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Comparing methods for identifying G-SIBs in Europe

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Abstract

The extra loss absorbency requirement for global systemically important banks (G-SIBs) is one of the macroprudential reforms in Basel III aimed at lowering the systemic risk in the financial system. Systemic risk is difficult to define and measure and academics have proposed alternative ways to measure banks' systemic importance. This study analyses how the rankings of systemically important banks in Europe differ between the G-SIB methodology and the SRISK measure of systemic risk proposed by Brownlees and Engle (2016). In contrast to previous studies, this is the first study that empirically and theoretically compares the G-SIB classification methodology with a systemic risk measure proposed by academics. The study contributes to existing research by bridging the gap between the regulatory and academic approaches for measuring systemic risk and by providing an up-to-date view of systemic risk levels in Europe. I show that the two methods give similar rankings most of the time but some large inconsistencies are observed as a result of that regulators' and academics' view on systemic risk does not align. The results also indicate that the systemic risk level in Europe is currently at its lowest since 2005.

JEL Classification Numbers: C63, G17, G18, G21, G28, G32

Keywords: Risk Analysis, Basel Accords, Financial Regulation, Simulation Modeling, Volatility Forecasting, Risk Assessment, Bank Regulation

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Introduction

The financial crisis in 2007-2009 showed that the failure of one financial institution can have a drastic negative impact on the financial system as a whole which might spill over to the real economy. The high costs associated with the financial crisis highlighted the need of a financial regulatory framework that properly deals with the systemic risk in the financial system (Chan-Lau, 2010). As pointed out by Berger et al. (2014), the financial regulation before the crisis was mainly micro prudential and designed to contain the risks of individual banks and not the risk of the financial system. The pre-crisis regulation incentivized large banks to adopt advanced risk measurement approaches, which resulted in them facing a lower regulatory capital requirement. This regulation completely ignored the fact that large banks pose a greater risk to the financial system and therefore should be required to hold higher capital buffers. Following the financial crisis, systemic risk rose to the top of the policy agenda which resulted in a large academic and regulatory response. Several new global agencies were established, the Basel III framework designed to deal with systemic risk was developed and many suggestions on how to measure and regulate systemic risk were proposed (Benoit et al., 2017). One of the regulatory tools aimed at limiting the systemic risk is the extra capital requirements applying to banks that are regarded as systemically important. The risk these global systemically important banks (G-SIBs) pose to the financial system is assessed by the Basel Committee on Banking Supervision (BCBS) using a weighted indicator-based measurement approach that includes quantitative and qualitative elements. As pointed out by Bisias et al. (2012), systemic risk and financial stability are very complex topics that are not yet fully understood which makes measurement and regulation in these areas challenging. It is not clear whether the method used by the BCBS is the most accurate and suitable for identifying the banks contributing the most to systemic risk. In fact, even defining systemic risk is not straightforward, researchers and regulators have not yet been able to agree on a common definition and there are many competing - and sometimes contradictory - definitions. The many possible definitions have resulted in a large number of models and measures emphasizing different aspects of systemic risk.

In the light of the above discussion, this study aims to analyse the differences between two methods for identifying systemically important banks; the G-SIB classification methodology currently used in practice and SRISK proposed by Brownlees and Engle (2016). This is done by comparing the outcomes from the G-SIB measurement approach adopted by the BCBS with the SRISK measure, which is one of the most popular measures for quantifying systemic risk proposed by academics. The research questions are: (i) how has the systemic risk in Europe developed in the past years according to the two different measurement methods and (ii) do the two different systemic risk measurement methods identify the same banks as the most systemically important in Europe and if not, what are the differences and why?

The SRISK measure identifies each banks contribution to the overall risk in the financial system based on its expected capital shortfall conditional on a financial crisis. Using a sample of European banks based on the sample used by the European banking Authority (EBA) for their stress tests, I follow the methodology for calculating SRISK proposed by Brownlees and Engle (2016) and identify the most systemically important banks in Europe. By constructing yearly rankings between 2012 and 2017 of the banks in terms of their systemic importance, I compare these rankings to the annually updated list of G-SIBs and analyse the differences. The approach adopted by the BCBS has its starting point in a loss-given-default framework in which systemic importance is measured in terms of the impact a bank's failure would have on the financial system and the wider economy, not taking the probability of such an event happening into account. The setting in which SRISK is developed is different, in this framework systemic risk is thought of in terms of a bank's capital shortfall during a period when the financial system as a whole is undercapitalized. The SRISK measure takes into account how likely it is that each bank will experience a capital shortfall based on the expected drop in the stock price during a financial crisis period. Comparing the outcomes of these two different measures is relevant to understand how differing initial views on systemic risk affect the actual systemic risk measurement.

The results suggest that the rankings of systemically important banks do align in large between the two approaches but in the case of HSBC, large inconsistencies were observed. The study provides a deeper understanding of the drivers of systemic risk and the results make it evident that no single systemic risk measurement approach will be enough to capture the complexity of the financial system.

This thesis is related to the extensive literature on how to look at and how to measure systemic risk in the financial system. Most previous research within this field consists of proposals of new ways to measures systemic risk (see *e.g.* Acharya et al. (2017), Adrian and Brunnermeier (2016) and Huang et al. (2009)). Some studies have set out to compare different systemic risk measures, for example Bisias et al. (2012) perform a survey of 31 quantitative systemic risk measures which are discussed and compared on a theoretical level but they leave it up to the reader to find advantages and disadvantages with each. Benoit et al. (2017) review the whole systemic risk literature in an extensive survey of more than 200 papers connected to systemic risk and connect these to the current regulatory debate. They conclude that there are many methods available that can identify different sources of systemic risk but it is unclear how to link the measures to clear regulatory interventions.

In contrast to previous studies, this is to my knowledge the first study that empirically compares a systemic risk measure proposed by academics with the actual measurement approach for identifying G-SIBs used by the BCBS. This study helps to close the gap between regulatory and academic measures of systemic risk and sheds light on the differences between the two measurement approaches both theoretically and empirically.

Only a few papers set out to explicitly analyse differences in systemic risk measures empirically. One exception is Benoit et al. (2013) that compare four major systemic risk measures that rely on public market data: SRISK, MES, SES and ΔCoVaR both theoretically and empirically. They base their study on a sample of US financial institutions and rank institutions based on their systemic importance calculated using the respective systemic risk measures. They find that the different systemic risk measures identify different systemically important financial institutions (SIFIs) and that in some cases, no financial institution is simultaneously ranked among the top-10 most risky institutions by the three measures.

As previous literature has shown, academic measures of systemic risk are not consistent when identifying SIFIs and viewing systemic risk from different perspectives can lead to different conclusions regarding the factors driving systemic risk. Therefore, performing a deep theoretical and empirical analysis and comparison between one of the most popular academic systemic risk measures and the measurement method currently used in practice by regulators is highly relevant.

This study contributes to the academic literature on systemic risk in several ways. First and foremost, it connects the regulatory approach of measuring systemic risk to the systemic risk measures proposed in the academic literature, which has to my knowledge not been studied before. Secondly, I am also able to show that the difference in the outcomes is a result of that the regulatory and academic view on systemic risk does not align. Moreover, the study serves as an up-to-date review of the systemic risk in Europe posed by banks and the SRISK calculations indicate that the aggregate systemic risk level in the financial system is currently at its lowest level since 2005. The results of this study could also be valuable and helpful for regulators and supervisory authorities in their evaluation and continuous work on deciding which methods to use for measuring systemic risk and identifying systemically important banks.

The rest of the thesis is organized as follows: In Section 2, systemic risk is explained in detail with regard to definitions, concepts and how to measure it. Section 3 provides an overview of the assessment methodology used by the BCBS to identify G-SIBs. Section 4 describes the dataset and the firm-specific data needed for the calculation of SRISK. In Section 5, the SRISK measure is treated in detail including the estimation and calculation procedure as well as the economic intuition behind. Section 6 presents the results from the SRISK calculation along with the analysis and comparison with the BCBS-methodology. Section 7 concludes.

2

Theoretical background

2.1 Defining systemic risk

Even though systemic risk rose to the top of the policy agenda after the financial crisis, regulators and academics have not yet managed to agree on a common definition of systemic risk. A variety of definitions have been proposed by academics depending on the perspective from which they look at systemic risk. As Bisias et al. (2012) point out, the many possible definitions highlight the complexity of the financial system and that it might not be possible - nor desirable - to agree on one single definition. A general view that many seem to agree upon is that systemic risk is a risk that threatens the stability of the financial system which can lead to negative externalities in the real economy. For example, the following definition is used by the European Central Bank (ECB): *a risk of financial instability so widespread that it impairs the functioning of the financial system to the point where economic growth and welfare suffer materially* (ECB, 2010, p.129).

The Bank for International Settlements (BIS) [1] has together with the Financial Stability Board (FSB) and the International Monetary Fund (IMF) suggested the following definition of systemic risk: *"a risk of disruption to financial services that is caused by an impairment of all or parts of the financial system and has the potential to have serious negative consequences for the real economy"* (FSB et al., 2009, p.5). The BCBS does not explicitly provide a definition of systemic risk in their publication describing the G-SIB assessment methodology. They state that the policy measures directed towards G-SIBs should address the negative externalities posed by institutions that are perceived as not being allowed to fail due to their systemic importance

[1] The BCBS that has developed the G-SIB assessment methodology is a division of BIS

(BCBS, 2013b).

