Master’s Thesis

MSc Finance and Strategic Management (cand.merc.)

The Impact of the Basel III Regulatory Framework on Systematic and Idiosyncratic Risk in the Global Banking Sector

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Abstract

This paper examines the impact of the Basel III regulations on both systematic and idiosyncratic risk of internationally active banks between 2014 and 2019. It presents a review of empirical literature on the determinants of risk in- and outside of the global banking sector and uses a sample of 65 internationally active banks to investigate how the time variation of risk within the sample can be explained by the implementation of liquidity and capital measures imposed by Basel III. For robustness, the sample is divided into global systemically important banks (G-SIBs) and non-G-SIBs, systematic risk is estimated using a static approach (rolling ordinary least squares regression) and a dynamic estimate (Kalman Filter), and a distributed lag model is employed to account for potential lags of the explanatory variables. Our results show that the dynamic causal effects of the Basel measures on risk in the global banking sector is weak. This finding can be explained by the fact that the implementation of the Basel III regulatory framework is still in progress and that the overall good condition of the economy over the observation period lead to a lower impact on risk as Basel III regulations are specifically designed to add resilience to the banking sector during economic downturns.

JEL Classification: C32, C33, G21, G28, G32

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Abbreviations

ADF	Augmented Dickey Fuller
AIC	Akaike Information Criterion
ARCH	Autoregressive Conditional Heteroskedasticity
AT1	Additional Tier 1
BCBS	Basel Committee on Banking Supervision
BIS	Bank of International Settlements
CAPM	Capital Asset Pricing Model
CET1	Common Equity Tier 1

CT1	Core Tier 1
ES	Expected Shortfall
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GDP	Gross Domestic Product
HQLA	High-Quality Liquid Assets
MAE	Mean Absolute Error
M-GARCH	Multivariate Generalized Autoregressive Conditional Heteroskedasticity
MSCI	Morgan Stanley Capital International
NSFR	Net Stable Funding Ratio
OECD	Organization for Economic Cooperation and Development
OLS	Ordinary Least Squares
OTC	Over the Counter
RWA	Risk Weighted Assets
SER	Standard Error of Residuals
SML	Security Market Line
SSR	Sum of Squared Residuals
TDS	Thomson DataStream
TSS	Total Sum of Squares
VAR	Value at Risk
VIF	Variance Inflation Factor

1. Introduction

The introductory chapter is structured as followed: First, we will motivate our topic selection by outlining the research context. Based on the identification of the gap that persists in existing research towards the end of the first section, we will define our research question in section 1.2. The subsequent section covers important delimitations of this thesis and section 1.4 provides an overview of the structure and logic our study is based upon.

1.1 Research Context

It has long been recognized that the banking sector is integral for the well-functioning of the economy since banks act as intermediaries between savers and borrowers. At the core of the banking sector is the idea that banks are holding financial assets for others in return for interest on the deposition of these assets and the promise that said assets can be withdrawn at will. Subsequently, banks invest assets in form of loans to business or private individuals thereby financing real economic growth but also creating additional wealth for themselves through the spread between the cost of funds and their lending rate (Bhattacharya et al., 1998). However, profitable banking operations are linked to inherent risks associated with the banking business model that are exacerbated by the massive scale of the global financial sector and its ever-increasing interconnectedness. Several types of risk are underlying financial institutions like credit, market or liquidity risks and can severely expose them to losses. This in itself is not a problem, but due to the systemic nature of the industry, banks are directly connected among themselves as well as to the real economy. Hence, financial distress of banks can cause a domino effect within the industry that eventually spills over into the real economy causing significant damage, like it was the case with the collapse of Lehman Brothers in 2008 (Hull, 2018). Banks are aware of their crucial role within the economy, but paradoxically, this incentivizes them to take on even more risk since they know that they would be eventually be bailed out by their government. If their risk-taking behavior pays off, they get to keep the return, but in case of excessive losses, consequences would be borne by the taxpayer. Moreover, it is often hard to detect when banks engage in excessive risk-taking, since risk is usually built up in economically prosperous times and is only revealed when the state of the economy deteriorates and it is harder for the banks to take corrective action (Boissay & Cappiello, 2014). The aim of regulation is to minimize the potential of excessive risk-taking throughout the intermediation process by moderating the extent to which banks can invest into high-risk/high-return assets in order to avoid systemic failure in the banking sector (Morgan, 2002). The following sections will outline how risk will be measured in the context of our research approach and why the risk measures we are investigating should be of concern to regulators.

1.1.1 Relevant Types of Risk

The following section has the purpose of thematically integrating the concepts of risk and its determinants in the banking sector with the dynamics of regulation. Based on these foundations we will formulate the central research question this thesis is based upon. Initially, it is crucial to clearly define the two risk-measures which are at the heart of this thesis. On the one hand, there will be an examination of how the specific dynamics resulting from regulation will impact the idiosyncratic risk of banks in the industry over the specified time-period. *Idiosyncratic risk*, which will be interchangeably used with the term *unsystematic risk*, is risk that is inherent in each individual company and pertains to the particular characteristics and operations of a single firm (Bodie et al., 2014). On the other hand, we will investigate the *systematic risk* in the banking sector and how changes in the regulatory landscape will affect the development of the banks' sensitivity to the market through time. Systematic risk, which will also be referred to as beta, refers to the risk-sources that impact the complete market and are not beholden to one single company (Brealey et al., 2017). In portfolio theory, the total risk of a portfolio is made up of both the idiosyncratic and the market risk of its constituents (Bodie et al., 2014). However, investors have the opportunity to effectually erase the impact of the idiosyncratic risk of their stocks through diversification. This means that for investors only the systematic risk of a stock is of importance since unsystematic risk can be neglected assuming any investor can hold a perfectly diversified portfolio, i.e. the market portfolio and thereby diversify away any idiosyncratic risk. The potentially negative impact of one risky asset is offset through the multitude of uncorrelated other securities.

1.1.2 Implications of Risk for Regulators

From an economy and industry perspective it is similar since companies outside the financial sector are not as highly interconnected and therefore a failure does not cause massive disruptions to the working of the overall industry or economy (Muns & Bijlsma, 2012). In the case of the banking sector however, idiosyncratic risk is of crucial importance due to the highly interdependent structure of the global financial system. This is what will be referred to as systemic risk. For clarification, systemic risk relates to an event that can cause a major negative ripple effect in one industry while systematic risk stems from the movement in the overall economy (Haldane & May, 2011). The impact of this inherent systemic risk in the banking industry became apparent after the collapse of Lehman Brothers in 2008. Since Lehman Brothers was a large bank which was deeply ingrained in the financial system and the economy as a whole, its collapse created a domino effect causing immense danger to the global financial markets and eventually the economy as a whole. As mentioned above, investors can disregard idiosyncratic risk by means of diversification, regulation in the banking sector has the main goal of reducing idiosyncratic bank risk in order to mitigate the threat of systemic failure in the industry (Mohanty et al., 2018). While the mechanics used in regulatory frameworks like Basel III are targeting idiosyncratic risk, the potential impact of these regulation on systematic risk should be considered as well. In general, the goal of macroeconomic policy is always to reach a state of stability and reduced risk. Therefore, one could argue that rather than focusing solely on idiosyncratic risk of banks, regulators should also consider the impact of regulation on the systematic risk in the industry. By reducing uncertainty and fostering stability, regulators want to create an environment that leads to better real investment decisions resulting in improved capital allocation (Barth, Caprio, & Levine, 2001). Moreover, systematic risk is an integral component in the pricing of assets. Since equity markets are an important source of funding for banks, the question of how regulation impacts their systematic risk is therefore also relevant for the policy design and efficient capital allocation (Grout & Zalewska, 2006). Since equity markets are an important source of funding for banks, the question of how regulation impacts their systematic risk is therefore also relevant for the policy design (Grout & Zalewska, 2006). Adam et al. (2016) argue that banks' intermediary role between the real sector and the financial sector make them inherently vulnerable to shocks from both sources, which implies that regulators should be concerned with the banking sectors' overall sensitivity to the real economy which is measured via its systematic risk factor.

1.1.3 Previous Literature and Research Gap

There is already a notable amount of literature that investigates the levels of risk in the banking industry in the context of regulatory frameworks: The development of bank risk over periods of high and low regulatory intervention in the banking sector has been subject of several research efforts. Many scholars. especially from the late 80s to the early 00s, have studied the impact of (de)regulation on systematic risk in Australia (Harper & Scheit, 1992; Hogan & Sharpe, 1984) and in the US (Allen & Wilhelm, 1988; Bundt et al., 1992). The methodology applied in these studies was predicated on defining periods of deregulation and examining changes in bank risk with models that detect structural breaks in the betas' development. However, the results from these research efforts only provide inconclusive evidence as to how (de)regulation affects levels of systematic and unsystematic risk. There are several reasons why the evidence from these research efforts tuned out to be inconsistent. First, the studies differed in the way they calculated measures of both systematic and unsystematic risk, with some of them using the static standard market model while others employed dynamic estimation techniques. Furthermore, the regulation frameworks assessed in this body of literature deal with domestic regulation and do not have a global context. Finally, these studies do not directly examine how he regulation exactly impacts risk levels but rather how risk levels behave over time periods in which regulation was prevalent. More recently, there are some studies that look at more modern regulation frameworks like the Dodd-Frank Act and Basel Accords and how they affect unsystematic and systematic risk levels (Akhigbe et al., 2016; Mohanty et al., 2018). These authors regress betas and residual variances against certain explanatory variables at firm level. However, they do not use metrics that are imposed from regulation bur rather ones that proxy the effect of regulation ad use static models for estimating the risk measures. While there is already a sizeable body of relevant literature, our research approach seeks to provide a more wholistic assessment of how regulation influences levels of systematic and unsystematic risk in the banking sector. We will look at the impact of regulation on the firm-level and how it translates into changing risk-levels for both systematic and idiosyncratic risk. Moreover, are we using distinct explanatory variables that are developed in the context of the regulation framework, which to our knowledge has not been done before. Finally, we acknowledge that the risk-measures underlying our analysis are time-varying which is why we include a dynamic estimation approach.

1.1.4 Regulatory Framework

The regulatory regime underlying our analysis is the Basel III framework, which is developed by the Basel Committee on Banking Supervision (BCBS) at the Bank of International Settlements

(BIS). Basel III is a macroprudential regulatory framework that applies to all internationally active banks as well as certain domestic institutions. Micro- and macro-prudential regulation both target individual institutions by using similar instruments, however, with a different focus (Boissay & Cappiello, 2014). Micro-prudential supervision aims to safeguard individual financial institutions from unsystematic risks, in particular, by preventing them from engaging in excessive risk-taking. However, the 2008 financial crisis revealed that individual financial institutions' strength alone is not enough to ensure the stability of the financial system as a whole. Therefore, regulators introduced a complementary macro-prudential supervisory approach. Macro-prudential supervision accounts for the interactions among individual institutions in the financial sector and takes into consideration the feedback loops of the financial sector with the real economy. This is an additional argument for why regulators should be concerned with systematic risk and therefore additional justification for the examination of both idiosyncratic and systematic risk within our research context.

While Basel III is a macroprudential framework, it still targets institutions on an individual level by requiring banks to comply with specific capital and liquidity requirements that are subject to disclosure in reports. This poses a logical conjecture for investigating potential effects on institutions' idiosyncratic risk since the regulations are directly targeted at influencing firm-specific accounting measures. Systematic risk, on the other hand, cannot be directly managed by regulators since it stems from movements in the overall economy, the Basel III framework still can impact the firms' sensitivity to those market movements as expressed by the equity beta of the bank. However, it is hypothesized that the balance sheet effects imposed by Basel III also influence systematic risk. Past literature provides ample evidence concerning the influence of accounting measures on the systematic risk of banks and regular companies and will be discussed granularly in a later section (Beaver et al., 1970; Biase & D'Apolito, 2012; Rosenberg & Perry, 1981; Vander Vennet & De Jonghe, 2005). These findings provide the empirical groundwork and rationale for connecting the evolution of both idiosyncratic and systematic risk in the banking sector since the implementation of the Basel III rules.

1.2 Research Question

After setting up the context of this thesis' research approach, the following section will present the underlying research question of our study. The research question draws inspiration from prior work on the firm-specific determinants of risk measures for companies. These theoretical concepts will be examined in the context of the banking industry where regulation at the firm-level is employed to explicitly target risk-levels in the industry. Hence, we formulate our research question as follows:

How do the liquidity and capital requirements within the Basel III regulatory framework influence the systematic and idiosyncratic risk levels of internationally active banks?

