STOXX Europe 600 indices are Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Norway, Poland, Portugal, Spain, Sweden, Switzerland and the United Kingdom.

Table A4: List of Euro STOXX Supersector Indices Used to mirror large corporates

Index	Sector
EURO STOXX® Automobiles & Parts Index EUR	Automobiles & Parts
EURO STOXX® Banks Index EUR	Banks
EURO STOXX® Basic Resources Index EUR	Basic Resources
EURO STOXX® Chemicals Index EUR	Chemicals
EURO STOXX® Construction & Materials	Construction & Materials
EURO STOXX® Financial Services Index EUR	Financial Services
EURO STOXX® Food & Beverage Index EUR	Food & Beverage
EURO STOXX® Health Care Index USD	Health care
EURO STOXX® Industrials Index EUR	Industrial Goods & Services
EURO STOXX® Insurance Index EUR	Insurance
EURO STOXX® Media Index EUR	Media
EURO STOXX® Oil & Gas	Oil & Gas
EURO STOXX® Personal & Household Goods Index EUR	Personal & Household Goods
EURO STOXX® Real Estate Index EUR	Real Estate
EURO STOXX® Retail Index EUR	Retail
EURO STOXX® Technology Index EUR	Technology
EURO STOXX® Telecommunications Index EUR	Telecommunications
EURO STOXX® Travel & Leisure	Travel & Leisure
EURO STOXX® Utilities Index EUR	Utilities

Note: The 11 countries included in the EURO STOXX indices are Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Portugal and Spain.

Table A5: STOXX 600 Supersector indices returns during Mars 2020

Sector	Date	Max	Date	Min	11th to 26th Mar	16th to 20th Mar	Volatility Mar
Travel & Leisure	2020-03-26	12%	2020-03-16	-13%	-46%	-38%	**6.3%**
Insurance	2020-03-26	15%	2020-03-16	-15%	-37%	-29%	6.0%
Oil & Gas	2020-03-26	16%	2020-03-11	-17%	-36%	-28%	**7.0%**
Financial Services	2020-03-26	13%	2020-03-16	-13%	-35%	-26%	5.3%
Real Estate	2020-03-26	9%	2020-03-16	-12%	-34%	-30%	4.6%
Automobiles & Parts	2020-03-26	15%	2020-03-16	-16%	-34%	-27%	6.2%
Industrial Goods & Services	2020-03-26	10%	2020-03-16	-12%	-33%	-24%	5.0%
Construction & Materials	2020-03-26	9%	2020-03-16	-14%	-32%	-26%	5.5%
Media	2020-03-26	8%	2020-03-16	-11%	-31%	-19%	4.1%
Banks	2020-03-26	10%	2020-03-16	-14%	-29%	-20%	5.3%
Utilities	2020-03-26	6%	2020-03-16	-14%	-29%	-10%	4.7%
Basic Resources	2020-03-26	16%	2020-03-16	-14%	-29%	-15%	6.2%
Personal & Household Goods	2020-03-26	6%	2020-03-16	-9%	-20%	-10%	3.6%
Technology	2020-03-26	10%	2020-03-16	-11%	-20%	-19%	4.3%
Retail	2020-03-26	7%	2020-03-16	-10%	-20%	-8%	3.7%
Chemicals	2020-03-26	7%	2020-03-16	-9%	-18%	-11%	3.9%
Telecommunications	2020-03-19	10%	2020-03-16	-11%	-16%	-6%	4.4%
Health care	2020-03-26	5%	2020-03-16	-9%	-16%	-8%	3.2%
Food & Beverage	2020-03-23	5%	2020-03-16	-9%	-16%	-9%	3.5%

Note: Columns 2 to 5 illustrates the maximum and minimum daily returns witnessed since the start of 2020 until 1st of July 2020 for each corresponding Supersector index. Column 6 and 7 illustrates the accumulated total negative returns since the start of the decline over a short period where the stock market was hit the most. While column 7 only includes the periods during the "black days", column 6 takes into a count some additional days. The last column, column 8, visualize the average volatility in returns during March 2020.