The definition of systemic risk within the SRISK framework is also connected to negative externalities posed by potential bank failures, but their definition is more specific. Engle et al. (2014), who calculated SRISK for 196 European firms, have the following view of what systemic risk is (the same view is shared by Acharya et al. (2012)): *"the externality that generates systemic risk is the propensity of a financial institution to be undercapitalized when the financial system as a whole is undercapitalized"* (Engle et al., 2014, p.146). The rationale behind this definition is that a financial system where there is a capital shortage will lead to a reduced availability of credit which will constrain businesses and cause negative effects on output and unemployment (Brownlees and Engle, 2016). Acharya et al. (2012) argue further that systemic risk should not be thought of in terms of a financial institution's failure but in the context of the financial institution's contribution to a system-wide failure. The reason is that a failure in normal times will be absorbed by the other banks in the financial system but this is not possible during a crisis when the aggregate capital in the system is low.

The key difference between the two definitions is that in the SRISK framework, a default of a financial institution under usual market conditions is not necessarily a systemic threat since it can be absorbed by the other banks in the system. This distinction is not considered by the BCBS.

Since the aim of this thesis is to compare two measures of systemic risk with different views on systemic risk, I will not attempt to come up with my own definition, however I will shortly explain my view. The definitions proposed by the ECB and BIS/FSB/IMF are both very general and do not exclude any channels that can give rise to systemic risk. But while they clearly convey that systemic risk is a risk of negative externalities caused by a malfunctioning financial system, they are completely uninformative regarding specific sources from which the risks arise.

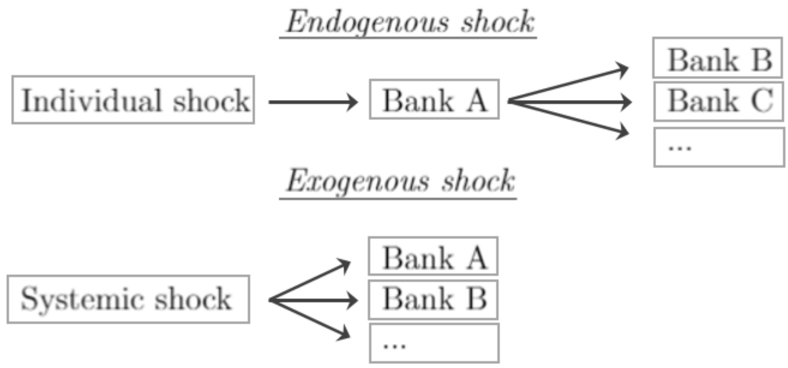
On the other hand, the definition used by Engle et al. (2014) might be too specific and narrow since it only focuses on the propensity of undercapitalization without mentioning factors such as size, leverage, international presence and interconnectedness. However, I believe that their definition is simply poorly formulated because the SRISK measure derived from the definition is an absolute value of capital shortfall which has accounted for leverage and size. I also like the fact that they distinguish between normal market times and crisis periods and I agree on that the real systemic risk occurs in the case of a bank failure in an undercapitalized system. In this thesis, I acknowledge the definition of systemic risk used within the SRISK framework while keeping in mind that it does not capture all sources of systemic risk such as interconnectedness and complexity.

2.2 Conceptualizing systemic risk

A useful starting point in order to understand systemic risk is to look at it from a conceptual point of view. Caruana (2010) divides systemic risk into two dimensions, a cross-sectional dimension and a time dimension. The cross-sectional dimension comprises the structure of the financial system, such as common exposures across institutions and through network interconnections. The time dimension treats how risk in the financial system is built up over time and how it is connected to the macroeconomic cycle.

The cross-section of systemic risk is related to how the financial system through the exposures responds to a shock and how it is amplified and thus becoming systemic. Key aspects here are the distribution of the risks within the financial system at a given point in time and the type of shock that occurs. As discussed by Caruana (2010), a shock to the financial system can mainly take two forms, either it arises endogenously within the financial system (for example the failure of one institution) or exogenously through a macroeconomic event such as a wide downturn in the real estate market. Because the financial system is a network of interconnected balance sheets, a shock hitting one institution can become systemic through the spider web of network connections and thus harm other institutions that are otherwise sound. On the other hand, an exogenous shock can harm all institutions in the financial system directly and thus become systemic through the direct common exposures. Figure 2.1 depicts the relation between the banks and the financial system for these two types of shocks.

Figure 2.1: Types of systemic shocks



The figure shows how the contagion from a shock spreads through the financial system. An endogenous shock affects one bank but due to the interconnectedness, this shock will spread through the financial system and affect other banks. An exogenous shock happens outside of the financial system which leads to that all banks are affected directly.

The ways to measure and treat systemic risk depend on which type of shock that is assumed. If the initial assumption is that systemic risk arises endogenously within the system, the focus should be on measuring systemic risk in terms of the banks' *systemic risk contribution.* The question that needs to be answered then is: *How does a single financial institution contribute to systemic risk?* What needs to be estimated then is the impact a failure of Bank A in the upper part of Figure2.1 would have on the rest of the banks. If however, the initial assumption is that systemic risk arises as a result of an exogenous event, the concern is about each bank's *systemic risk sensitivity* and the question that should be asked is: *To what extent is a single institution affected by a systemic event?* One then has to estimate the losses that would occur to each bank as a result of a shock to the whole financial system (Kleinow and Nell, 2015).

The second dimension of systemic risk, the time dimension, concerns the procyclicality and progressive build-up of systemic risk along with how the aggregate level of risk in the financial system evolves over time. The reason for the procyclicality of risk levels is the dynamics of the financial system. In periods of economic growth, the financial system and the real economy reinforce each other by creating confidence in the markets leading to stronger credit growth and higher asset prices. In this manner, strong economic periods tend to amplify themselves, leading to high systemic risk levels in the financial system (Caruana, 2010).

Because of the many aspects and the complexity of systemic risk, regulators face a real challenge in developing useful techniques and polices to measure and contain the systemic risk.

2.3 Measuring systemic risk

There are many recent papers taking on different approaches for measuring systemic risk. One strand of papers propose measures of systemic risk based on contingent claims analysis of banks' assets[2]. For example, Jobst and Gray (2013) present a forward-looking measure based on market-implied expected losses derived using the Merton option pricing model. Then aggregate systemic solvency risk measures are obtained by estimating the joint default risk of multiple institutions using multivariate extreme value theory. However, contingent claims analysis can be problematic to use in practice due to that strong assumptions about the liability structure needs to be made.[3] Other studies have used market-data to back out measures of systemic risk. Huang et al. (2009) develop a systemic risk measure in which the risk is calculated as the expected credit losses above a certain liability threshold by using data on credit default swaps (CDSs). Kleinow and Moreira (2016) also use data on CDSs and measure the dependence between financial institutions by using copulas.

The most popular systemic risk measures[4] are CoVaR (Adrian and Brunnermeier, 2016) followed by Systemic Expected Shortfall (Acharya et al., 2017) and SRISK by Brownlees and Engle (2016). CoVaR stands for Conditional/Contagion/Co-movement Value at Risk and is defined as the Value at Risk of the financial system conditional on an institution being in distress. The CoVaR is a measure of systemic risk contribution and aims to capture how financial distress in one institution can spread across the financial system. One advantage with CoVaR is that it is connected to the standard framework of VaR which is already used as a regulatory tool by regulators. However, there are some undesirable properties with CoVaR that arise because the conditioning set is not constant (the financial institution in distress conditioned on

[2]See *e.g.* Lehar (2005) and Gray et al. (2007)

[3]This problem is also discussed by Acharya et al. (2017). The contingent claims (CCA) analysis framework is based on the Merton model for pricing of corporate debt Merton (1974) where one of the assumptions is that a firm's liabilities consist only of a single class of debt. Fridson and Jonsson (1997) show that the underlying assumptions in the CCA framework do not hold in practice.

[4]As measured by the number of paper citations.

varies cross-sectionally). This can in some cases lead to that the CoVaR-measure is identical for two firms that have the same return correlation with the market even though one firm might have much higher return volatility (Acharya et al., 2012). Another problem which is a general critique to VaR is that it is unable to capture losses in the tail of the distribution. The VaR is the value which the losses with alpha percent probability will not exceed, but it is completely uninformative about the size of the losses if they exceed the VaR. As Acharya et al. (2017) point out, this is a major shortcoming because losses greater than the VaR are often resolved by government bailouts which might lead to excessive risk-taking among banks[5].

Acharya et al. (2017) propose a measure of systemic risk sensitivity called Systemic Expected Shortfall (SES) that does not have the undesired properties of the CoVaR. They define SES as the amount a banks equity drops below its required level, conditional on that there is a financial crisis where the aggregate banking capital in the system is less than its required level. Calculating absolute measures of systemic risk by using SES is not straight-forward since it requires knowing the probability of a financial crisis occurring. Based on the same way of looking at systemic risk as SES, Brownlees and Engle (2016) propose an alternative measure of systemic risk sensitivity called SRISK where systemic risk can be quantified without having to assume a probability of a crisis occurring. The SRISK combines market- and balance sheet information of financial firms and the result is a calculable measure of systemic risk depending not only on equity volatility and correlation, but also on the size and leverage of a financial firm.