At the core of the analysis there will be three distinct accounting ratios that are directly related to the Basel III regulatory framework.

(1) The Liquidity Coverage Ratio
(2) The Leverage Ratio
(3) The Capital Adequacy Ratio based on Common Equity Capital

These three ratios are the most prominent components of the Basel III framework. Moreover, they are highly relevant in the context of this and previous researchers' work since liquidity, leverage and capital levels have been found to significantly impact risk levels in banks. It is important to mention that apart from these capital requirements, the macroprudential nature of Basel III also entails cross-border supervision and reporting implications for all affected banks. While these qualitative measures are integral for the overall soundness of the regulation, the quantitative nature of our analysis leads us to focus on the quantifiable components from this regulatory framework which are manifested on the balance sheet. Due to the fact that there is no prior research that directly evaluates the regulator's chosen measures concerning their impact on risk in the banking industry, the goal of this thesis is to provide a first investigation of the effectiveness of the Basel III framework, which is still fairly new. This is achieved on the one hand through a thorough literature review in which we aim to provide a more detailed insight how the mechanics of regulation are hypothesized to impact risk in the banking sector. On the other hand, we are utilizing a sample of 65 internationally active banks to empirically investigate the dynamic causal effect of Basel III on systematic and idiosyncratic risk on these banks.

1.3 Delimitation

It is integral to a genuine research process to acknowledge potential delimitations. These relate to the characteristics that limit the scope of our work and establish the conceptual boundaries of our study.

Basel III was subject to changes based on learnings generated from the initial phase of implementation. The time period we are observing (2014 – 2019) in the context of our research encompasses the very beginning of the regulatory framework. The initial rules and guidelines were supposed to be phased-in in between 2013 and 2019 with some of the relevant capital and liquidity ratios gradually approaching the target levels over the course of this time frame as can be seen in figures 9-13. Furthermore, reporting becomes mandatory only over the course of the observation period and can, on top of that, not be legally enforced by the Basel committee, but only by national legislators. Therefore, many banks fail to report the measures especially in earlier years of the investigated time horizon. Furthermore, the BCBS proposed several changes to the manner with which some of the metrics will be calculated and defined. These changes will be implemented by 2023. However, these changes were not yet applicable during the time span investigated in our research. Consequently, the transferability of our results may be limited to the extent that upcoming changes in the methods of calculations do not materially affect the value of the measures, and subsequently results obtained in the analysis.

Moreover, it is important to mention that Basel III entails a multitude of provisions and frameworks that are designed to ensure that bank risk is mitigated. This thesis focuses on the quantifiable aspects of the regulation since we are examining the aptitude of firm-specific financial metrics to explain risk measures. Nonetheless, Basel III is comprised of more than capital requirements and liquidity thresholds, but also imposes qualitative controls like best practices for valuation and corporate governance as well as guidelines for effective supervisory review of the financial metrics. Those are not directly considered within the confines of this thesis.

At the core of our analysis is a multivariate regression with the market-based measures of risk as the dependent variables, and the Basel III metrics as well as particular control variables as the explanatory variables. The risk measures as dependent variables are defined specifically in the context of the Capital Asset Pricing Model (CAPM), with two distinct calculation approaches for systematic risk. The unsystematic risk is defined as the residual variance for each of the two beta measures. It has to be acknowledged that the are more ways to define risk, especially idiosyncratic risk, and that the market-based approach does not constitute the exclusive path to measuring risk. Moreover, there are alternative ways to analyze the relationship between the measures of risk and the explanatory variables than a linear multivariate time-series regression. Nonetheless, this does not take away from the relevance and aptness inherent in our research design.

1.4 Structure

In order to provide a more wholistic understanding of how the aforementioned research question will be approached and answered, this section will provide an outline of the way this study integrates its different thematic concepts over the course of its chapters: The following chapter, *Chapter 2*, has the purpose of providing a detailed review of the theoretical concepts and existing empirical research that is central to our research question. *Chapter 3* outlines the methodological underpinnings of our work. By starting out with our perspective on the philosophy of science, we then proceed to point out how this view relates to the practical methodological process. The final section of the chapter specifies the empirical methods that will be utilized in the data analysis process. Subsequently, *Chapter 4* provides insight into the data used in the analyses. The sub-sections illustrate the sample composition, data characteristics and transformation steps that are necessary to prepare the data for the regression analysis. In *Chapter 5* we will present the findings with regards to the development of the dependent and independent variables as well as the regression results, followed by a detailed interpretation and discussion of the implications of the results in *Chapter 6*. Finally, *Chapter 7* will conclude with a final summary and reflections on the thesis.

2. Theory and Literature Review

This chapter can be divided into three parts: It starts with an in-depth review of the theoretical concepts underlying the risk calculation methods we use (section 2.1). In this section, the CAPM, and its underlying assumption of the static nature of risk will be discussed in detail due to the relevance to obtain time-varying systematic risk estimates for our empirical analysis. We then define idiosyncratic risk as the variance of the error term in the OLS regression for each of the different beta estimates. The second part of this chapter deals with the empirical research that has established a causal relationship of various macroeconomic- as well as firm-level factors on systematic and idiosyncratic risk across industries (section 2.2) and in the banking sector specifically (section 2.3.) The third part presents the Basel regulatory framework in detail (section 2.4) and develops hypotheses on how the three core measures of Basel III are likely to influence systematic and idiosyncratic risk of our sample of banks (section 2.5) – based on the findings from section 2.2, but especially 2.3. Finally, section 2.6 completes this chapter by explaining which control variables we pick to add robustness to our analysis.

2.1 Measures of Risk

2.1.1 Foundations: The Capital Asset Pricing Model

The CAPM was put forth independently by Treynor (1962), Sharpe (1964), Lintner (1965) and Mossin (1966) and is based on the portfolio optimization theory proposed by Markowitz (1952). At the core of portfolio optimization and later the CAPM lies the relationship between risk and expected return (Bodie et al., 2014). Markowitz (1952) shows how investors seek to construct mean-variance efficient portfolios, by shifting the weights in their asset allocation in order to minimize portfolio variance while maximizing expected returns. The CAPM research by Sharpe (1964) and Lintner (1965) expanded on this logic by assuming that all investors know the distribution of each asset's return in the market and that they can lend and borrow at the risk-free rate. By lending at the risk-free rate, investors are able to further decrease their exposure to risk, yet also decreasing expected returns. The opposite is true when borrowing is involved. This homogeneity of information will result in all investors holding the same asset mix, the market portfolio, which is the value-weighted portfolio of all assets in the investable universe (Bodie et al., 2014).

It is true for every portfolio, that the marginal contribution of the assets' risk within said portfolio make up the total risk of the portfolio (Brealey et al., 2017). However, it is important to distinguish the risk contribution of each asset into the security's idiosyncratic and systematic risk component. By definition, a well-diversified portfolio will not be impacted by the idiosyncratic risk of the individual securities as diversification effects remove all individual risk from the portfolio (Brealey et al., 2017). Hence, only the securities' systematic risk component will have an impact on the expected return demanded by investors. Since investors want to be compensated for taking on additional risk, they demand a risk premium, which is defined as the return of the market portfolio minus the risk-free rate (Brealey et al., 2017). In this context, the CAPM provides a sensitivity factor beta to each asset in the portfolio which measures the assets' exposure to the systematic risk of the market. While portfolio theory aims at modelling mean-variance efficient portfolios according to pre-determined input variables, the CAPM models expected returns according to the single-factor beta (Bodie et al., 2014).

The CAPM and beta seek to explain why returns differ across assets and employ the market returns as the single explanatory factor. Mathematically, beta is the result of dividing the covariance of the market and asset return by the variance of the market as can be seen in this formula (Brealey et al., 2017).

$$\beta_i = \frac{CoVar(R_i,R_M)}{\sigma^2(R_M)} \tag{1}$$

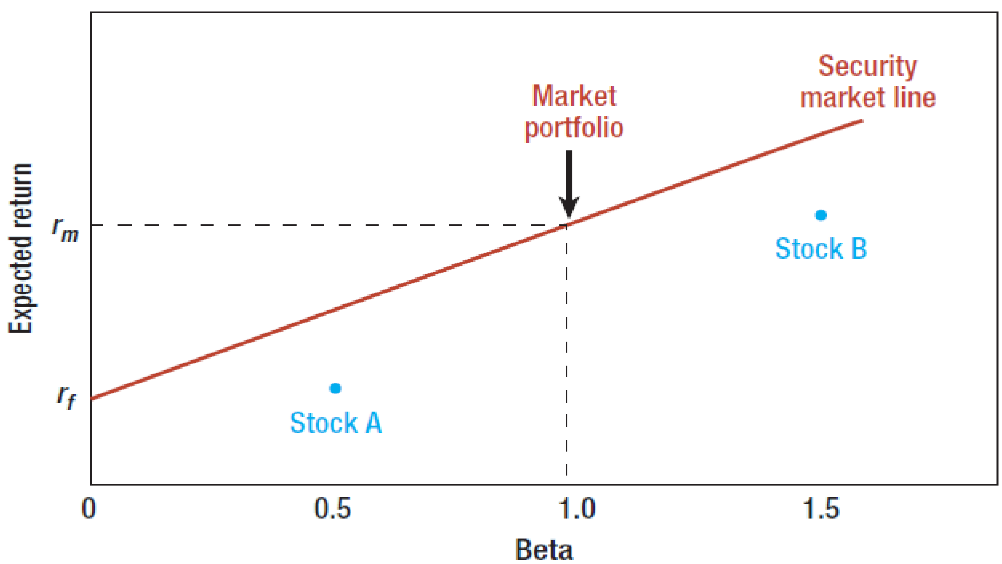
Logically, the market portfolio always has a beta equal to one, since the covariance of the market return with itself is just the variance of its returns. A beta that is greater than one therefore implies that the corresponding asset is riskier than the market and therefore demands a higher return. Vice versa is the case for a beta below one.

Apart from being compensated for systematic risk, investors also seek compensation for the time value of money when thinking about expected returns of an investment. Therefore, the CAPM includes the risk-free interest rate into the equation as a baseline return. The formula to explain the expected asset returns in the CAPM framework therefore looks like this:

$$E(R_{i,t}) = r_{f,t} + \beta_{i,t}(E(r_{M,t}) - r_{f,t}) \quad (2)$$

Thus, according to the CAPM the expected return of a security is predicted by sum of the risk-free rate $r_{f,t}$, and the market-risk component $\beta_{i,t}(E(r_{M,t}) - r_{f,t})$. If the CAPM would hold, the expected returns from Equation (2) would be the same as the actual observed returns since market movements are supposed to be the only predictor of asset returns from an investor's perspective who can erase unsystematic risk through diversification. Figure X showcases the linear relationship between beta and the expected return of a security.

Figure 1: The Security Market Line



Source: Brealey et al. (2014)

Depicted is the security market line (SML), which graphs individual assets risk premiums as a function of asset risk. The relevant measure of risk for individual assets held as parts of well-diversified portfolio is the contribution of the asset to the portfolio variance, which we measure by the asset's beta. If a stock is mispriced it will plot below or above the SML and market forces due to arbitrage opportunities will bid the security's price down or up until it plots on the line again.

It was established that both idiosyncratic risk and systematic risk contribute to the return of the stock but in the CAPM only the systematic risk is integral to the pricing of assets since idiosyncratic risk is assumed to be irrelevant by means of diversification. However, in the banking industry regulators are very much concerned with unsystematic risk since individual bank failure can lead to contagion effects and systemic risk as was pointed out before (Bessler et al., 2015). Both of the underlying risk measures in our analysis are rooted in the CAPM, which is why it is necessary to examine the assumptions pertaining to this model.

Underlying assumptions of the CAPM

There are several key assumptions underlying the CAPM that can be linked into individual investor behavior and market structure (Bodie et al., 2014):

1. Individual behavior
    a. Investors are rational, mean-variance optimizers.
    b. Their planning horizon is a single period.
    c. Investors have homogeneous expectations (identical input lists).
2. Market structure
    a. All assets are publicly held and trade on public exchanges, short positions are allowed, and investors can borrow or lend at a common risk-free rate.
    b. All information is publicly available.
    c. No taxes.
    d. No transaction costs.

An extensive amount of literature has materialized over the past decades, criticizing those assumptions. In light of our own research question we will focus on one particular assumption that is integral for how to model the evolution of risk through time.