Table A6: STOXX 600 Supersector indices cumulative returns since the start of 2020

Sector	Date	Min	Min-Max	Days Max-Min	Accumulated returns as of July 2020: Since start of the year	Accumulated returns as of July 2020: Since yearly low	Accumulated returns as of 2 months after Min: Since start of the year	Accumulated returns as of 2 months after Min: Since yearly low
Travel & Leisure	**2020-03-20**	**-55%**	**-56%**	**74**	**-37%**	**18%**	**-38%**	**17%**
Oil & Gas	**2020-03-20**	**-53%**	**-56%**	**72**	**-33%**	**20%**	**-33%**	**20%**
Automobiles & Parts	2020-03-20	-48%	-49%	66	-24%	23%	-30%	17%
Insurance	2020-03-20	-44%	-49%	28	-23%	21%	-31%	12%
Banks	**2020-04-21**	**-44%**	**-48%**	64	**-35%**	10%	-34%	10%
Financial Services	2020-03-20	-37%	-46%	28	-9%	28%	-14%	23%
Basic Resources	2020-03-25	-43%	-44%	79	-16%	27%	-21%	22%
Industrial Goods & Services	2020-03-20	-40%	-43%	35	-15%	25%	-22%	18%
Real Estate	2020-03-20	-36%	-43%	28	-21%	16%	-26%	10%
Construction & Materials	2020-03-20	-40%	-43%	30	-14%	26%	-21%	19%
Media	2020-03-25	-38%	-40%	44	-20%	18%	-23%	16%
Technology	**2020-03-20**	**-32%**	**-40%**	**28**	**5%**	**37%**	**-4%**	**28%**
Utilities	**2020-03-25**	**-22%**	**-39%**	**33**	**-2%**	**20%**	**-10%**	**12%**
Telecommunications	2020-03-18	-30%	-36%	26	-14%	16%	-15%	15%
Chemicals	2020-03-18	-29%	-33%	28	-6%	23%	-12%	17%
Retail	2020-03-18	-29%	-32%	26	-9%	20%	-14%	16%
Personal & Household Goods	2020-03-18	-26%	-31%	26	-6%	20%	-11%	15%
Food & Beverage	2020-03-18	-26%	-29%	26	-13%	12%	-14%	11%
Health care	**2020-03-25**	**-20%**	**-27%**	**33**	**2%**	**21%**	**3%**	**23%**

Note: The date and corresponding value "Min" corresponds to the time and corresponding cumulative return since the start of the year where each Supersector index was at its yearly lowest level. The Max-Min relates to the drop of the index since the highest value observed this year before the COVID-19 outbreak. Accumulated/cumulative return is simply the discretely compounded returns computed since the start of the year or (as in column 7 and 9) since the lowest level observed this year (the date of the Min stated in column 2).

Table A7: Delta (Difference between all corporates and large corporates only) as of 1st July 2020

Sector	Delta (ALL-BIG)
Basic Resources	10%
Food & Beverage	8%
Construction & Materials	3%
Industrial Goods & Services	2%
Chemicals	1%
Health care	1%
Banks	1%
Automobiles & Parts	0%
Insurance	-1%
Real Estate	-1%
Utilities	-1%
Oil & Gas	-2%
Personal & Household Goods	-2%
Technology	-3%
Telecommunications	-4%
Retail	-5%
Media	-5%
Financial Services	-7%
Travel & Leisure	-9%

Note: The table illustrates the differences between the accumulated performance of all corporates and large corporates as of 1st July 2020.

Table A8: Table of Acronyms

Acronym	Meaning
CPI	Consumer Price Index
ECB	European Central Bank
FED	Federal Reserve
GFC	Great Financial Crisis (2007-2009)
IMF	International Monetary Fund
n.a.	Missing value
OECD	Organization for Economic Cooperation and Development

END OF MASTER THESIS II