This study will use SRISK because it is the most recent and comprehensive of the most popular systemic risk measures and also enables quantification without the need of assigning a probability for a financial crisis occurring. Before moving on to the Data-section and a more detailed introduction of the SRISK measure, a section describing the systemic risk components of Basel III and the G-SIB classification methodology follows.

[5]Banks typically set aside enough capital to cover for losses corresponding to their VaR calculations. If losses turn out to be greater than the VaR, they might not be able to cover these losses on their own and hence, a government bailout might be required.

3

Basel III and systemic risk

3.1 BCBS, FSB and Basel III

The BCBS is the primary global standard setter for the regulation of banks. Their goal is to promote financial stability worldwide by strengthening the financial regulation and banking supervision. As a response to the financial crisis, BCBS issued the Basel III accord which is a regulatory set of measures aimed at creating a more resistent financial system. The FSB is another supervisory authority that was created in 2009 with the mandate of promoting international financial stability through coordinating national financial authorities and international standard-setting organisations. The FSB acts as a macro prudential supervisor that tries to identify weaknesses in the global financial system as well as promotes a level playing field that ensures a coherent implementation of new regulation and policies. It is the FSB that every year publishes a list of the identified G-SIBs based on the methodology developed by the BCBS.

The Basel III framework addresses several shortcomings in the pre-crisis regulation and serves as a foundation for a resilient banking system that will help to avoid the build-up of systemic vulnerabilities. The main features of the Basel III regulation are higher capital requirements, minimum leverage ratio, stricter definition of capital, countercyclical capital buffers, extra capital requirements for G-SIBs and a framework for managing liquidity risk (BCBS, 2017). Especially the countercyclical capital buffers and the extra capital requirements for G-SIBs are directly aimed at managing the systemic risk in the financial system. The countercyclical capital buffer requires banks to hold between 0-2.5 percent more common equity in times when it is judged that credit growth leads to an unacceptable build-up of systemic risk. The goal of the countercyclical capital buffer is to protect the banking sector from excessive credit growth that is often associated with high levels of systemic risk (BCBS, 2017). This tool is clearly addressing the procyclicality of systemic risk that has been discussed earlier. In contrast, the extra capital requirement for G-SIBs is targeting the cross-sectional dimension of systemic risk. This extra capital requirement ranges between 0-3.5 percent and applies to banks that are identified as systemically important. The rationale behind is that banks that pose a greater risk to the financial system should have a higher loss absorbency capacity. The methodology used by the BCBS to identify G-SIBs will be discussed in more detail in the following section.

3.2 The G-SIB classification methodology

Every year since 2011 the FSB publishes a list of G-SIBs which determines the extra capital requirement applying to each G-SIB. These banks are identified using an indicator-based measurement approach developed by the BCBS. There are five indicators which are given an equal weight of 20%, these are: size, global (cross-jurisdictional) activity, complexity, interconnectedness and substitutability/financial institution infrastructure. For all indicators except size, different sub-categories have been identified which are given equal weight within the indicator. The global activity indicator aims at capturing the fact that a bank's distress or failure would likely be more difficult to resolve the greater the global reach and thus leading to more widespread spillover effects. The same way of reasoning applies to the complexity indicator; the failure of a bank with high structural and operational complexity is expected to lead to a larger systemic impact due to the difficulties occurring at the resolution. Including an interconnectedness indicator is based on the intuitive fact that the more interconnected a bank is to other banks through loans or securities, the higher is the systemic impact in case of financial distress or bankruptcy. The substitutability indicator is included to pick the relative importance of a bank within a certain business line or service, such as payment systems. The rationale is that the more important role the bank has in a certain business area and the lesser the presence of substitute banks is, the larger will the systemic disruption costs be in case of a failure. Table 3.1 gives an overview of the methodology along with the indicator weightings and their sub-categories (BCBS, 2013b).

Table 3.1: BCBS G-SIB indicators

Indicator (weighting)	**Sub-category**	**Indicator weight**
Size (20%)	Total exposures (according to Basel III def.)	20%
Cross-jurisdictional activity (20%)	Cross-jurisdictional claims	10%
	Cross-jurisdictional liabilities	10%
Interconnectedness (20%)	Intra-financial system assets	6.67%
	Intra-financial system liabilities	6.67%
	Securities outstanding	6.67%
Substitutability (20%)	Assets under custody	6.67%
	Payments activity	6.67%
	Underwritten transactions	6.67%
Complexity (20%)	Notional amount OTC-derivatives	6.67%
	Level 3 assets	6.67%
	Trading and available-for-sale-securities	6.67%

Based on Table 1 in (BCBS, 2013b, p.6)

After these indicators have been observed, a score is calculated and banks that produce a score that exceeds a cutoff level set by the BCBS are classified as G-SIBs. The bank identified as G-SIBs are then divided into five buckets with varying extra loss absorbency requirements depending on their systemic importance as calculated by the score. The buckets and their corresponding extra loss absorbency requirement (in the form of common equity as a percentage of risk-weighted assets) are: 1 (1.0%), 2 (1.5%), 3 (2.0%), 4 (2.5%) and 5 (3.5%) (BCBS, 2013b).

It is worth to note the starting point from which the BCBS looks at systemic risk which is very different from most of the views adopted by academics proposing systemic risk measures. The BCBS is of the view that systemic risk should be measured as the impact a banks failure would have on the global financial system and the wider economy, not taking the probability of such a default happening into account. Their approach could be thought of in a loss-given-default setting rather than probability of default. The consequences of that this view differs from the one adopted by Brownlees and Engle (2016) with SRISK will be analysed in more detail in the empirical section.

4

Data

Since the aim of the study is to compare the rankings of the European G-SIBs, the banks in my sample will include all European banks that have been or currently are on the G-SIB list. The G-SIB list has been updated and published every year since 2011. The list published in November 2017 contains 30 banks of which 14 are headquartered in Europe. In 2011, G-SIBs were identified without sorting them into buckets, therefore the analysis will start in 2012 which is the first year the G-SIBs were ranked and sorted according to their systemic importance.

For the purpose of showing how the SRISK for the banks has developed over time, including the period around the financial crisis, SRISK is calculated on a quarterly basis from 2005-2017. It is possible to calculate SRISK measures for each day but this is not done because the information gain from daily calculations is largely outweighed by the significant increase in computation time.

In order to check whether there are other systemically important banks in Europe identified by the SRISK measure that are not on the G-SIB list, I include an additional set of banks for the SRISK calculation. As a base for identifying other important banks in Europe, I use the EBA stress test sample used by the European Banking Authority (EBA) for their regular EU-wide stress tests. The EBA sample contains 48 of the largest and most important banks in the European UnionEBA (2018). Due to the fact that market data is required for the estimation of the Long Run Marginal Expected Shortfall (LRMES) which is a component of SRISK, it is only possible to include the publicly listed banks in this sample. All European banks identified as G-SIBs are included in the EBA stress test sample. Including all publicly listed banks in the EBA sample and the European banks from the G-SIB list results in a total sample size of 28 banks. The bank names and their tickers can be found in the Appendix.

The bank specific data needed for the SRISK calculation consists of daily market price data along with yearly data on total assets and common equity between 2011 and 2017. This data is obtained from Bloomberg. Daily market data on stock prices is obtained from year 2000 in order to have a large estimation window in the GARCH-DCC model that includes both the IT-crisis and the financial crisis in 2007-2009.

5

Measuring SRISK

5.1 Intuition and economic framework

The SRISK measure of systemic risk was introduced by Brownlees and Engle (2016) and is defined as the expected capital shortfall of a bank conditional on a long and severe market decline. SRISK builds on the economic model of systemic risk proposed by Acharya et al. (2017) where it is assumed that undercapitalization of the financial system as a whole leads to a systemic risk externality that can harm the real economy. The intuition behind the model can be derived to the financial crisis where it became evident that undercapitalization of a large financial institution when the financial system as a whole is undercapitalized can lead to large negative externalities. In this framework, a bankruptcy of a bank in normal times when the financial system is well-capitalized will not impose any negative externality on the economy because the losses will be absorbed by other banks in the financial system. However, in a financial crisis when the economy is in a downturn and the financial system as a whole is undercapitalized, the default of a large bank cannot be absorbed by other banks and thus, the real economy will suffer. The SRISK is calculated for each bank and is a function of a bank's size, leverage and expected equity loss conditional on a crisis. SRISK is larger for large and highly leveraged banks with a high sensitivity to market declines. Since SRISK is the expected capital shortfall conditional on a long and severe market decline, a more precise definition of capital shortfall is useful for the intuition. In this model, capital shortfall is defined as the amount the equity of a firm is below its regulatory required level. Inserting some notation, we have the following:

$$CS_{it} = \theta A_{it} - W_{it} = \theta(D_{it} + W_{it}) - W_{it} \tag{5.1}$$

where CS_{it} is the capital shortfall for bank i at time t, θ is the required regulatory capital fraction, A_{it} is the asset value, D_{it} is the book value of debt and W_{it} is the market value of the equity. The capital shortfall becomes positive when a banks equity falls below the required capital fraction times its assets. In this study, θ is set to 5.5% in line with Engle et al. (2014) who calculated SRISK for European banks.