The assumption critical to our research concerns the *simple periodicity of the CAPM*. The model assumes investors to optimize their portfolio based on a single-period planning horizon (Bodie et al., 2014). When using the CAPM to infer an asset's expected return, the investor must establish the appropriate risk-return relationship for the asset. As pointed out above, in the market model, an asset's beta is its sensitivity to the movement of the market returns and therefore its measure of systematic risk. However, the systematic risk is unobservable in the present moment, and therefore has to be modelled based on past data through ex post modelling via a regression equation:

$$R_{i,t} = a_t + \beta_{i,t}(R_{M,t}) + e_{i,t} \tag{3}$$

Where $R_{i,t}$ is the observed excess asset return, $r_{M,t}$ is the observed market return, a_t is the intercept, and $e_{i,t}$, the residual component, which is assumed to have zero-mean and assumed to be uncorrelated with the market factor and across securities (Bodie et al., 2014). Equation (3) provides the two risk measures that will be employed in our research context to investigate systematic and idiosyncratic risk over a specified time-period. Systematic risk will be represented by beta and idiosyncratic is defined as the variance of the error terms over the time-series. In this context the value of $e_i$will be dependent upon which beta will be inserted into Equation (2. In practice, beta is estimated by regressing the time-series of the asset's return against that of the market portfolio proxied by an index like the S&P 500 while assuming that the asset returns follow a normal distribution (Brealey et al., 2017). The result is an Ordinary Least Squares (OLS) linear regression with the market returns as the sole regressor in the model. It is also possible to add multiple explanatory variables akin to the Fama-French three-factor model, resulting in a multivariate regression since multiple independent variables are involved. Mathematically, the OLS estimation method takes the following form:

$$y_i = \sum_{j=1}^{p} x_{ij}\beta_j + \epsilon_i \tag{4}$$

The OLS method estimates beta as the line that minimizes the sum of the squares in the difference between the predicted and observed values of the dependent variable (Stock & Watson, 2019).

There are several assumptions that are imposed on linear regression models (Stock & Watson, 2019):

(1) *x* and *y* are observed without measurement errors.

(2) The dependent variable *y* and independent variables *x* have a linear relationship.

(3) Strict exogeneity: the errors in the regression should have a conditional mean of zero according to $E\{\epsilon_i|X\} = 0$.

(4) Homoscedasticity: $E\{\epsilon_i^2|X\} = \sigma_\epsilon^2$ meaning that the error term has the same variance σ^2 in each observation

(5) Independent and identically distributed observations: (x_i, y_i) is independent from, and has the same distribution as (x_j, y_j) for all $i \neq j$

When multiple regressors are involved there is need for an additional assumption:

(6) No perfect multicollinearity: if there are multiple regressors, they must all be linearly independent of each other

When beta is estimated with a linear regression along the above specified assumptions, the resulting beta is time-invariant over the estimation period and Equation (3) changes to

$$R_{i,t} = a_t + \beta_i(R_{M,t}) + e_{i,t} \tag{5}$$

where β_i and the variance of $e_{i,t}$ are static through time (Garbade & Rentzler, 1981). This becomes apparent when visualizing the OLS regression as a scatterplot of the returns for the asset and the market portfolio. In this context, beta is the constant (time-invariant) slope of the line that best fits the scatterplot.

Notwithstanding the wide-spread practical application of the market CAPM estimated via classical linear regression, it has been repeatedly shown that betas and the variance of the error term are time-varying (Bos & Newbold, 1984; Brooks et al., 1998; Collins et al., 1987; Fabozzi & Francis, 1978; Sunder, 1980). The results of the work of Fabozzi and Francis (1978) suggest that the beta calculated from an OLS regression based on the market model are in fact time-varying and describe beta as a factor best modelled by a random coefficient model. They also indicate that the problems arising from the constant beta estimation will be exacerbated the longer the estimation time frame is. Sunder (1980) points out clear evidence against the null hypothesis of non-stationarity in beta over the full sample size. Two alternatives next to the null hypothesis were tested. One in which market risk follows a random walk and one in which it follows a first-order autoregressive process.

He finds that both approaches reject the null hypothesis and that the level of non-stationarity varies when comparing different subperiods of the sample. Bos and Newbold (1984) model systematic risk by allowing beta to be stochastic in a first-order autoregressive process. Their results indicate non-stationarity but could not confirm that beta is autocorrelated rather than following a random walk. To investigate further whether the stochastic nature of beta is purely random or exhibits autocorrelation over time, Collins et al. (1987) implement a model in which beta can behave both randomly and autoregressively. In line with the other papers, they find clear evidence to reject the hypothesis of stationarity. When turning to the nature of the stochastic variation of beta, they find stronger evidence for an autoregressive tendency in portfolio betas than for betas at the individual security level.

The ample evidence of beta instability has severe implications for the validity of the standard market model when beta is estimated as a constant parameter. The assumption that beta is time-invariant is commonly reflected in the fact that the CAPM beta is used to make predictions about the future value of an asset (Groenewold & Fraser, 1999). This assumption, as shown previously, is unrealistic and is reflected in the fact that betas for the static CAPM are usually calculated over relatively short time-frames of three to five years and that the CAPM performs better over short periods than long ones (Groenewold & Fraser, 1999). Nonetheless, the simple market beta is regularly used by investors to estimate an asset's sensitivity to the overall market, by CFOs when calculating the appropriate cost of capital and building valuation models as well as in performance measurement of asset managers (Brealey et al., 2017). This versatile use of beta highlights the impact an imprecisely calculated beta might have in practice.

Over the course of the past decades there have emerged several approaches to calculate a market beta that allows the regression parameter to change through time. Among the many methods to estimate a dynamic market beta, two approaches are featured most prominently in the majority of the research from the past years and will be presented in the following section.

2.1.2 Methods accounting for time-variance of beta

Autoregressive Conditional Heteroskedasticity Models

The first approach that will be considered for time-varying beta estimates are Autoregressive Conditional Heteroskedasticity (ARCH) models. Engle (1982) was the first to propose econometric techniques that account for time-varying volatility in form of the ARCH models. These models allow volatility in a time-series to change over time and that past observations of volatility can be used to optimally estimate future levels of volatility. This means, that an ARCH approach models the error variance at a point in time as the function of the past squared error values. Depending on the order of the ARCH model, a different amount of lagged squared error residuals can be included in the equation. Generalized, an ARCH model of order p, ARCH(p) takes the following form:

$$\sigma_t^2 = \alpha_0 + \alpha_1\epsilon_{t-1}^2 + \alpha_2\epsilon_{t-2}^2 + \cdots + \alpha_p\epsilon_{t-p}^2 \qquad (7)$$

The model assumes the error term ϵ_t to have zero-mean and variance σ_t^2 and α_0, α_1,…α_p are unknown coefficents. Bollerslev (1986) extended the ARCH to a generalized approach called GARCH in which the variance depends on its own lags in addition to the lags of the squared error terms. In a GARCH(p,q) variance is described by the following equation:

$$\sigma_t^2 = \alpha_0 + \alpha_1\epsilon_{t-1}^2 + \alpha_2\epsilon_{t-2}^2 + \cdots + \alpha_p\epsilon_{t-p}^2 + \Phi_1\sigma_{t-1}^2 + \cdots + \Phi_q\sigma_{t-q}^2 \qquad (8)$$

Analogous to the ARCH model, α_0, α_1,…α_p, ϕ_1 … ϕ_q unknown coefficients. It is recognized that the GARCH method is a better fit for modelling time-series that exhibits heteroskedasticity since it can capture changes in the volatility with fewer parameters than the ARCH due to the addition of the lag terms for σ_t^2. Therefore, based on various extensions of the GARCH-models, several studies have been conducted that demonstrate the time-varying nature of beta across industries and geographies (Asgharian & Hansson, 2000; Bollerslev et al., 1988; Brooks et al., 1998; Grout & Zalewska, 2006; Koutmos & Knif, 2002).

Kalman Filter

Alternatively to ARCH-based approaches, which are in fact volatility-based models that estimate market risk sensitivities indirectly by using the estimated conditional variance, researchers also used alternative methods like the Kalman filter to estimate beta directly. (Brooks et al., 1998; Cisse et al., 2019; Groenewold & Fraser, 1999; Mergner & Bulla, 2008). Originally developed for spacecraft engineering and astrophysical applications, the Kalman filter provides a linear estimation method for a linear Gaussian system that can be represented in a state space form (Punales, 2011). A state-space representation is a mathematical model of a system described by a set of state, input and output variables. The state variables vary over time depending on their previous state at a time *t* and the relevant input variables. The output variables in turn depend on the values of the state variables. The following explanations on the state space models are based on Harvey and Koopman (2009) and Yao and Gao (2004) unless otherwise specified. A general linear Gaussian state space model can be notated mathematically like this,

$$\boldsymbol{\alpha}_{t+1} = \boldsymbol{d}_t + \boldsymbol{T}_t * \boldsymbol{a}_t + \boldsymbol{H}_t * \boldsymbol{\eta}_t \tag{9}$$

$$\boldsymbol{\theta}_t = \boldsymbol{c}_t + \boldsymbol{Z}_t * \boldsymbol{a}_t \tag{10}$$

$$\boldsymbol{y}_t = \boldsymbol{\theta}_t + \boldsymbol{G}_t * \boldsymbol{\varepsilon}_t \tag{11}$$

Where $t = 1,..,n$ and

$$\boldsymbol{a}_1 \sim N(\boldsymbol{a}, \boldsymbol{P}) \tag{12}$$

$$\boldsymbol{\eta}_t \sim iid\ N(0, \boldsymbol{I}_r) \tag{13}$$

$$\boldsymbol{\varepsilon}_t \sim iid\ N(0, \boldsymbol{I}_N) \tag{14}$$

While a further assumption is

$$E\left[\boldsymbol{\varepsilon}_t \boldsymbol{\eta'}_t\right] = \mathbf{0} \tag{15}$$

$\boldsymbol{a}_t$ is the state vector and contains unobserved stochastic processes and effects that are unknown. **P** is the variance matrix of the initial state vector. Equation (9) is the transition equation and models the state vector through time. Equation (11) is called the measurement equation and models the observation vector $\boldsymbol{y}_t$ by means of the state vector $\boldsymbol{a}_1$ through a signal vector $\boldsymbol{\theta}_t$ as well as $\boldsymbol{\varepsilon}_t$ which is a vector for disturbances in the measurement. This model assumes that the innovations in both the measurement and the transition equation are independent. $\boldsymbol{G}_t$, $\boldsymbol{H}_t$, $\boldsymbol{T}_t$ and $\boldsymbol{Z}_t$ are system matrices. $\boldsymbol{c}_t$ and $\boldsymbol{d}_t$ are matrices that have for fixed components to account for known effects or patterns. If those are not present, then they are just equal to zero.

In finance and economics, many time-series models can be represented in state-space form e.g. time-varying regression models (Mergner & Bulla, 2008). The changing regression parameters within state space models can evolve according to different stochastic properties. The most prominently discussed categories are the following (Fabozzi & Francis, 1978; Punales, 2011; Rosenberg, 1973; Yao & Gao, 2004):

$$\beta_t = \bar{\beta} + \xi_t \quad \text{(Random coefficient model)}$$
$$\beta_t = \beta_{t-1} + \xi_t \quad \text{(Random walk model)}$$
$$\beta_t = \phi\left(\beta_{t-1} - \bar{\beta}\right) + \bar{\beta} + \epsilon_t \quad \text{(Mean reverting AR(1) model)}$$

In our research we model the general linear regression CAPM model with time-varying intercept and slope according to a random walk:

$$R_t = \alpha_t + \beta_t R_{M,t} + u_t, u_t \sim GW\ N(0, \sigma_u^2) \tag{16}$$
$$\alpha_t = \alpha_{t-1} + \xi_t, \xi_t \sim GW\ N(0, \sigma_\xi^2) \tag{17}$$
$$\beta_t = \beta_{t-1} + \varsigma_t, \varsigma_t \sim GW\ N(0, \sigma_\varsigma^2) \tag{18}$$

The state-space form in the context of the time-varying market model can be expressed as:

$$R_t = \boldsymbol{X_t} \boldsymbol{B_t} + u_t\ ,\ u \sim N(0, \sigma_u^2) \tag{19}$$
$$\boldsymbol{B_t} = \boldsymbol{\Phi}\, \boldsymbol{B_{t-1}} + \boldsymbol{w_t}\ ,\ \boldsymbol{w_t} \sim N(\boldsymbol{0}, \boldsymbol{\Omega}) \tag{20}$$

where $R_t$is the asset return; $\boldsymbol{X}_t = (1, R_{M,t})'$, $r_{M,t}$ is the market return at time *t* and $\boldsymbol{B_t} = (\alpha_t, \beta_t)$', and both u_t and $\boldsymbol{w_t}$ are Gaussian and mutually independent. By setting the values for $\boldsymbol{\Phi}$ one can derive the specification of the way the parameters will be modelled like a random coefficient, mean reverting process or random walk.

To compute the conditional state space variables the Kalman Filter approach is used. Practically, the Kalman Filter is an iterative mathematical process to quickly estimate the true value of a state variable when measured values contain unpredicted and random error or uncertainty. The Kalman Filter combines all available measurement data, plus prior knowledge about the system and measuring devices to produce an estimation of the desired variables. In other words, the Kalman Filter can be thought of as updating process in which one takes a preliminary guess about the state of variable and then correcting that guess. The degree of correction is determined by how well the guess did in forecasting the following observation. The Kalman Filter consists of prediction and updating equations:

Prediction

When we think of period *t*-1 as the initial period, the estimate of the state vector and its covariance at time *t*, based on the information available at time *t*-1, can be describe as:

$$\boldsymbol{B}_{\boldsymbol{t|t-1}} = \boldsymbol{\Phi}\, \boldsymbol{B}_{\boldsymbol{t-1|t-1}} \tag{21}$$

$$\boldsymbol{\Sigma}_{\boldsymbol{t|t-1}} = \boldsymbol{\Phi}\, \boldsymbol{\Sigma}_{\boldsymbol{t-1|t-1}}\, \boldsymbol{\Phi}' + \boldsymbol{\Omega} \tag{22}$$

As soon as the new observations and corresponding $\boldsymbol{X}_t$ are available, the new prediction error and its variance can be derived from:

$$u_{t|t-1} = R_t - R_{t|t-1} \tag{23}$$

$$f_{t|t-1} = \boldsymbol{X}_{\boldsymbol{t}}\, \boldsymbol{\Sigma}_{\boldsymbol{t|t-1}}\, \boldsymbol{X}'_{\boldsymbol{t}} + \sigma^2 \tag{24}$$

Updating

The new prediction contains information regarding $\boldsymbol{B}_{\boldsymbol{t}}$ that was not contained in $\boldsymbol{B}_{\boldsymbol{t|t-1}}$. Therefore, after the observation of r_t we can make a more precise inference about $\boldsymbol{B}_{\boldsymbol{t}}$. The inference of $\boldsymbol{B}_{\boldsymbol{t}}$ based on the information available up to time *t* can be described like this:

$$B_{t|t} = B_{t|t-1} + K_t u_{t|t-1} \tag{25}$$

K_t is the weight assigned to new information about $\boldsymbol{B_t}$ contained in the prediction error. Similarly, the new covariance of the parameters is obtained from:

$$\boldsymbol{\Sigma_{t|t}} = \boldsymbol{\Sigma_{t|t-1}} - \boldsymbol{K_t X_t \Sigma_{t|t-1}} \, , \tag{26}$$

where each $\boldsymbol{K_t} = \boldsymbol{X'_t \Sigma_{t|t-1}} f_{t|t-1}^{-1}$ is the Kalman Gain. The Kalman Gain determines the weight that is assigned to information about $\boldsymbol{B_t}$ in the prediction error.

2.1.3 Empirical Body of Work for ARCH and Kalman Filter

There is a vast body of literature that deals with the time-varying nature of the CAPM beta. The following section showcases several studies that applied the above specified beta calculation approaches in different research contexts. Engle et al. (1988) apply a variation of the GARCH approach to estimate the conditional covariance of their assets' returns to that of the market portfolio. They found that the conditional covariances are time-varying and are a determinant of time-varying systematic risk. Koutmos and Knif (2002) propose a vector GARCH model to calculate time-varying betas. Their model allows an asymmetrical response to past innovations in the conditional variance of their investigated portfolios returns and the conditional covariance of the portfolio and market returns. Their results show the betas to be significantly time-varying but give mixed indications regrading an asymmetric development, with half of the betas being high during market declines and vice versa. More recently, French (2016) utilizes different GARCH models to estimate the market return variance in the denominator of the beta calculation. They assume the covariance between the portfolio and market returns to be constant. They find that out of sample forecasts are best described by time-varying GARCH betas, but surprisingly in-sample forecasts are best explained by the ex-post constant beta.

Groenewold and Fraser (1999) investigated Kalman betas for different sectors in Australia from 1979 to 1994 assuming they vary about a certain mean and how they can be explained by time-trends. Their results suggest that beta does not vary around a fixed mean but follows a random walk process. Furthermore, they find that the properties of those Kalman betas differ from sectors and that they can be grouped into two groups. One with non-stationary betas that can significantly be regressed against a time trend and one group that has stationary betas and only insignificant regressors. The banking sector belongs to the former group, indicating that banking betas in the sample used by the authors are in fact time varying. Yao and Gao (2004) use the Kalman filter technique but with four different underlying stochastic state-space models: ARMA(1,1), mean-reverting model, random coefficient and random walk. They formed nineteen industrial and found that the portfolio widely vary in the way their beta develops through. There was no consistent conclusion that beta follows only one of the specified state-space categories. Adrian and Franzoni (2009) implement a CAPM with conditional time-varying betas. Their main goal is to investigate long-term changes in the factor loadings when testing the model against return series. To calculate the changing factor loadings they implement a mean-reverting Kalman filter approach. Their findings are that Kalman betas significantly reduce pricing errors.

Apart from isolated studies of the individual estimation techniques, there are multiple papers that compare the forecasting performance of different beta estimates, including ARCH-based approaches and Kalman techniques on a variety of return series. Brooks et al. (1998) used betas estimated by the Kalman filter and a multivariate GARCH approach to explain returns of seventeen sector portfolios in Australia between 1974 and 1996. They found that among the beta-modelling technique used, the Kalman filter approach was the best at explaining the portfolio returns when beta is shown to be non-stationary. Lie et al. (2000) expand on the work of Brooks et al. (1998) by estimating equity beta risk for fifteen Australian companies in the financial sector with GARCH and Kalman filter approaches. They show that there is consistent variability in day-to-day betas and using daily beta estimates they show that the Kalman method is superior in explaining the returns in the Australian financial sector. In a European context, Mergner and Bulla (2008) test a wide array of beta estimation methods. Two of those estimation techniques are Kalman filter models assuming a random walk and mean-reverting behavior respectively, while another one uses a GARCH approach. Among all the beta-modelling techniques used, the Kalman filter with a random walk assumption produced the lowest mean absolute error (MAE) and lowest mean squared error for in-sample return forecasts for the European industry portfolios. Most recently, Cisse et al.(2019) employ both, betas estimated by means of Kalman filter, assuming a random walk, and Markov switching to explain returns of the Regional Stock Exchange in West Africa. For both the one-factor market model as well as a two-factor model with a small-minus-big factor the Kalman beta was a better fit for explaining returns, indicating that beta is not only non-stationary best modelled by a random walk.

2.1.4 Risk Measure Calculation

As was pointed out previously, our central research theme focuses on the firm-specific determinants of risk in the banking sector against the regulatory backdrop of Basel III. The two risk measures that are central to our research question are systematic and idiosyncratic risk of banks. The previous section outlined that systematic risk, as measured by beta, and idiosyncratic risk, as measured by the variance of the error term, are rooted in the CAPM equations. This section will outline the how these measures will be calculated after having reviewed the CAPMs underlying assumptions and pitfalls when it comes to the OLS estimation method.

Systematic Risk

Systematic risk is defined as a stock's beta and therefore beta will be the underlying variable when investigating which factors are influencing systematic risk. It was established that it is common practice to estimate beta via a linear regression model which assumes that beta is static over the estimated time frame. However, it has been repeatedly shown in a sizeable body of literature that this assumption is inaccurate (Bos & Newbold, 1984; Collins et al., 1987; Groenewold & Fraser, 1999; Sunder, 1980). To account for the time-variation of beta we will employ two alternative calculation methods. The first estimation method is a rolling regression technique. Similar to an OLS regression, the analysis seeks to model the relationship between the market returns and assets returns. The rationale of a rolling regression is to estimate the parameter of interest across different subsample periods within the observation time frame (Zanin & Marra, 2012). The sub-periods need to have identical temporal dimensions, which are called window sizes. The selected window size determines the number of observations in each rolling regression. If the beta was stable than, the coefficients should be similar to one another. However, when the estimated parameters are different over the complete observation periods it indicates that the parameter is in fact time varying. The resulting equation for the rolling regression is the same as Equation (4). But instead of regressing the returns over the complete observation period of six years, we use only a window size of two years rolling the regression over the individual observation dates, therefore creating a time-series of betas that fluctuates over the complete observation period.

Window size choice is one of the main drawbacks of rolling regression because it can heavily affect the behavior of the estimates over time. We use a window of two years due to the fact that our observation period is comparatively short. This will be discussed in further detail in *section 4.5.1.* It should be pointed out that while a rolling regression is typically employed to produce time-varying coefficients, the estimates within the chosen samples are constant. Strictly speaking, this means that in principle such an approach cannot produce reliable time-varying parameter estimates.

In order to add robustness to our research we will utilize a second beta estimation method that allows for truly dynamic modelling of time-varying betas. As mentioned in the previous paragraph, the rolling window regression produces a varying time-series of betas across the sampling period, but at its core it is still subject to the static parameter assumption of the OLS regression. *Section 2.1.2* presented the Kalman Filter and ARCH-models, the two most prominently featured beta calculation methods that account for time-variance of the parameters. After reviewing the empirical performance of both models which suggested superior estimation accuracy for a Kalman Filter approach, we decided to adopt this approach for a truly dynamic calculation of time-varying systematic risk. The calculation of the Kalman Filter beta will adhere to the equations in *Section 2.1.2*. The state-space representation of the time varying market model looks like this:

$$r_t = \boldsymbol{X_t}\,\boldsymbol{B_t} + u_t\,,\ u_t \sim N(0, \sigma_u^2) \tag{27}$$

$$\boldsymbol{B_t} = \boldsymbol{\Phi}\,\boldsymbol{B_{t-1}} + \boldsymbol{w_t}\,,\ \boldsymbol{w_t} \sim N(\boldsymbol{0}, \boldsymbol{\Omega}) \tag{28}$$

By setting the transition matrix **Φ** equal to the identity matrix **I** we model the parameters along a random walk specification. The identity is a square matrix whose diagonals are all of value 1 while other entries are of value 0 (Stock & Watson, 2019). The exact specification looks as follows:

$$\begin{pmatrix}\alpha_t\\ \beta_t\end{pmatrix} = \begin{pmatrix}1 & 0\\ 0 & 1\end{pmatrix} * \begin{pmatrix}\alpha_{t-1}\\ \beta_{t-1}\end{pmatrix} + \begin{pmatrix}w_{1t}\\ w_{2t}\end{pmatrix},\ \begin{pmatrix}w_{1t}\\ w_{2t}\end{pmatrix} \sim N\left(\begin{pmatrix}0\\ 0\end{pmatrix}; \begin{pmatrix}\sigma_a^2 & 0\\ 0 & \sigma_b^2\end{pmatrix}\right) \tag{29}$$

Each $(w_{1t}; w_{2t})$ is assumed to be normally distributed wit zero mean and a constant covariance matrix $\mathbf{\Omega}$. Moreover, the noise vector is also assumed to be serially uncorrelated. This leads to $\mathbf{\Omega}$ just having σ_a^2 and σ_b^2 as diagonal elements. To estimate beta with the above specified models via the Kalman Filter, it is therefore necessary to specify different initial values. First, we need to set initial values for the state variables α_t and β_t, which in the context of the random walk specification is done via OLS regression. The other parameters σ_a^2 and σ_b^2 are estimated via a log likelihood function. From there out the Kalman Filter algorithm runs the iterations of predicting and updating the equations over the observation period.