The next step is to define a long and severe market decline which in this setting is used as a proxy for a financial crisis. In line with Engle et al. (2014), I define it as a stock market decline of at least 40% during a six-month period. This has only happened once during the last 15 years, namely during the financial crisis. As a proxy for the market return, the European stock index EuroStoxx50 is used since it is a blue-chip[1] index representing the performance of the 50 largest companies in the Eurozone. I denote the stock market decline as the market return of EuroStoxx50 between period $t+1$ and $t+h$ where h is the number of trading days during the six-month period: $R_{m,t+1:t+h} < -40\%$.

It now follows that the SRISK can be written as:

$$SRISK_{it} = E_t[CS_{it+h}|R_{m,t+1:t+h} < -40\%] = E_t[(\theta(D_{it+h} + W_{it+h}) - W_{it+h}|R_{m,t+1:t+h} < -40\%] \tag{5.2}$$

and by some simplifications we get:

$$\theta E_t[D_{it+h}|R_{m,t+1:t+h} < -40\%] - (1-\theta)E_t[W_{it+h}|R_{m,t+1:t+h} < -40\%] \tag{5.3}$$

Another simplification that can be made is to assume that the market decline does not affect whether the debt can be renegotiated or not, which implies that: $E_t[D_{it+h}|R_{m,t+1:t+h} < -40\%] = D_{it}$. Using this assumption, the formula can now be written as:

$$SRISK_{it} = \theta D_{it} - (1-\theta)E_t[W_{it+h}|R_{m,t+1:t+h} < -40\%] = \theta D_{it} - (1-\theta)W_{it}(1-LRMES_{it}) \tag{5.4}$$

where $LRMES_{it}$ is the Long Run Marginal Expected Shortfall, defined as the expected equity

[1] A blue-chip index is an index that consists of the shares of financially stable and well-established companies whose share price tend to move similar to the whole economy which makes it appropriate to use as a market proxy

return for firm i during a severe market decline: $E_t[R_{i,t+1:t+h}|R_{m,t+1:t+h} < -40\%]$. By simplifying, factoring out W_{it} and introducing the leverage ratio (LVG_{it}) denoted $(D_{it} + W_{it})/W_{it}$, one ends up with the final formula for the SRISK:

$$SRISK_{it} = W_{it}(\theta LVG_{it} + (1-\theta)LRMES_{it} - 1) \tag{5.5}$$

Calculating this yields a prediction of the capital shortfall of bank i that it would suffer in case of a financial crisis. Based on the calculated capital shortfall, rankings can be constructed according to systemic risk importance.

5.2 LRMES Simulation

5.2.1 Model specification

In order to obtain estimators for the computation of the LRMES, a model that estimates the evolution of volatilities and correlation is required. The model used in this study is a GARCH-DCC (Generalized Auto Regressive Conditional Heteroskedasticity Dynamics Conditional Correlation) model which is widely used in financial time series analysis, developed by Engle (2002) and also used by Brownlees and Engle (2016). The intuition behind the model is very clear, it captures the fact that volatility as well as correlations between stocks are time varying variables. For example, the volatility of stock returns tends to go up during crisis periods and high volatility in the markets occurs in periods, so called "volatility clustering". Similarly, the correlation between a firm and the market is also likely to change over time, for example if a firm changes its line of business. A change of business likely changes the valuation of the company which will lead to changes in asset prices and correlations with other firms and the market Engle (2002). The GARCH-DCC model takes these facts into account by building a process where the conditional volatilities and correlations are estimated conditional on the information from the previous day. The equations for the dynamics of the market and firm volatilities in the GARCH process are as follows

$$\sigma_{it}^2 = \omega_i + \alpha_i r_{it-1}^2 + \beta_i \sigma_{it-1}^2 \tag{5.6}$$

and

$$\sigma_{mt}^2 = \omega_m + \alpha_m r_{mt-1}^2 + \beta_m \sigma_{mt-1}^2 \tag{5.7}$$

The time-varying correlations are estimated through the DCC model where a pseudo correlation matrix Q_{it} needs to be estimated before obtaining the real conditional correlations. The model equations are as follows

$$Q_{it} = (1 - \alpha_i - \beta_i) S_i + \alpha_i \begin{bmatrix} \epsilon_{it-1} \\ \epsilon_{mt-1} \end{bmatrix} \begin{bmatrix} \epsilon_{it-1} \\ \epsilon_{mt-1} \end{bmatrix}' + \beta_i Q_{it-1} \tag{5.8}$$

where $\epsilon_{mt} = r_{mt}/\sigma_{mt}$ and $\epsilon_{it} = r_{it}/\sigma_{it}$ are volatility adjusted returns and S_i is the unconditional correlation matrix between the firm and market adjusted returns. From here, the correlation matrix is computed through the volatility adjusted returns as

$$Corr\Big(\epsilon_{it}, \epsilon_{mt}\Big) = \begin{bmatrix} 1 & \rho_{it} \\ \rho_{it} & 1 \end{bmatrix} = diag(Q_{it})^{-1/2} Q_{it} diag(Q_{it})^{-1/2} \tag{5.9}$$

The parameters in the GARCH model are estimated through a Maximum Likelihood Estimation and the DCC parameters are estimated through a Quasi Maximum Likelihood Estimation.

5.2.2 Simulation procedure

The LRMES is estimated using MATLAB on a quarterly basis from 2005-2017. The estimation procedure that is used for each of these simulation periods is described below.

The first step is to run the GARCH-DCC model using de-meaned daily returns from January 2000 for the market and each company up to time T (this step is performed for each market-firm pair, 28 times). This step is implemented using the dcc-function from the MFE-Toolbox developed by Kevin Sheppard (University of Oxford). The output from this estimation is the parameters specified in the GARCH and DCC equations as well as daily conditional covariance matrices for each day up to time T.

$$\begin{bmatrix} \sigma_{it}^2 & \rho_{it}\sigma_{it}\sigma_{mt} \\ \rho_{it}\sigma_{it}\sigma_{mt} & \sigma_{mt}^2 \end{bmatrix} \qquad t = 1, ..., T$$

From the daily conditional covariances found in the off-diagonal, conditional correlations are obtained using the standard formula for correlation: $\rho_{it} = Cov(i, m)_t / \sigma_{mt}\sigma_{it}$.

Then, standardized innovations are calculated for both the market and the individual firms (or volatility- and correlation-adjusted returns) according to the following:

$$\epsilon_{mt} = \frac{r_{mt}}{\sigma_{mt}} \tag{5.10}$$

$$\zeta_{it} = \left(\frac{r_{it}}{\sigma_{it}} - \rho_{it} \frac{r_{mt}}{\sigma_{mt}} \right) \Big/ \sqrt{1 - \rho_{it}^2} \tag{5.11}$$

for each $t = 1, ..., T$.

The next step is to simulate possible returns in a financial crisis. Since the goal is to simulate returns during the coming H days (six months $\rightarrow H = 125$), the first step is to randomly sample 125 market returns with replacement from the return history, S times. This yields a matrix of size 125xS with random return sequences. For these sequences, the cumulative returns at $H = 125$ are calculated for each S and all sequences fulfilling the financial crisis condition are saved, that is:

$$R^s_{m,t+1:t+125} < -40\%] \tag{5.12}$$

where s denotes pseudo returns.

In this study, $S = 500000$ is used since it strikes a good balance between the number of simulated crisis sequences and reasonable computation time. The returns in the crisis sequence vectors are then replaced with the corresponding standardized innovations calculated previously, resulting in S pairs of pseudo innovations from $T+1$ to $T+125$, that is:

$$\begin{bmatrix} \zeta^s_{iT+t} \\ \epsilon^s_{mT+t} \end{bmatrix}_{t=1,...,H} \qquad k = 1, ..., K$$

where K denotes the sequences that fulfill the crisis condition.

The pseudo innovations are then used as inputs for the GARCH and DCC equations along with the last values of the conditional correlation ρ_{it} and variances σ^2_{mt} and σ^2_{it}. The conditional market variance and the variance for firm i for day $T+1$ are then calculated using the GARCH equations (Equation 5.6 and 5.7). Similarly, the conditional correlation for day $T+1$ is calculated using the equations for the DCC model (Equation 5.8 and 5.9)

Since both market variance, firm variance, correlation and the standardized pseudo innovations at time $T+1$ are known, it is now possible to calculate the returns for the market and for firm i during the first day of the crisis sequences by backing out r_{mt} and r_{it} from Equation 5.10 and 5.11 and replacing t by $T+1$. This gives

$$r_{m,T+1} = \epsilon_{m,T+1}\sigma_{m,T+1} + \bar{r_m} \tag{5.13}$$

$$r_{i,T+1} = \left(\zeta_{i,T+1}\sqrt{1-\rho^2_{i,T+1}} + \rho_{i,T+1}\frac{r_{m,T+1}}{\sigma_{m,T+1}} - \bar{r}_i\right)\sigma_{i,T+1} \tag{5.14}$$

where $\bar{r_m}$ and $\bar{r}_i$ are the mean of the returns that have to be added since the GARCH-DCC was estimated with de-meaned returns as inputs.

Repeating these steps for $t = 1, .., 125$ gives K samples of simulated 125-day returns conditional on the realized process F up to time T, that is

$$\left.\begin{bmatrix} r^s_{iT+t} \\ r^s_{mT+t} \end{bmatrix}_{t=1,...,H}\right| F_T \qquad k = 1, ..., K \tag{5.15}$$

Finally, the $LRMES_{it}$ is then calculated as the Monte Carlo average of the calculated cumulative return at $t = T + 125$ for each simulated crisis sequence k, that is

$$LRMES_{it} = -\frac{1}{k} \sum_{k=1}^{K} R^s_{i,T+125} \tag{5.16}$$

where R denotes the cumulative return.