Unsystematic Risk

Like the measure of systematic risk, we derive our measure of unsystematic risk from the regression equation (3) in the CAPM context:

$$R_{i,t} = a_t + \beta_{i,t}(R_{M,t}) + e_{i,t}$$

When modelling observed returns with Equation (30), idiosyncratic risk is defined as the portion of the return that is not explained by movements in the market and is measured by the variance of the residual term $e_{i,t}$ (Bodie et al., 2014). We will estimate the variance of residuals (σ_e^2) for each bank returns series on basis of a two-year rolling window similar to the rolling regression estimation underlying the beta calculation. Hence, like for the systematic risk, we will produce sets of idiosyncratic risk measures. One time-series of (σ_e^2) will be based upon the residuals produced by the rolling window beta and the other based upon the Kalman beta. While the two produced time-series are still technically static, for the (σ_e^2) time-series with the underlying Kalman beta the time-variance is implied by the fact that the corresponding beta was estimated through a dynamic process. We desisted from calculating the (σ_e^2) directly with a dynamic approach like GARCH models, since it would have gone beyond the scope of our thesis. We want to mention that there would be the possibility to proxy idiosyncratic risk with other measures as well. Especially, in the banking sector and in a risk management context one could proxy the idiosyncratic risk of an institution with its Value-at-Risk (VaR) figure. VaR calculates the highest potential loss a bank could incur over a specified period of time and within a certain degree of confidence. Alternatively, one could look at the Expected Shortfall (ES) measure. This value indicates the average loss a bank would occur beyond that predicted by the VaR. Therefore, one has to first calculate the VaR and then based on the confidence interval and time frame used, can estimate ES. The decision to use the variance of the error term from the regression was routed in the fact that we wanted both risk measures to be rooted in the CAPM in order to have a coherent methodology underlying our analysis.

When time-varying coefficients are used to price assets or calculate expected returns, the CAPM model becomes a “conditional CAPM” as opposed to an unconditional model. The underlying rationale of conditional models generalizing the CAPM to multiple periods making them more in line with reality (Bodie et al., 2014). Several approaches are used in conditional models: those with several factors (Jagannathan and Wang, 1996; Lettau and Ludvigson, 2001), those that models covariances varying over time (Harvey et al., 1992; Bollerslev et al., 1988), and those that estimate a time varying market beta directly. In the context of our work, we assume a conditional CAPM by modelling the time variance of systematic risk directly through rolling regression and Kalman Filter. The time-variance in beta might be caused by a set of conditioning factors like macroeconomic influences or firm-specific variables (Bodie et al., 2014). While we are modelling only beta directly as time varying, idiosyncratic risk will be indirectly affected by these dynamics as well, since the variance of the error term will not remain constant with changing beta estimates. Understanding if there are conditioning factors of systematic and idiosyncratic risk is highly relevant to our work since we want to investigate whether regulatory measures introduced through the Basel regulation are actually determinants of systematic and idiosyncratic risk levels in banks.

2.2 Determinants of Risk

The core of our work concerns the determinants of both systematic and idiosyncratic risk in the banking sector. Before diving into in the specific dynamics of risk within the banking industry we deem it relevant to cast a wider net on the empirical research that has been conducted on the topic of risk determinants across several research settings and industries. This provides us with the opportunity to gain a more comprehensive understanding of the nature of risk and if the banking sector has similar or different risk determinants from those in the real economy.

2.2.1 Determinants of Idiosyncratic Risk

The literature on factors influencing idiosyncratic risk measures in companies outside the banking sector is scarce. However, Rosenberg and McKibben (1973) are part of an early group of researchers investigating the effects of several microeconomic variables on company risk. While all of these studies are focused on systematic risk, the authors also included the square of the residuals from the beta regressions as a measure of unsystematic risk. Their findings suggest a positive relationship between idiosyncratic risk and the volatility of earnings growth, magnitude of dividend cuts, and both financial and operating leverage. More recently, Spiegel and Wang (2005) established a connection of the liquidity of firms' stock and idiosyncratic risk as measured by the variance of the regression residuals. It essential to point out that they investigate the relative simplicity with which a stock can be bought in sold and do not refer to financial liquidity of the firms. They find that with increased liquidity of a firm's shares, there is a corresponding decrease in idiosyncratic risk. In a framework centering around macro-economic factors, Bartram et al. (2011) examine the impact of national determinants on idiosyncratic risk defined as the volatility of the regression residual from the CAPM equation. Their results indicate that idiosyncratic risk is lower for companies in countries with a high degree of political stability and strong law enforcement as well as corporate disclosure quality. Conversely, shareholder protection and equity market development go along with an increase in unsystematic risk.

2.2.2 Determinants of Systematic Risk

The research that was dedicated to systematic risk and its macro- and microeconomic determinants is significantly more ample than for idiosyncratic risk. Hence, in order to not lose track of the relevant studies, this section will split the research efforts related to macro- and microeconomic variables.

Macroeconomic Factors

Robichek and Cohn (1973) examine the relationship of beta and inflation, measured as the change in the Consumer Price Index (CPI), and the real economic growth which as proxied by the rate change in monthly personal income. The rationale behind the inclusion of these variables was the assumption that they best model the "national economy" and are at the core of most monetary and fiscal policy. Their findings suggest that there is only a small set of companies in their sample whose beta is a function of these two variables. Abell and Krueger (1989) investigate how a set of various macroeconomic variables might be able to influence systematic risk of different portfolios when it is allowed to vary in time in the context of the single index market model. Their results outline that the portfolio betas are indeed sensitive to a number of macroeconomic variables. Interest rates, budget deficits, trade deficits as well as oil prices were found to have significant explanatory power over changes in beta. In a second step, they showed that when predicting future betas, the variable beta model that accounts for significant economic variables, has superior forecasting power than just the one based on simple historical return series. A more recent paper by Yayvak et al. (2015) examines time-varying market betas in industry portfolios composed from stocks that are traded at the Istanbul stock exchange. They apply a conditional CAPM model called the threshold CAPM where beta is defined as a function of an underlying variable. In their research those underlying "threshold" variables are macroeconomic factors that enable beta to change between different regimes as soon as those variables hit a certain threshold value. The underlying threshold variables are defined as the interest rate, currency basket, real effective currency index and market volatility. The authors find significant time-variation of betas connected to changes in the monthly rate of the currency basket. In this context they point out that the impact of the threshold variables differs across industries. Some industry portfolios exhibit a higher beta when currency basket levels rise, while industries whose profitability increases with an appreciation of the currency basket, experience reduced market risk levels.

In addition to a broader cross-industry market analysis, there are also studies that take a deeper dive into how specific industry betas are affected by macroeconomic development. Focusing on the renewable energies sector, Sadorsky (2012) applies the same variable beta model as Abell and Krueger (1989) to examine beta determinants in the renewable energies industry. From the macroeconomic factors applied, they found that oil price returns have a positive relationship with systematic risk as measured by beta. Drobetz et al. (2016) explore, among others, the effects of macroeconomic variables on systematic risk in the shipping sector, based on a Kalman beta estimate. Their underlying macro factors are the USD exchange rate volatility, inflation, credit spread, freight rate volatility and industrial production growth. Their results suggest that macro-factors with a strong industry relation like freight rate volatility and credit spread (as measured by the spread between BAA- and AAA-rated corporate bonds) have a significant impact on beta levels in the shipping industry.

Microeconomic Factors

Even more extensively than the macroeconomic determinants, researchers investigate the impact of firm-specific variables on the level of systematic in companies and industries. Beaver et al. (1970) lay the groundwork for investigating the effect of firm-specific accounting measures on systematic risk. Their research examines the impact of dividend payout, growth, leverage, liquidity, asset size, variability of earnings and covariance of earnings as the most important determinants of systematic risk in the context of accounting measures. Their approach suggests that the above-mentioned accounting measures are surrogates for both idiosyncratic and systematic risk and should therefore in part explain the variation in levels of beta. Subsequent to Beaver's et al. (1970) paper there were several other empirical investigation the impact of financial accounting variables on company beta (Ben-Zion & Shalit, 1982; Bowman, 1979; Breen & Lerner, 1973; Lev, 1794; Logue & Merville, 1972; Rosenberg & McKibben, 1973). More recent studies examining the relationship between firm-specific measures and systematic risk include Iqbal and Ali Shah (2012) who regress eight accounting variables against betas of companies listed on the Karachi stock exchange. Lee and Hooy (2012) apply a panel regression of different explanatory variables on a betas in the airline industry clustered by different geographies. Moreover, Drobetz et al. (2016) find strong evidence that both macro- and micro-economic factors have significant influence on the level of systematic risk in the shipping industry.

In order to gain a deeper understanding of the dynamics between firm-specific financials and systematic risk the following section will look at the individual financial variables that are most prominently featured in studies about beta determinants.

(1) Operating leverage

Brealey et al. (2017) define operating leverage as the relationship between fixed costs and variable costs in a project or in a company. Therefore, if the ratio of fixed costs to variable costs is high, the company or the project is said to have high operating leverage. They show that a company or project beta is proportional to the ratio of the present value of fixed costs to the present value of the cash flows from the company or project. This implies that companies with high operating leverage should exhibit a high beta. Lev (1974) established an empirical link between high operating leverage and high systematic risk levels by regressing the levels of operating leverage against industry betas for portfolios in three capital intensive industries (utilities, steel and oil). His findings clearly indicate a positive relationship between operating leverage and beta. Moreover, Mandelker and Rhee (1982) examine the joint impact of operating leverage as well as financial leverage – which will be reviewed separately in the next section – on the levels of portfolio betas. Their findings are congruent with the results outlined by Lev (1974) that operating leverage explain the variation to a large extent and that higher operating leverage implies a higher equity beta. In the specific shipping industry setting, Drobetz et al. (2016) examine operating leverage as a determinant of beta levels. They regress a multitude of macro- and micro-economic factors against a time-series of Kalman beta estimates for shipping portfolios. Among the firm-specific factors, operating leverage was found to have significant positive impact on beta levels.

(2) Financial leverage

As already pointed out above, Mandelker and Rhee (1982) executed an analysis of the joint impact of operating leverage and financial leverage and found both to be significant beta determinants. Modigliani's and Miller's second proposition states that a company's cost of capital moves proportionally to its leverage level. An increase in leverage results in a higher default probability and therefore add additional risk that investors want to be compensated for (Brealey et al., 2017). Empirically, the effect of financial leverage has been studied by several researchers. Hamada (1972) shows cross-sectionally that there is a positive relationship between systematic risk of companies' equity and leverage level. Based on Hamada's work, Dejong and Collins (1985) investigate the effect of leverage on the level of beta. They employ various variable parameter regression models with mean-reverting, random-walk, random coefficient and autoregressive specifications. In this context Dejong and Collins (1985) use the estimated variance in each of the specification frameworks as the dependent variable. Their findings suggest firms which are highly leveraged showcase higher beta level. More recently, Lee et al. (2015) research firm-specific factors in the online travel agency industry. They regress several accounting measures including leverage against an OLS beta. However, they found that leverage is not a significant explanatory variable with regards to systematic risk in the tourism industry. In the context of the abundant literature detailing the empirically significant impact of leverage, they rationalize this finding with the financial structure in the industry. Characterized as a highly liquid industry, the authors suggest that the liquidity abundance offsets the risky effects of increased debt.

(3) Liquidity

As mentioned in the last study in the previous paragraph, liquidity is hypothesized to be negatively correlated with the level of beta. Corporate liquidity metrics as measured by current or quick ratios may affect systematic risk levels through two channels. On the one hand, it is possible to argue that current or liquid assets provide less volatile stock returns than non-current assets. Beaver et al. (1970) describe cash as the most liquid asset to highlight that current assets may have an expected return of zero implying zero volatility, when inflation is disregarded. Thus, it can be expected that firms with larger proportions of liquid assets seem to have less volatile overall equity returns and arguably lower systematic risk levels. Moreover, firms with higher liquidity ratios may be more flexible in crisis periods and less sensitive to fluctuations in the economy, again implying a lower beta. In contrast there are also studies that point out that liquidity can have a positive impact on beta since with increasing liquidity there might be an increase in the agency costs of free cash flows and therefore might result in higher systematic risk (Jensen, 1986; W. S. Lee et al., 2015; Moyer & Chatfield, 1983). Logue & Merville (1972) regress several accounting measures on a time-series of portfolio betas of estimated via OLS regression. The four portfolios were constructed with 287 industrial companies from the automotive, building, electronics and machinery sectors. They hypothesized liquidity to have an inverse (negative) relationship with beta, but ultimately found liquidity to not be a significant explanatory variable albeit having a negative coefficient. Specifically, studies within the hospitality and tourism industry also show a clear and significant inverse correlation between systematic risk and liquidity factors indicating that these companies are able to meet their short-term obligations (C. H. Lee & Hooy, 2012; W. S. Lee et al., 2015).

(4) Profitability

Profitability reflects a company's ability to efficiently manage the company's assets in order to generate profits and control costs (Brealey et al., 2017). When it comes to profitability measures

– previous studies mostly employ return on assets or profit margin -, there are conflicting suggestions as to how they impact the systematic risk of a company. Logue and Merville (1972) find that when profitability measures are regressed against beta, they have negative signs and are statistically significant. Rosenberg and McKibben (1973) on the other hand find profitability to be non-significant when regressed against beta. Later studies also don't give conclusive evidence on the impact of profitability on beta. Gu & Kim (1998) for the casino industry and Lee and Jang (2007) for the aviation sector find a negative impact for profitability while Borde et al. (1994) establishes a positive relationship between profitability and systematic risk for insurance companies, arguing that more readily available cash can lead finance companies to take on more credit risk. Those contradicting findings might suggest profitability's impact on beta to be industry dependent.

(5) Firm size

The size of a company is also frequently considered a determinant of beta. Both amount of total assets and market capitalization are the financial proxies that are used in the majority of the literature. In this context, larger firms are assumed to be less risky. Ben-Zion and Shalit (1975) outline four arguments for this assumption which are that large firms' assets are more readily marketable and there is lower probability of bankruptcy. In their subsequent empirical analysis of 1000 U.S. industrial stocks they regress firm size and two other hypothesized determinants against different measures of risk one of which defined as beta from the OLS regression. Their results yield significant negative coefficients for the beta regression indicating that firm size moves inversely with the level of systematic risk. Breen and Lerner (1973) reach the same conclusion against the backdrop of a similar research design albeit their regression contains more additional independent variables.

To summarize the vast literature that examines the dynamics between clusters of firm-specific variables and systematic risk, shows that accounting metrics are important determinants of systematic risk but that there is some disparity between the findings.

2.3 Determinants of Risk in the Banking Industry

Now that we established the widespread empirical relevance of macro- and microeconomic factors for the level of systematic as well as idiosyncratic risk across different industries, the next section will examine how these factors are thought to impact risk specifically in the banking industry. We purposely detached the literature on risk determinants in the banking sector for the following reason: As can be seen in section 2.2, many of the factors which are believed to impact risk – particularly operating leverage, financial leverage and liquidity – are dependent on the business model of a company. While business models vary tremendously across and even within various industries, they share the commonality that revenue is ultimately generated through the employment of real assets. This commonality does not apply to the banking industry, which is clearly distinctive from other industries as revenue is generated through financial assets instead of real assets. Because the banking sector is at the core of our research approach, we will briefly present different business model profiles adopted by banks to better understand how risk is related to different types of banks and which determinants of risks have been identified in prior literature.

2.3.1 Banking Business Models

There are several classification schemes for banking business models and the majority of banks operate some sort of hybrid business models obtaining revenues from several sources. Banks can also change their business models over time, transitioning their focus from one activity to another. We will root our discussion in the framework provided from Roengpitya et al. (2017) based on the fact that it was developed at the BIS. From a sample of 178 internationally active banks across 34 jurisdictions, the authors identify four business model profile clusters in which banks have a different focus regarding their core activities and balance sheet structures. The first group of banks is classified as commercial retail-funded banks. A high share of loans on the balance sheet and heavy reliance on stable funding sources like deposits are characteristics of this business model profile. The second group is classified as commercial wholesale-funded banks, that have a similar asset profile like the retail-funded banks with a large loan book and a small trading book. The main difference pertains to the funding mix. The second group derives its funds mainly from wholesale debt as compared to deposits and is more active in the interbank market. The third group of banks are capital-markets oriented and hold most of their assets in the form of tradeable assets.

Accordingly, they have a substantial trading book and a relatively small loan book. Funds are mainly raised from the wholesale and interbank market. Finally, the authors group banks with a universal model together, since they appear to balance all the previous approaches to some extent. While having moderately sized loan book they also engage to a greater extent in trading activities and derive funding from both deposits and wholesale sources. Generally, it can be said that banks in the first two groups are characterized by high net interest income and high gross loans to total assets. Those profiles tend to thrive when interest rates are rising and there is an increase in loan growth. However, especially credit shocks and liquidity shortages can have extremely negative impact on these types of banks. Trading banks on the other hand are less dependent on stable loan funding but more exposed to market risk and sudden depreciation of assets in their trading book.

Our sample, as introduced later, mostly consists of universal and trading banks. This is due to the fact that we are only analyzing the largest internationally active banks and according to the study of Roengpitya et al. (2017) the majority of those are universal banks with some banks placing greater focus on trading and capital-market activities. According to the Gujrati (2016), it will be those banks that are most heavily affected by the Basel III regulation due to their diverse business activities and large trading books that will be significantly impacted by the higher risk weights connected to these exposures. This makes sense, because those banks are most at risk to cause systemic shocks in the case of default. Underlying business models of banks are important in the context of risk since their underlying balance sheet characteristics are shown to have an influence on the levels of idiosyncratic and systematic risk. Nonetheless, it should be mentioned that the lines between categorizations can be blurred and that banks might transition from one business model to another during the time-period under consideration.

This section gave context of how banks operate their business models and what funding and balance sheet implications go along with the underlying profile. Moreover, it showcased how the different business models are vulnerable to certain sources of risk. The following section will now examine which risk determinants were identified in previous empirical settings in the context of the banking sector.

2.3.2 Determinants of Systematic Risk in the Banking Industry

Regarding macroeconomic determinants, there is little literature published that is dedicated to the examination of economy-wide factors influence on the systematic risk of banks. Although the effect of macroeconomic variables on systematic risk are scarcely mentioned in the literature, the firm-specific factors are studied in more detail. In reference specifically to the banking industry, a considerable amount of studies has examined systematic risk and its determinants. As previously mentioned, Rosenberg and Perry (1981) investigate the determinants of both unsystematic and systematic risk for U.S. BHCs. They regress beta estimates from a simple OLS model against those measures. Their results indicate that the most important predictors of bank beta are size, dividend yield, equity capitalization and the long-term liability to asset ratio, with equity capitalization and long-term liabilities having a negative impact on beta. In a similar study, Lee and Brewer (1985) underline that leverage increases bank betas, whereas the dividend payout decreases it. As pointed out before, Vander Vennet and De Jonghe (2005) analyze the determinants of both systematic and idiosyncratic risk for European banking institutions. Systematic risk is estimated by OLS regression using different factor models. They show that the proportion of loans to core deposits in total assets and capital levels are negatively correlated with bank systematic risk, while higher levels of diversification and loan loss provisions tend to increase systematic risk. For the Italian banking sector, Biase and D'Apolito (2012) provide insight into the firm-specific determinants of the systematic risks of banks. Regressing several accounting factors against betas estimated by OLS and time-varying models, they find a positive relationship of beta with bank size and volume of loans and a negative correlation of systematic risk with liquidity, profitability and loan loss provisions. Finally, Using a global perspective, Mohanty et al. (2018) compare risk levels for global banks over the 2008 financial crisis and the 2012 European sovereign debt crisis in the context of Basel III and Dodd-Frank regulation. The authors explore the impact of firm-specific metrics connected to this regulation on total risk, systematic and idiosyncratic risk. They also account for geographical location and systemic importance of the different banks in the regression equation by introducing dummy variables. Their results show that equity levels have a significant positive effect on systematic risk for globally important banks counterintuitively and is not a significant predictor of the beta of less important banks.

2.3.3 Determinants of Idiosyncratic Risk in the Banking Industry

Most of the literature published on determinants of idiosyncratic is relatively new with exception of Rosenberg and Perry (1981), reflecting the post-crisis realization that idiosyncratic risk is an important risk measure to study in the banking sector due to its systemic importance.

Macroeconomic

Most authors link the development of macroeconomic variables to measures of the idiosyncratic risk of banks (Altunbas et al., 2014; Bohachova, 2008). The former finds that low interest rates over a prolonged time span increase idiosyncratic banking risk. The author argues that a low interest rate environment may influence banks attitude towards risk due to its impact on cash flows and valuations. Moreover, banks might engage in a more aggressive yield seeking behavior. Bohachova (2008) investigates in detail the relationship of macroeconomic conditions and individual bank risk in both countries from the Organization for Economic Co-operation and Development (OECD) and non-OECD countries proxied by a capital ratio, implying that a higher capital ratio reduces idiosyncratic risk. She finds that banks in OECD countries have increased capital buffers in business cycle highs as measured by growth in gross domestic product (GDP), in order to hedge against downturns, while non-OECD banks tend to accumulate more risk during prosperous time putting them in distress when economic conditions change and asset quality deteriorates. Moreover, heightened inflation is connected to higher capital ratios, leading to the assumption that banks restrict lending during economic uncertainty caused by inflation.

Microeconomic

Rosenberg and Perry (1981), based on data on U.S. bank holding companies (BHC) between 1969 and 1977, build a large empirical model which relates both bank systematic and specific risk to a wide range of accounting variables. Their findings suggest that idiosyncratic bank risk is significantly determined by earnings variability and leverage. Vander Vennet and De Jonghe (2005) investigate a cluster of bank-specific accounting variables on both systematic and idiosyncratic risk. The findings for the former are presented in the next section. Idiosyncratic risk as measured as the volatility of the regression residuals is positively correlated with higher capital ratios, which is surprising since higher capital charges are assumed to make individual banks less risky. However, the authors point out that when they control for asset size the relationship gets reversed indicating that the positive correlation of capital and idiosyncratic risk mostly holds for small banks. This is underlined by the finding that total assets were a significant explanatory variable with negative relation to idiosyncratic risk implying that bigger banks are less risky. Moreover, the level of loan loss provisions is found to have a positive relationship with unsystematic risk since higher loan loss provisions might indicate deteriorating asset quality. Finally, it was outlined that banks which are highly diversified in their operations show lower levels of unsystematic risk. Haq and Heaney (2012) also find that both capital levels an size are significant and negatively related to idiosyncratic risk when it is measured as the residual variance from the market model. Furthermore, dividend payout ratio is also found to have a negative impact on unsystematic risk. On the opposite, off-balance sheet activities and charter value of banks tend to increase idiosyncratic risk. In accordance with the other literature, Bessler et al. (2015) emphasize a negative relationship between idiosyncratic risk and equity capital levels as well as profitability defined as return on assets. They are also congruent in their findings with previous research that higher loan loss provisions indicate increased idiosyncratic risk levels. The most recent study by Mohanty et al. (2018) on this topic is the only study that does not find capital levels to be an apt predictor of unsystematic risk in banks. They define unsystematic risk as the variance of the error term in the CAPM equation and find profitability as measured by return on assets, loan-loss provisions and non-interest income to be significant determinants.

The research conducted on the determinants of systematic and idiosyncratic risk in the banking sector indicates that bank-specific accounting metrics and seem to be related to the evolution of banking risk through time. A clear relationship between the variables is established, although the results are not congruent with regards to the direction in which risk is influenced. Those findings also carry integral relevance for our thesis' research question, which is dealing with the effects of regulation on systematic and idiosyncratic risk. It offers an interesting departure point for our research since we examine the effect of bank-specific accounting measures on systematic risk in the context of a regulatory framework. In order to better understand how Basel III relates to banking variables it is crucial to understand the frameworks structure and the regulators intention behind the imposed rules. Hence, the following section will outline the Basel III framework.

2.4 Basel Accords

The Basel Accords are a series of – as of now – three regulatory frameworks that build on up on each other. Provided by the BCBS, the Basel Accords contain guidelines regarding capital risk, market risk and operational risk with the ultimate goal of ensuring that banks are able to stay operational and liquid in times of unexpected shocks or crises. The Basel Committee on Banking Supervision was founded in 1974 and has since then been a place for cooperation between central banks and financial regulatory bodies from all over the world. As of now it counts 45 members from 28 jurisdictions. The committee was formed during a time in which the financial markets became increasingly globalized while regulation remained largely the domain of domestic institutions. With the goal of working towards sustained financial stability by means of improved supervisory quality, the Basel Committee on Banking Supervision has been helping national supervisory bodies to adapt to a more consolidated and comprehensive approach to banking regulation (Hull, 2018). As already mentioned, the regulatory frameworks implemented up to today are all related to one another. Thus, before examining Basel III and its connection to the firm-specific determinants of systematic risk, it is imperative to give a short introduction to the two frameworks that preceded Basel III.