6

Results

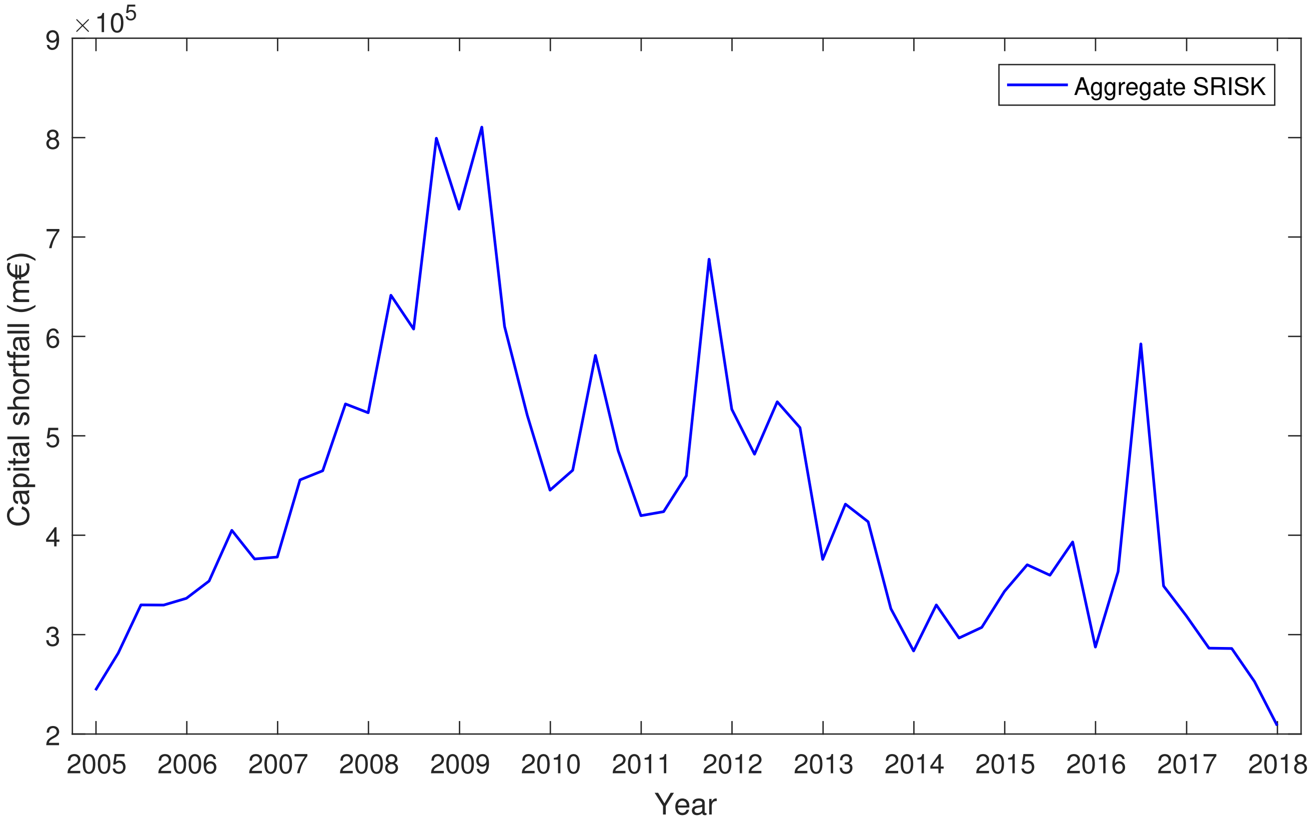
6.1 SRISK from 2005-2017

The SRISK was calculated on a quarterly basis for each of the 28 banks during the time period 2005-2017. By summing the SRISK over all banks, it is possible to get an approximation of how the total systemic risk in the European financial system has developed over time according to the SRISK measure. As can be seen in Figure 6.1, the combined SRISK for all banks shows a clear spike during the financial crisis period in 2007 and has thereafter mainly been decreasing with some exceptions. Worth noting is that the aggregate SRISK at the end of 2017 is at its lowest level since the start of the calculation period in 2005, indicating that the systemic risk borne by the 28 banks is currently at a historically low level. The largest increases in SRISK since the financial crisis are found in the third quarter of 2011 at the peak of the Euro crisis and in mid-2016 in connection to the Brexit referendum. The downward-sloping shape of the SRISK curve confirms that the SRISK measure is able to capture the procyclicality of systemic risk on an aggregate level. Note that there are a number of other large European banks that are not included in this SRISK aggregation and hence it should not be interpreted as the total systemic risk in Europe[1]. Instead, it is included to illustrate that SRISK manages to capture systemic risk changes over time. However, a graph including SRISK for all banks in Europe would likely have a similar shape.

The size of the expected capital shortfalls calculated by SRISK has fluctuated strongly during the time period under review. At the start of the measurement period in 2005, the total SRISK

[1] Real time total SRISK for different countries or regions is provided by the Volatility Lab of NYU Stern Business School of which Robert Engle (one of the authors that proposed SRISK) is a member, available at: https://vlab.stern.nyu.edu/welcome/risk/.

Figure 6.1: Total SRISK for 28 large European banks



for the 28 banks was 244 billion €. During the financial crisis in Q1-2009, it reached its peak at 811 billion € and the lowest SRISK value was observed at the end of 2017, the amount was then 209 billion €. Engle et al. (2014) calculated SRISK for 196 European financial institutions and reported a total SRISK in Europe for 1 219 billion € at the end of their study period which was August 30, 2012. The total SRISK for the 28 banks in my sample in September 30, 2012 was at 508 billion € and considering that the banks in my sample account for approximately 50% of the total banking assets in Europe[2], this result seems fully plausible.

6.2 SRISK rankings and comparison with G-SIBs

The SRISK calculation gives a number which should be interpreted as the expected capital shortfall (*i.e.* equity missing in order to remain solvent) in a financial crisis. The banks are

[2]The approximation is derived from the fact that the EBA Stress Test Sample covers 70% of the European banking assets and by subtracting the assets of the banks not included, 50% was reached.

ranked according to the size of the SRISK measure. The banks with the highest expected capital shortfall are considered to be the ones contributing the most to systemic risk and are therefore ranked the highest. In order to make it clear how the rankings are constructed, Table 6.1 shows the calculated SRISK value for each bank at the end of year 2017[3]. The table shows that in the end of 2017, BNP Paribas contributed the most to systemic risk with an expected capital shortfall in a crisis of 34.8 billion €. OTP Bank, AIBG Group and HSBC all show negative SRISK which indicates that they have enough equity to remain solvent in a financial crisis. The asterisk after some of the banks in the table indicates that they are classified as G-SIBs by the BCBS/FSB. As can be seen, the 13 banks with the highest SRISK ranking are in all cases except two (Lloyds Banking Group and Danske Bank) identified as G-SIBs which indicates that the result from the two different methods align well. However, a large inconsistency becomes evident when looking at the last position in the table. HSBC has according to the SRISK measure enough equity to not suffer a capital shortfall in a crisis and hence it does not pose a risk to the financial system. On the other hand, it is identified as one of the most risky G-SIBs by the BCBS which indicates that they are of the view that it poses a high risk to the financial system. This finding will be analyzed in detail in Section 6.2.

Table 6.2 and Table 6.3 show the ranking positions for all banks in the sample from year 2012 to 2017[4] including the G-SIB bucket classification and the corresponding extra loss absorbency requirement. The banks for which the G-SIB bucket column is empty are not classified as G-SIBs. As can be seen at a first glance, the SRISK measure and the BCBS measurement approach identify in large the same banks as the most systemically important. If the results from the two methods would align perfectly, the G-SIB bucket columns would not have any blank areas in the top half and the bucket number would start at its highest and then fall. The finding that the methods seem to align relatively well is not consistent with what Benoit et al. (2013) found when they compared daily rankings of 94 US banks constructed by SRISK, Marginal Expected Shortfall (MES) (Acharya et al., 2017) and CoVaR (Adrian and Brunnermeier, 2016). They compare the rankings of the top 10 most systemically important banks identified by each

[3]For absolute SRISK calculations for year 2012-2016, see the Appendix.

[4]Note that G-SIBs are identified in November each year based on data from the previous year-end. That means that, for example the 2012 G-SIB classifications are based on data from December 2011. The SRISK rankings are calculated correspondingly at the relevant year-end.

Table 6.1: SRISK rankings at end-2017

Rank	Ticker	Bank Name	SRISK (mn€)
1	BNP	BNP Paribas*	34770
2	DBK	Deutsche Bank*	32763
3	BARC	Barclays*	24867
4	GLE	Societe Generale*	24380
5	LLOY	Lloyds Banking Group	11640
6	SAN	Santander*	11552
7	CSGN	Credit Suisse*	10446
8	DANSKE	Danske Bank	9172
9	INGA	ING Bank*	8887
10	UBCG	UBS*	7558
11	RBS	Royal Bank of Scotland*	7472
12	UCG	Unicredit*	6317
13	NDA	Nordea Bank*	6217
14	CBK	Commerzbank	6056
15	ISP	Intesa Sanpaolo	5347
16	BBVA	Banco Bilbao	3648
17	KBC	KBC Group	3289
18	SHBA	Svenska Handelsbanken	3254
19	SEBA	SEB	2798
20	EBS	Erste Group	2767
21	SWEDA	Swedbank	1758
22	BMPS	Banca Monte dei Paschi	1674
23	JYSK	Jyske Bank	1022
24	DNB	DNB	402
25	BIRG	Bank of Ireland Group	216
26	OTP	OTP Bank	-1037
27	AIBG	AIBG Group	-2160
28	HSBA	HSBC*	-16553

* Classified as G-SIB in 2017

Table 6.2: Comparison SRISK vs BCBS 2012-2014

	2012		2013		2014	
Rank	SRISK Ranking	G-SIB Bucket	SRISK Ranking	G-SIB Bucket	SRISK Ranking	G-SIB Bucket
1	DBK	4 (2.5%)	DBK	3 (2.0%)	DBK	3 (2.0%)
2	BNP	3 (2.0%)	BARC	3 (2.0%)	BARC	3 (2.0%)
3	BARC	3 (2.0%)	BNP	3 (2.0%)	BNP	3 (2.0%)
4	RBS	2 (1.5%)	GLE	1 (1.0%)	GLE	1 (1.0%)
5	INGA	1 (1.0%)	RBS	2 (1.5%)	INGA	1 (1.0%)
6	GLE	1 (1.0%)	UBCG	2 (1.5%)	LLOY	
7	LLOY	1 (1.0%)	LLOY		RBS	2 (1.5%)
8	UBCG	2 (1.5%)	INGA	1 (1.0%)	UBCG	1 (1.0%)
9	CSGN	2 (1.5%)	CBK		CBK	
10	CBK		CSGN	2 (1.5%)	CSGN	2 (1.5%)
11	UCG	1 (1.0%)	NDA	1 (1.0%)	NDA	1 (1.0%)
12	NDA	1 (1.0%)	SAN	1 (1.0%)	UCG	1 (1.0%)
13	SAN	1 (1.0%)	DANSKE		DANSKE	
14	DANSKE		BMPS		SAN	1 (1.0%)
15	ISP		UCG	1 (1.0%)	BMPS	
16	HSBA	4 (2.5%)	KBC		SHBA	
17	KBC		SEBA		SEBA	
18	BBVA	1 (1.0%)	SHBA		ISP	
19	BMPS		DNB		KBC	
20	SHBA		ISP		DNB	
21	SEBA		EBS		EBS	
22	DNB		BIRG		SWEDA	
23	EBS		SWEDA		BBVA	1 (1.0%)
24	SWEDA		BBVA	1 (1.0%)	BIRG	
25	BIRG		AIBG		AIBG	
26	AIBG		JYSK		JYSK	
27	JYSK		OTP		OTP	
28	OTP		HSBA	4 (2.5%)	HSBA	4 (2.5%)

The table compares the rankings obtained by SRISK with the G-SIB classifications between year 2012 and 2014. The numbers in the G-SIB Bucket-column indicate which G-SIB bucket the respective bank is placed in and the the percentage numbers in the parantheses are the corresponding extra loss absorbency requirements.

measure and find that during 1263 out of 2767 (45.6%) days in their sample, none of the 94 financial institutions were jointly ranked among the top 10 by the three risk measures. The fact that the G-SIB rankings and SRISK rankings are similar but not the rankings of SRISK compared to CoVaR and MES, suggests that SRISK is the academic systemic risk measure that is most closely related to the G-SIB measurement approach used in practice.

As can be seen in the tables, Deutsche Bank (DBK), BNP Paribas (BNP) and Barclays (BARC) are consistently ranked top-3 by SRISK as the three banks contributing the most to systemic risk. This result is in line with the G-SIB classifications since these banks (with HSBA as only exception) have been placed in higher buckets than the other G-SIBs.

Looking at Table 6.2 and 6.3, one sees that the changes on the G-SIB list and SRISK rankings from year to year are not drastic which indicates that both measurement approaches are stable through time. The result is in line with the findings of Benoit et al. (2013) who find that there is little variation between the rankings over time within each measure. As pointed out by Benoit et al. (2013), this is a nice property because a systemic risk measure where the identified banks varies heavily during short time periods would not be particularly helpful.

A trend towards lowering the extra loss absorbency requirement over time can be seen in the G-SIB classifications. In year 2012, the distribution in the buckets was the following: Bucket 4: 2 banks, Bucket 3: 2 banks, Bucket 2: 3 banks, Bucket 1: 7 banks and in 2017 it was: Bucket 4: 0 banks, Bucket 3: 2 banks, Bucket 2: 2 banks, Bucket 1: 8 banks. This indicates that the FSB and BCBS are of the view that large European banks have become less risky over the last six years. Deutsche Bank, BNP Paribas and Barclays have all been moved to a lower bucket during the period. As can be seen in Figure 6.2, the SRISK measures have been decreasing for all three banks during the period which further strengthens the evidence that both risk measurement approaches capture changes in systemic importance over time in a similar manner.

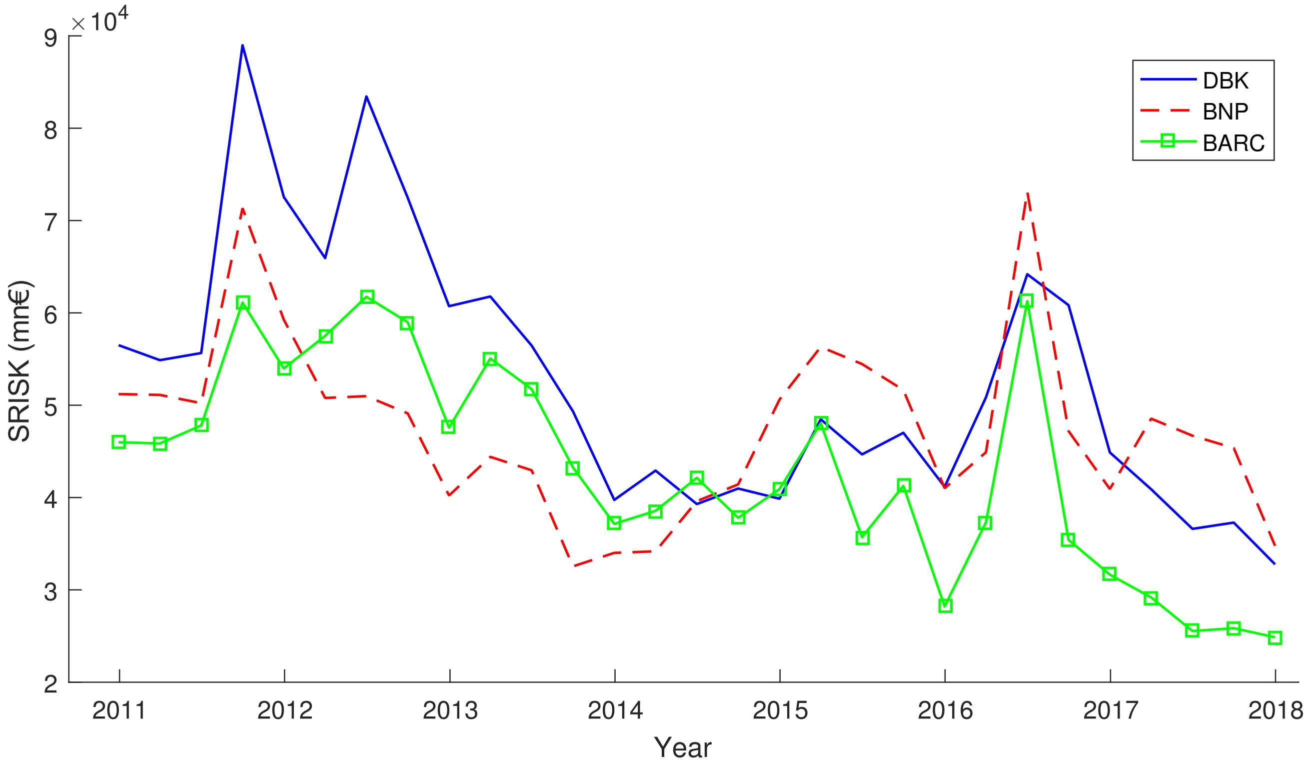
There are also several differences between the two methods. For example, Societe Generale (GLE) is consistently ranked high (rank 4 in 2013-2017) by the SRISK measure but is during the whole sample period placed in Bucket 1 on the G-SIB list indicating the lowest degree of