Basel I

Basel I was proposed in 1988 and fully implemented by all of the committee members, which at that time in 1992 included the G10 nations. Ultimately, the framework was introduced in virtually all countries with internationally active banks. The first Basel accord focused on the capital adequacy of the bank. Capital adequacy risk refers to the risk that banks do not have enough high-quality capital in case of unexpected losses. In the context of Basel I, banks' capital adequacy was measured by the Cooke ratio, where the financial institutions' ratio of capital had to be at least 8% of its total risk weighted assets.

$$\frac{Total\ Capital}{Risk\ Weighted\ Assets} \geq\ 8\%$$

The denominator, risk-weighted assets, is a measure of a bank's total credit exposure where all of its on- and off-balance sheet items as well as potential over-the-counter (OTC) derivatives are assigned weights according to their level of risk. The numerator is subdivided into two tiers. Tier 1 capital is comprised of core capital (CT1), which is common stock and retained earnings, and additional tier 1 capital (AT1) which are capital instruments without fixed maturity like preferred shares and convertible securities. Tier 2 capital refers to supplementary capital such as loan capital, undisclosed reserves, subordinated debt like hybrid instruments and deposits. In addition to the required level of 8% *Capital Adequacy Ratio*, the share of tier 1 capital had to be at least 4% and half of this had to come from common equity. Basel I was subject to multiple amendments after its implementation. Once in 1991 where clarification was provided on the way in which general loan loss reserves and general provision should be included in the capital adequacy calculation. The amendment of 1995 addressed the effects of multilateral netting in institutions' credit exposures for derivative products and also altered the add-on matrix for the risk-weight calculation of off-balance sheet items. Finally, in 1996, an amendment was passed that addressed market risk arising from exposure to foreign exchange exposures, traded debt securities and equities, options and commodities. Before, Basel I only focused on the credit risk, but neglected all the assets and liabilities it had as a result of its trading operations. Now the capital adequacy calculation also accounted for the banks' exposures in its trading book, where its market exposures were also expressed in the form of risk-weighted assets (RWA) resulting in a new capital adequacy formula:

$$\frac{Total\ Capital}{(Credit\ RWA + Market\ RWA)} \geq 8\%$$

Basel II

The second Basel Accord was proposed in 2004 and supposed to be implemented by 2008 but the global financial crisis impeded the full adaption of the new framework. It came into existence as a means to fix some of the weaknesses in Basel I that had materialized since its implementation. The Basel II framework is based upon three pillars:

(1) *Capital Adequacy*

The capital adequacy pillar is comprised of three component that ought to account for a banks quantifiable risk exposure. The first part is the market risk component, which has not been changed from the way it should be calculated from the 1996 amendment. The second component relates to the operational risk facing banks like losses from failures of the banks procedures or losses incurred due to uncontrollable external events. The third component addresses the credit risk of the financial institution. In this domain, Basel II implemented the most significant changes as compared to Basel I. Within the Basel I framework, all types of credit exposures were allocated risk-weights that were classified along four levels. However, this approach was considered not granular enough. For bonds and loans, the new approach considered allocation weights according to both the counterparty type and the corresponding credit rating. Moreover, Basel II also accounts for default correlation within the banks' credit exposures. With those innovations to the calculation and the addition of the operational risk component the new *Capital Adequacy Ratio* still had to be at least 8% of the total RWA and half of that had to stem from tier 1 capital:

$$\frac{Total\ Capital}{(Credit\ RWA + Operational\ RWA + \ Market\ RWA)} \geq \ 8\%$$

The value of risk-weighted assets for the different components under Basel II can be calculated based on different methods that depend upon how sophisticated the individual institution is (BCBS, 2020a).

(2) Supervisory Review

The second pillar addresses the way supervisors are supposed to conduct the review process. It provides guidelines for supervisors regarding the way in which compel banks to adhere to the minimum capital requirements, monitor the internal strategies banks use to manage risk and urge them to intervene at an early stage in case exposures are mismanaged.

(3) Market Discipline

The third pillar of the Basel II framework relates to the disclosure of information by banks. The power of regulators to compel banks to disclose more information can vary from country to country but most banks accept directives from supervisory bodies since they know that regulators apply less leniency in other areas if the banks do not comply. Moreover, in order to calculate the components of the *Capital Adequacy Ratio* based on particular approaches, banks are required to disclose certain information. It is important to mention that regulatory disclosures differ from accounting disclosures and do not necessarily appear on the annual reports, but separately.

All in all, the goals of Basel II were to ensure that capital allocation was more risk-sensitive, enhancing disclosure practices to allow the market to monitor the capital adequacy of banks, and ensuring that credit, market and operational risk can be uniformly calculated based on quantifiable data. There are some voices criticizing Basel II and suggesting it facilitated the global financial crisis in 2008 due to the fact that banks had too much freedom when calculating the risk-weighted asset allocations thereby manipulating the required capital ratios. Therefore, in a complete overhaul of the previous frameworks, Basel III was introduced in 2010.

Basel III

After laying the groundwork for a sound understanding of the evolution of the Basel regulation, this following section will examine the details of Basel III. In connection with the previously reviewed literature we will develop hypotheses regarding the effect of certain regulatory levers within Basel III on the level of systematic risk in the banking sector. The main goals of Basel III are to increase the quality and quantity of regulatory capital, with a special focus on reinforcing the level of common equity. Moreover, the framework imposed tighter restrictions on what defines equity capital. Finally, the regulators developed requirements aimed at keeping appropriate liquidity levels. Those objectives were manifested in six parts of the final proposal:

(1) Capital Requirements and Definitions
(2) Capital Conservation Buffer
(3) Countercyclical Buffer
(4) Leverage Ratio
(5) Liquidity Risk
(6) Counterparty Credit Risk

The standards and requirements put forth in this framework are minimum levels that apply to all internationally active banks, with some BCBS members applying the framework to all banks in their jurisdictions (BCBS, 2020a). The initial version of the regulation was published in December

2010 with disclosure starting in 2013. Finally, they were supposed to be fully implemented by the end of 2019. However, some of its individual components were subject to changes and full implementation got delayed up until 2022. Appendix 1 shows the initially planned phase-in arrangements planned by the BCBS. According to the BCBS (2020a), all minimum capital requirements have been fully phased in by the end of 2019. This relates to levels of common equity capital (CET1), total capital as well as the capital conservation buffer. The countercyclical buffer can be applied via the discretion of national regulators during time of high credit growth, which means that there is no timeline attached. Furthermore, the standardized approach to account for counterparty credit risk as well as interest rate risk in the banking book have all been fully effective. Some of the instruments that do not constitute Tier 1 or Tier 2 capital will be fully phased out in 2021. However, the calculation of the underlying risk-weighted assets according to revised approaches will only be fully implemented until 2022. With regards to the liquidity risk, both the Liquidity Coverage Ratio and the Net Stable Funding Ratio (NSFR) haven been fully implemented by 2018, gradually building up to a 100% (BCBS, 2020a). The leverage ratio has been tested sine 2013 and after an initial trial period, it is in full effect since 2018, but will be innovated by 2022 with a new way of measuring a bank's total exposure.

Additionally, after the 2008 financial crisis, there was great concern among supervisory bodies that banks and financial institutions that were systemically integral to the global financial network would not keep their levels of quality capital high enough. The failure of large interconnected banks during the crisis sent shocks through the entire financial system, eventually hurting the entire economy (Hull, 2018). The above-mentioned series of reforms developed by the BCBS is at the core of improving the resilience of the banking system. These policy measures will have a significant impact on *systematically important banks* (G-SIBs), since their business models are more focused around capital-markets and trading activities, which are directly addressed by the renewed capital requirements and risk coverage thresholds. Nonetheless, the committee adopted additional policy measures for banks that are considered to be G-SIBs to address their possible negative externalities and spillover risks. Those negative externalities associated with G-SIBs are arising from their size, interconnectedness, complexity, lack of substitutability and global scope and the decision to act in ways that are beneficial to the individual institution but are systemically dangerous. Furthermore, morally hazardous behavior can arise from the perception of being a bank that is “too big to fail” and therefore foster excessive risk-taking. Finally, due to the international consequences of an impairment of a G-SIB, it is a danger affecting not only domestic authorities and therefore must be addressed in a global context. G-SIB are required to hold additional equity capital in excess of that was is required anyway by the Basel III framework.

The BCBS’ methodology to asses which banks are considered *globally systematically important banks* (G-SIBs) is based on a scoring mechanism that includes five overall measures.

(1) Cross-jurisdictional activity

This segment measures a bank’s global footprint. Two indicators are used to assess the extent to which a bank is active outside of its home country. This is measured by cross-jurisdictional claims and cross-jurisdictional liabilities on the balance sheet. The rationale behind this indicator is to see the cross-border impact of a bank’s failure and the intuition that the bigger the cross-jurisdictional exposure, the harder the coordination to resolve risk-spillover from distress.

(2) Size

The global economy will be proportionally more hurt by a bank’s failure when its activities form a larger share of the global banking activity. The activities of larger banks will be harder to replace or substitute in case of distress and therefore cause greater disruptions to the financial system. Moreover, it can lead to a decrease of confidence in the financial markets as a whole. The indicator to measure banks’ size are their total exposure as calculated for the *Leverage Ratio*, which will be discussed in detail in a later section.

(3) Interconnectedness

If one bank is failing, there is an increased probability that other banks may experience distress themselves due to a network of contractual obligations. Interconnectedness therefore increases the systemic effect of a bank’s potential distress. The metrics to measure the level of interconnectedness are intra-financial system assets, intra-financial system liabilities and securities outstanding.

(4) Substitutability and financial infrastructure

The systemic impact of a bank's distress or failure an is to be negatively related to its degree of substitutability as both a market participant and client service provider. Hence, it is expected to be positively related to the extent to which the bank provides financial institution infrastructure. For example, the more important a bank's role in a line of business, or for the provision of services in the underlying market infrastructure, the larger the disruption will likely be following its failure, in terms of both service gaps and reduced flow of market and infrastructure liquidity. At the same time, the cost to the failed bank's customers in having to seek the same service from another institution is likely to be higher for a failed bank with relatively greater market share in providing the service. The three indicators used to measure substitutability and financial infrastructure are assets under custody, payments activity and underwritten transactions in debt and equity markets.

(5) Complexity

If a bank's overall level of complexity is high with regard to its structure, operations and business model it is assumed that the bank's systemic impact is large since it is more complex to resolve the bank's activities. The notion of complexity is measured by the amount of OTC-derivatives, Level 3 assets and trading and available for sale securities.

If a bank has a score based on this framework that exceeds the cutoff level set by the BCBS they will be considered a G-SIB. Additionally, the higher the banks score over the cutoff-value, the higher their extra loss absorbency requirement will be, as measured by CET1 divided by RWA. There are five "buckets" ranging from 1% extra common equity up to 3.5% extra CET1 capital[1]. The methodological approach utilizing the indicators as underlying measurement draws from a large sample of banks as proxy or the whole sector and uses the data supplied to calculate the individual scores (BCBS, 2020a). Banks that are considered in the sample include the 75 largest global banks as measured by their overall exposure. Likewise, banks that made the G-SIB list in the previous year will also be automatically part of the overall sample again. Every year the BCBS conducts its assessment again and re-allocates banks to the G-SIB list and the individual buckets.

[1] https://www.fsb.org/wp-content/uploads/P221119-1.pdf

Now that we have established the timeline regarding the different regulatory mechanisms and outlined how different banks are categorized under the Basel III framework the following section will examine the six regulatory levers previously outlined and how they relate to firm-specific determinants of systematic and idiosyncratic risk. In the context of this thesis we will take a closer look at the Liquidity Risk and the Capital Requirements, including the *Leverage Ratio* and CET1 over RWA ratio. The Capital Conservation Buffer, Countercyclical Buffer and the Counterparty Credit Risk will be briefly introduced but are not part of the hypothesis formulation due to either relevance to our research approach or data availability, which will be further elaborated upon in a later section.

2.5 Hypotheses

2.5.1 Liquidity Risk

Liquidity relates to a bank's ability to meet obligations when they come due and to finance an increase in assets while not incurring significant losses (Hull, 2018). Basel III focuses primarily on the funding liquidity risk. This refers to the risk that current and future cash outflows as well as collateral needs might not be met without disrupting the bank's daily operations or its financial condition. There is also market liquidity risk, which relates to the risk that a position cannot be offset or unwounded at market price due to a lack of market depth or bad market conditions. The maturity transformation process (borrowing money on shorter time spans than they lend out) makes banks inherently vulnerable to funding liquidity risk (BCBS, 2010). Many banks did not have an adequate framework to take care of liquidity risk during economically prosperous periods before the crash. Subsequently, the majority of the most distressed banks ran into trouble when they realized that certain products and business lines were not aligned with the bank's overall acceptable risk tolerance (BCBS, 2010).