Table 6.3: Comparison SRISK vs BCBS 2015-2017

	2015		2016		2017	
Rank	SRISK Ranking	G-SIB Bucket	SRISK Ranking	G-SIB Bucket	SRISK Ranking	G-SIB Bucket
1	BNP	3 (2.0%)	DBK	3 (2.0%)	DBK	3 (2.0%)
2	BARC	3 (2.0%)	BNP	3 (2.0%)	BNP	2 (1.5%)
3	DBK	3 (2.0%)	BARC	2 (1.5%)	BARC	2 (1.5%)
4	GLE	1 (1.0%)	GLE	1 (1.0%)	GLE	1 (1.0%)
5	RBS	1 (1.0%)	INGA	1 (1.0%)	UCG	1 (1.0%)
6	INGA	1 (1.0%)	SAN	1 (1.0%)	LLOY	
7	LLOY		LLOY		CSGN	1 (1.0%)
8	UCG	1 (1.0%)	RBS	1 (1.0%)	RBS	1 (1.0%)
9	CSGN	2 (1.5%)	UCG	1 (1.0%)	SAN	1 (1.0%)
10	NDA	1 (1.0%)	NDA	1 (1.0%)	INGA	1 (1.0%)
11	UBCG	1 (1.0%)	CBK		ISP	
12	SAN	1 (1.0%)	BBVA		UBCG	1 (1.0%)
13	CBK		DANSKE		DANSKE	
14	DANSKE		UBCG	1 (1.0%)	CBK	
15	ISP		CSGN	2 (1.5%)	NDA	1 (1.0%)
16	BMPS		ISP		BBVA	
17	SHBA		SHBA		BMPS	
18	EBS		KBC		KBC	
19	SEBA		BMPS		SEBA	
20	KBC		SEBA		EBS	
21	DNB		EBS		SHBA	
22	SWEDA		SWEDA		SWEDA	
23	BIRG		AIBG		BIRG	
24	BBVA		DNB		DNB	
25	JYSK		JYSK		JYSK	
26	AIBG		BIRG		AIBG	
27	OTP		OTP		OTP	
28	HSBA	4 (2.5%)	HSBA	3 (2.0%)	HSBA	3 (2.0%)

The table compares the rankings obtained by SRISK with the G-SIB classifications between year 2015 and 2017. The numbers in the G-SIB Bucket-column indicate which G-SIB bucket the respective bank is placed in and the the percentage numbers in the parantheses are the corresponding extra loss absorbency requirements.

Figure 6.2: Top 3 risky banks according to SRISK



The figure shows how the SRISK has developed over time for the three most risky banks in the sample: Deutsche Bank (DBK), BNP Paribas (BNP) and Barclays (BARC) systemic importance on the list. Another differences can be noticed when looking at Lloyds Banking Group (LLOY). It was on the G-SIB list in Bucket 1 in 2012 but was then removed in 2013 because its systemic importance has decreased according to the BCBS methodology. This view is not consistent with the SRISK results. According to the SRISK rankings, Lloyds continues to be ranked either #6 or #7 during the whole sample period which indicates that its systemic importance has not decreased.

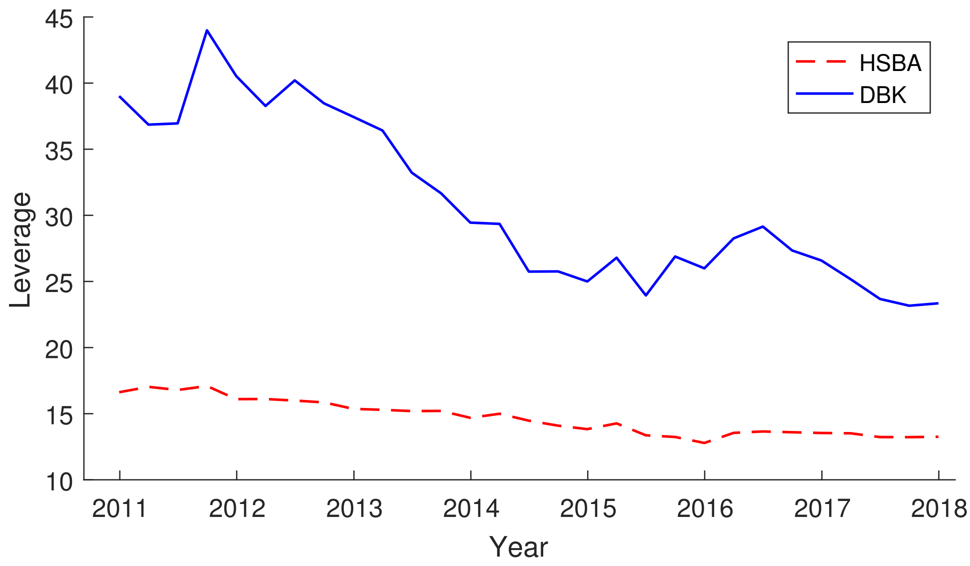
The most striking difference is that HSBC (HSBA) is ranked last by SRISK in each year from 2013 to 2017 even though it has consistently been identified as the most systemically important bank in Europe by the BCBS (placed in bucket 4 from 2012-2015 and in bucket 3 from 2016-2017).

6.3 HSBC vs Deutsche Bank

In this section, a comparison of the firm characteristics of Deutsche Bank (DBK) and HSBC (HSBA) is conducted to examine why the SRISK measure consistently ranks Deutsche Bank among the top riskiest banks in Europe every year while HSBC that is the largest bank in Europe has the lowest expected capital shortfall of all banks between 2013 and 2017. The BCBS has placed HSBC in the same or in a higher bucket than Deutsche Bank during the whole sample period which indicates that BCBS is of the view that HSBC is at least as risky as Deutsche Bank. But according to SRISK, HSBC ranks 16 in 2012 and then 28 during the coming years due to its negative SRISK which suggests that it does not contribute to the systemic risk at all.

Comparing three variables (Assets, Leverage and LRMES) that are relevant for the SRISK calculation yields some insights about the large differences between HSBC and Deutsche Bank. Firstly, by looking at the leverage in Figure 6.3, one can quickly see that Deutsche Bank appears much more risky because of the higher leverage. From 2011 to 2014, Deutsche Bank had more than twice as high leverage compared to HSBC. As can be seen in Figure 6.3, Deutsche Bank has lowered its leverage from 44 in 2012 to 23 at the end of 2017, however it is still much

Figure 6.3: Leverage for HSBC and Deutsche Bank



higher than HSBC's leverage which was 13 at the end of 2017. Furthermore, by looking at the LRMES (the simulated expected equity devaluation in a crisis) in Figure 6.4, one sees that also the LRMES for Deutsche Bank is consistently higher than for HSBC during the whole sample period. This means that the Deutsche Bank's stock is expected to decrease more than HSBC in a financial crisis which is a result of higher expected future volatility and market correlation. The higher expected volatility is probably due to that investors are aware of Deutsche Bank's higher leverage and that it has a higher probability of default. On the contrary, HSBC has a low leverage which is a sign of stability and low probability of default. This leads to that investors are not that worried during bad market conditions which further leads to low expected future volatility and thereby a low LRMES. Looking at the Total Assets (Figure 6.5) does not help to explain why the SRISK measure ranks HSBC lower than Deutsche Banks. Apart from 2011-2013 HSBC has had higher Total Assets and from end-2013 and onwards, HSBC has had assets of at least 325 billion € more than Deutsche Bank.

After analyzing and comparing the components of SRISK, it becomes clear why SRISK ranks HSBC much lower than Deutsche Bank. The low leverage and low LRMES clearly indicate that HSBC has a lower default risk than Deutsche Bank and therefore seems to contribute less to the systemic risk.

Figure 6.4: LRMES for HSBC and Deutsche Bank

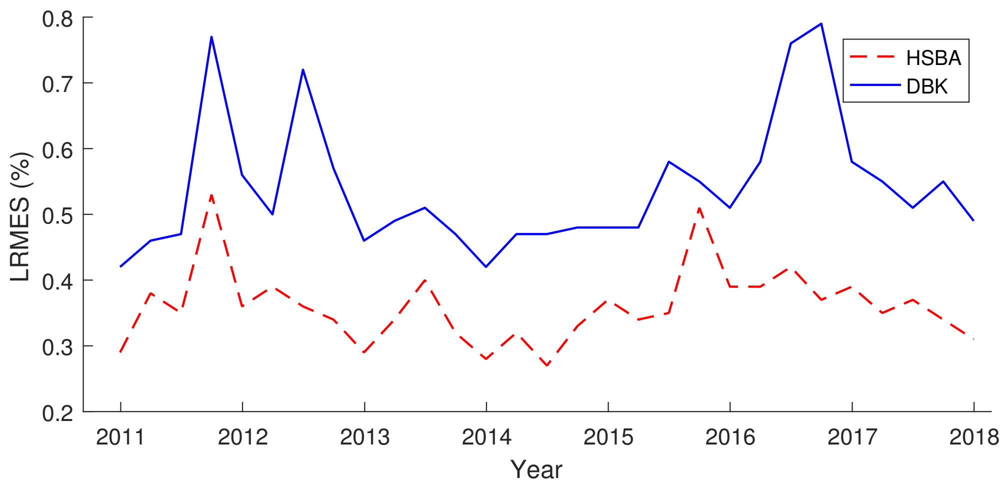
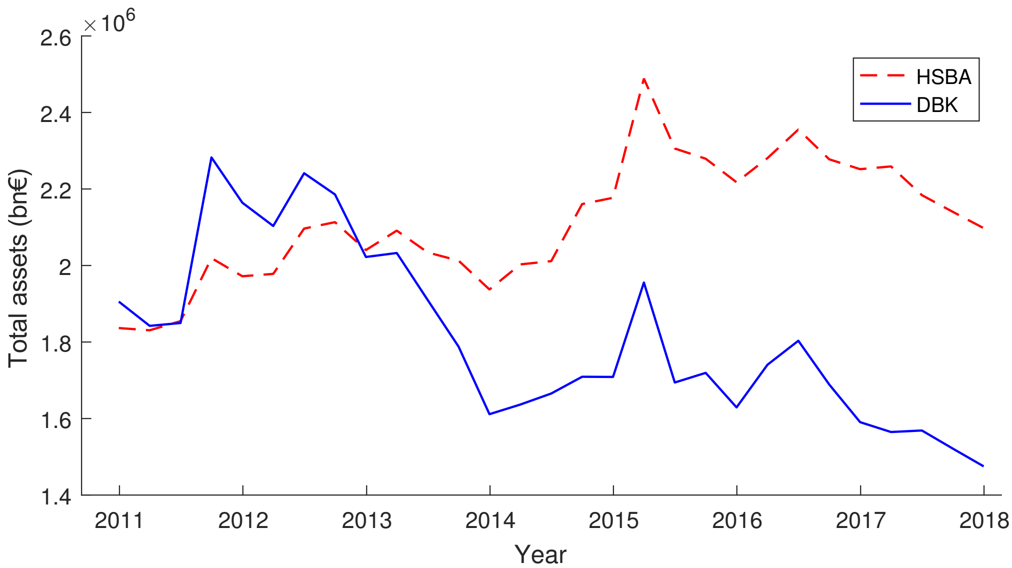


Figure 6.5: Assets for HSBC and Deutsche Bank



The reason why HSBC still is regarded as at least as systemically important as Deutsche Bank by the BCBS is clearly a result of their initial choice of viewing systemic risk from a loss given default perspective and not taking the probability of default into account. Since HSBC is larger than Deutsche Bank in terms of total assets, it might very well be true that HSBC is more *systemically important* but that is not necessarily equal to saying that it has a higher *systemic risk contribution*. The BCBS states the following regarding the rationale behind the extra loss absorbency requirement: *"G-SIBs must have higher loss absorbency capacity to reflect the greater risks that they pose to the financial system"* (BCBS, 2013a, p.1). This means that the BCBS is of the view that HSBC is posing at least as big risk to the financial system as Deutsche Bank even though its leverage is nearly half of that of Deutsche Bank. One should not forget that the G-SIB classification methodology also takes other indicators into account such as complexity and interconnectedness and it might be the case that HSBC score higher here than Deutsche Bank which could explain the high HSBC bucket classification. But even though HSBC is highly interconnected and complex (which BCBS argues leads to higher costs in case of bankruptcy), basing the extra loss absorbency requirement on factors that totally disregard leverage and probability of default seems insufficient.

To sum up this discussion, HSBC is ranked much lower compared to Deutsche Bank by the SRISK measure in terms of systemic risk contribution which is a result of consistently significantly lower leverage and LRMES. The reason why HSBC has during the whole sample period been classified in G-SIB Bucket 3 or 4 is because the BCBS does not take the probability of default into account when identifying the most risky banks. The results suggest that the BCBS does not separate the concepts of *systemic importance* and *systemic risk contribution*. The G-SIB classification framework classifies banks only according to their systemic importance while ignoring their real riskiness. The SRISK framework seems to better capture these different concepts since it identifies systemically important banks by assessing which banks that are most likely to experience a capital shortfall.

7

Conclusion

Systemic risk is a complex topic that is not yet fully understood which makes measurement and regulation challenging. The extra loss absorbency requirement for G-SIBs is one regulatory tool aiming at containing the systemic risk in the financial system. The definition of systemic risk and the approach currently used by the BCBS to identify the banks that should be classified as G-SIBs differs significantly compared to other systemic risk measurement approaches proposed by academics.

In this study, I analyse differences regarding the identification of systemically important banks in Europe between the G-SIB classification methodology and SRISK, which is one of the most influential systemic risk measures proposed in the academic literature. I calculate SRISK for 28 European banks and identify the most systemically important banks according to this measure. By constructing yearly rankings of the banks in terms of their systemic importance between 2012-2017, I compare these rankings to the annually updated list of G-SIBs and analyse the differences. Furthermore, SRISK is also calculated for all banks in the sample on a quarterly basis from year 2005-2017 for intuition purposes and to give an indication of how the systemic risk level in Europe has changed during the last 13 years. I find that the systemic risk level in Europe according to the aggregate SRISK for all banks is currently at its lowest level since the start of the estimation period in 2005. The results from the study show that the two approaches yield in large similar rankings most of the time and that both measures capture changes in systemic risk over time in a similar way. However, due to that the G-SIB methodology ignores probability of default, large inconsistencies can appear which became clear in the case of HSBC. The systemic importance of HSBC differed heavily depending on method which was a result of that the two measurement approaches have different views on systemic risk. The G-SIB methodology captures factors that the SRISK measure does not account for, but not considering the probability of default leads to that banks in which a capital shortfall is unlikely still become subject to strict loss absorbency requirements.

The main contribution of this study is that it bridges the gap between the regulatory and academic approaches for measuring systemic risk. The study makes it clear that regulators' and academics' view of systemic risk does not align which can in some cases give rise to large inconsistencies when identifying systemically important banks. The study also highlights the complexity of systemic risk and the many possible ways of looking at it. Neither the G-SIB classification methodology nor the SRISK measure manage to account for all aspects of systemic risk.

A suggestion for future research is to investigate how sensitive the SRISK rankings are to the choice of capital ratio θ. There might be differences depending on whether θ regards unweighted or risk-weighted assets as well as Tier 1 or Tier 2 capital. Another direction for future studies is to compare the G-SIB classification methodology to other academic measures of systemic risk in order to see whether similar results are obtained.

Appendix

Table 7.1: Data sample and tickers

Ticker	**Bank name**
AIBG	AIB Group
BARC	Barclays
BBVA	Banco Bilbao
BIRG	Bank of Ireland Group
BMPS	Banca Monte dei Paschi
BNP	BNP Paribas
CBK	Commerzbank
CSGN	Credit Suisse
DANSKE	Danske Bank
DBK	Deutsche Bank
DNB	DNB
EBS	Erste Group Bank
GLE	Societe Generale
HSBA	HSBC
INGA	ING Bank
ISP	Intesa Sanpaolo
JYSK	Jyske Bank
KBC	KBC Group
LLOY	Lloyds Banking Group
NDA	Nordea Bank
OTP	OTP Bank
RBS	Royal Bank of Scotland
SAN	Santander
SEBA	Skandinaviska Enskilda Banken
SHBA	Svenska Handelsbanken
SWEDA	Swedbank
UBCG	UBS
UCG	Unicredit Group

Table 7.2: Absolute SRISK for 2012-2016

	2012		2013		2014		2015		2016	
Rank	**Ticker**	**SRISK**	**Ticker**	**SRISK**	**Ticker**	**SRISK**	**Ticker**	**SRISK**	**Ticker**	**SRISK**
1	DBK	72548	DBK	60724	DBK	39742	BNP	50593	DBK	41160
2	BNP	59252	BARC	47565	BARC	37147	BARC	40907	BNP	41006
3	BARC	53980	BNP	40220	BNP	34004	DBK	39873	BARC	28200
4	RBS	37313	GLE	29368	GLE	25203	GLE	30660	GLE	28059
5	INGA	35951	RBS	24396	INGA	23740	RBS	23615	INGA	19513
6	GLE	34347	UBCG	23532	LLOY	15646	INGA	19466	SAN	17527
7	LLOY	30373	LLOY	21695	RBS	14534	LLOY	15226	LLOY	16238
8	UBCG	26687	INGA	21536	UBCG	12368	UCG	14252	RBS	12473
9	CSGN	23839	CBK	17396	CBK	11864	CSGN	13399	UCG	11501
10	CBK	20915	CSGN	17149	CSGN	11844	NDA	12863	NDA	11344
11	UCG	19634	NDA	12405	NDA	10372	UBCG	12681	CBK	9295
12	NDA	18482	SAN	12223	UCG	9304	SAN	12140	BBVA	8306
13	SAN	15205	DANSKE	9737	DANSKE	7316	CBK	11480	DANSKE	8290
14	DANSKE	10870	BMPS	6684	SAN	6949	DANSKE	9310	UBCG	8060
15	ISP	9781	UCG	5583	BMPS	6119	ISP	8364	CSGN	6829
16	HSBA	8543	KBC	5273	SHBA	4670	BMPS	5899	ISP	4773
17	KBC	8380	SEBA	4973	SEBA	4424	SHBA	4883	SHBA	3916
18	BBVA	6780	SHBA	4209	ISP	4229	EBS	4145	KBC	3756
19	BMPS	6168	DNB	3824	KBC	4215	SEBA	4032	BMPS	3399
20	SHBA	5853	ISP	2833	DNB	3049	KBC	4027	SEBA	3143
21	SEBA	5850	EBS	2525	EBS	2703	DNB	3606	EBS	2872
22	DNB	4368	BIRG	2360	SWEDA	1827	SWEDA	2521	SWEDA	2819
23	EBS	3840	SWEDA	2264	BBVA	1293	BIRG	1479	AIBG	1885
24	SWEDA	3561	BBVA	2189	BIRG	1263	BBVA	1041	DNB	1647
25	BIRG	3481	AIBG	603	AIBG	263	JYSK	1012	JYSK	835
26	AIBG	1114	JYSK	246	JYSK	139	AIBG	995	BIRG	451
27	JYSK	531	OTP	-1385	OTP	-1257	OTP	-630	OTP	-607
28	OTP	-921	HSBA	-4499	HSBA	-9411	HSBA	-4304	HSBA	-9228

SRISK values are quoted in million Euro

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