Net Stable Funding Ratio

Under Basel III liquidity risk is addressed with two measures. First there is the Net Stable Funding Ratio which demands a certain level of "stable" sources of funding in relation to the liquidity profiles of the bank's assets over one year. It also accounts for possible liquidity needs stemming from off-balance sheet positions. The following shows how the NSFR has to be calculated:

$$\frac{Amount\ of\ Stable\ Funding}{Required\ Amount\ of\ Stable\ Funding} > 100\%$$

The amount of stable funding is calculated by multiplying the different sources of funding employed by the bank like capital, retail deposits, term deposits etc. with an available funding factor. The same procedure is applied to the denominator where the items that require funding are multiplied by the required stable funding factor. Due to data availability issues our thesis will only examine the aptness of the Liquidity Coverage Ratio as a determinant for systematic risk.

Liquidity Coverage Ratio

Compared to the NSFR, the Liquidity Coverage Ratio focuses on a bank's liquidity over the short term. It is aimed at improving the bank's resilience in case possible disruptions in liquidity occur within a 30-day time span. By implementing this ratio, financial institutions are ought to be able to offset cash-outflows in short-term stress periods by having sufficient high-quality liquid assets. The equation for the *Liquidity Coverage Ratio* is defined by the BCBS as follows:

$$\frac{High - Quality\ Liquid\ Assets}{Net\ Cash\ Outflows\ over\ 30 - Day\ Period} > 100\%$$

In the calculation it assumed that the underlying 30-day period is characterized by high levels of stress on the institution. This involves a three-step downgrade of the bank's debt, loss on retail and wholesale deposits, haircuts on secured funding and drawdowns on credit lines. The high-quality liquid assets (HQLA) in the numerator are assets that can be quickly converted into cash in the open market without significant value loss. There are several characteristics underlying those assets. First there are the following fundamental characteristics that qualify assets to be included into the calculation:

(1) **Low risk**: assets that have lower risk tend to be more liquid in the open market.
(2) **Ease and certainty of valuation**: The liquidity of an asset may increase when markets agree on its valuation.

(3) **Low correlation with risky assets**: HQLA should not be highly correlated with risky assets that tend to be less liquid in times of distress.
(4) **Exchange-listed**: Increased transparency translates into increased liquidity.

Moreover, there are also market-based characteristics:

(1) **Active and deep market**: There should be an active sale or repo market for the asset at all times.
(2) **Low volatility**: Assets with stable prices are less likely to experience price declines.
(3) **Flight to quality**: Assets that have historically been relied upon in times of crisis.

In the end, qualifying assets are subdivided into two classes of assets that are included in the stock of HQLAs.

(i) **Level 1 Assets**: These assets can be included without limit into the HQLA calculation and are not subject to any haircuts. Instruments included are coins, banknotes, central bank reserves and marketable securities that represent claims or guarantees by sovereigns, central banks and other qualifying institutions if they carry 0% weight in the RWA framework.

(ii) **Level 2A Assets**: These assets can make up a maximum of 40% of the HQLA stock and a 15% haircut applies to their market value. Instruments included are marketable securities that represent claims or guarantees by sovereigns, central banks and other qualifying institutions if they carry 20% weight in the RWA framework. Moreover, they include corporate debt with a credit rating of at least AA-

(iii) **Level 2B Assets**: Level 2B Assets can make up of up to 15% of the HQLA stock but are subject to a 25% - 50% haircut. Instruments included are residential mortgage backed securities, corporate debt with a rating in between A+ and BBB- and common equity.

The net cash outflow over a 30-day period in the denominator is calculated according to following formula:

$$
\begin{aligned}
&Net\ Cash\ Outflows\ over\ next\ 30\ days \\
&\qquad = Total\ expected\ outflows \\
&\qquad - Min(Total\ expected\ inflows; 75\%\ of\ total\ expected\ outflows)
\end{aligned}
$$

Appendix 2 provides a summary of both the HQLA categories and components as well as the factors used in calculating the cash in- and outflows.

The *Liquidity Coverage Ratio* shall ensure that banks' have a sufficient amount of HQLA which can be converted easily into cash without incurring high losses, to meet obligations over a 30-day period that models a stressed environment akin to the market conditions during the financial crisis. The BCBS assumes that the span of 30 days provides enough time for sound corrective actions by managers and supervisors to when responding to a stressed situation. The framework also allows that in time of financial distress banks can use their stock of HQLA to meet short-term obligations thereby sliding below the 100% threshold. In an idiosyncratic context there is no literature that establishes any empirical relationship between liquidity and idiosyncratic risk. In the context of liquidity's impact on systematic risk the literature paints a clear picture. There is ample evidence where high liquidity levels are shown to be inversely related to risk in the banking, shipping and travel industry (Biase & D'Apolito, 2012; Drobetz et al., 2016; J. S. Lee & Jang, 2007; W. S. Lee et al., 2015). It is argued that liquid assets are indicative of less volatile stock returns. Thus, it can be expected that banks with larger proportions of liquid assets have generally less volatile stock returns resulting in lower levels of systematic risk. While there are also studies that do not show liquidity to have significant explanatory, there is no empirical evidence of a positive relationship between liquidity levels in a company and beta.

H_1: An increase in the Liquidity Coverage Ratio will have a negative effect on both the level systematic and idiosyncratic risk of internationally active banks

2.5.2 Capital Requirements

Capital Adequacy Ratio

During and after the 2008 financial crisis it became apparent the capital levels of many internationally active banks were inadequate (BCBS, 2020a). Furthermore, there was no standardized definition of what constitutes capital across jurisdictions and regulatory enforcement as well as disclosure requirements were non-comparable. Therefore, one of the main goals of the Basel III framework is to strengthen the capital buffers by increasing the level of required regulatory capital paired with unified and enforceable disclosure requirements (BCBS, 2020a). The framework defines the different capital categories as follows (BCBS, 2020a):

Tier 1 (going concern)	Common Equity Tier 1 (CET1)	Sum of common shares (equivalent for non-joint stock companies) and stock surplus, retained earnings, other comprehensive income, qualifying minority interest and regulatory adjustments	CET1 >4.5%
	Additional Tier 1 (AT1)	Sum of capital instruments meeting the criteria for AT1 and related surplus, additional qualifying minority interest and regulatory adjustments	CET1 + AT1 >6%
Tier 2 (gone concern)		Sum of capital instruments meeting the criteria for Tier 2 and related surplus, additional qualifying minority interest, qualifying loan loss provisions and regulatory adjustments	CET1 + AT1 + Tier 2 >8%

Hence the total available capital that is required is defined by these three categories. CET1 (also referred to as core capital) constitutes the highest-quality capital since it can absorb potential losses directly when they occur. It is comprised of share capital, retained earnings and qualifying minority interest as well as potential regulatory adjustments. AT1 capital also provides immediate loss absorption but does not qualify as common equity. An example would be debt instruments like perpetually contingent convertible instruments. Finally, Tier 2 capital includes hybrid capital instruments, subordinated debt, loan loss provisions and undisclosed funds that not appear on the financial statements. Tier 2 is only supplementary to Tier 1 since it is less reliable and harder to liquidate in times of need. CET1 and AT1 are referred to as "going-concern". When a bank is a "going-concern it has positive equity capital and losses can be absorbed instantly. Conversely, Tier

2 is labelled as “gone-concern”, which means that in case of a bank failure, Tier 2 capital will absorb the losses before depositors and creditors.

The capital requirements pertaining to each of these individual levels are minimum levels and banks are ought to operate well over those thresholds. CET1 must be at least 4.5% of RWA at all times and the sum of total Tier 1 capital has to be a minimum of 6% of RWA. The minimum total capital including Tier 2 must amount to at least 8% of total RWA. The minimum percentage levels of AT1 and Tier 2 are not defined but have to be in line with the required total sums of regulatory capital. Compared to past regulation from the Basel Committee the new capital requirement framework is significantly more demanding since both the percentages of required tiers have been raised, but also because the definitions of what constitutes capital have become more restricted. Furthermore, banks that are classified as G-SIBs will have to keep an additional surplus of CET1 capital according to their allocated bucket. Over the initial implementation period it can be seen that for both G-SIBs and non-G-SIBs the base level of core capital is rising. Especially G-SIBs experienced a substantial increase since the Basel III capital requirements have been started to be implemented.

In addition to those minimum capital requirements, banks must hold a Capital Conservation Buffer of an extra 2.5% of CET1 capital at all times. Moreover, at the discretion of national supervisory bodies, banks can be required to also add a Countercyclical Buffer of up to 2.5% CET1 capital in times of credit growth. The Countercyclical Buffer is meant to balance the banks’ capital ratio in times of high credit growth. Since both those measures are just additional CET1 capital on top of the minimum requirement they are captured in our measurement ratio of CET1 capital over total RWA and will not be part of a separate hypothesis. Throughout the thesis we will use the term “*Capital Adequacy Ratio*” in reference to the ratio of CET1 capital over RWA. The relevant formula for the *Capital Adequacy Ratio* takes the following form:

$$\frac{CET1}{(Credit\ RWA + Operational\ RWA + \ Market\ RWA)}$$

To calculate the relevant RWA banks may either use the standardized or internal-ratings-based approach, depending on their level of sophistication. The majority of banks in our sample will opt to use the internal-ratings-based approach since it can be used to yield more favorable risk weights.

The literature review introduced previous research which showed that (equity) capital levels in companies across industries and also in banks in particular have an inverse effect on the level of systematic risk. (Akhigbe & Whyte, 2001; Rosenberg & Perry, 1981; Vander Vennet & De Jonghe, 2005). Studies examining the effect of capital levels on idiosyncratic risk come to a similar conclusion (Bessler et al., 2015; Bohachova, 2008; Haq & Heaney, 2012; Vander Vennet & De Jonghe, 2005). Through higher capital levels the banks have increased loss absorbing capacity in case of deteriorating asset quality or increased credit risk. We want to highlight the findings of Bohachova (2008) and van der Vennet and De Johnghe (2005) in this context. The former linked higher capital ratio to banks that operate in developed markets and the latter show that the negative relationship between capital levels and idiosyncratic risk pertains mostly to large banks. This is extremely relevant to our research since our sample of banks is comprised of large banks from developed markets. Criticisms of the *Capital Adequacy Ratio* include that it might require banks to keep more funds than necessary leading to fewer business loans stifling economic growth. Similarly, unused funds can lead to agency problems (Jensen, 1986; Hull, 2018). It was also revealed the inconsistency in the definition of capital across jurisdictions and the lack of disclosure that would have enabled the market to fully assess and compare the quality of capital between institutions contributed to the crisis in 2008 which created significant information asymmetries (BCBS, 2020a). The Basel III framework severely increases capital requirements for high quality capital, especially for banks classified as G-SIBs, and forces banks to tougher disclosure regimes. Based on these dynamics we formulate the following hypotheses:

H_{2a}: An increase in the Capital Adequacy Ratio will have a negative effect on the level of both systematic and idiosyncratic risk of internationally active banks.

H_{2b}: A potential reduction in systematic and idiosyncratic risk will be higher for G-SIBs than for non-G-SIBs.

Leverage Ratio

One of the main origins and drivers of the 2008 financial crisis was steep build-up of on- and off-balance sheet leverage within the banking sector (BCBS, 2020a). Banks managed to increase their levered positions while keeping compliant with the risk-based capital requirements from the Basel II framework. During the crisis' peak, banks were forced to deleverage quickly putting increased downward pressure on asset prices which exacerbated the spiral of losses, inadequate capital reserves and scarce credit availability (BCBS, 2020a). To avoid this negative feedback loop, the BCBS introduced a simple, non-risk-based *Leverage Ratio* as a supplement to the risk-based *Capital Adequacy Ratio*s discussed previously. The goals of this measure are two-fold. It should limit the build-up of excessive leverage in the banking industry which in turn helps to prevent deleveraging dynamics that destabilize the financial system and eventually would hurt the overall economy and act as a backstop measure in connection to the risk-based *Capital Adequacy Ratio*.

In the Basel III framework, the *Leverage Ratio* is expressed as a percentage defined as the capital measure divided by the exposure measure:

$$\frac{Tier\ 1\ Capital}{Total\ Exposure} = Leverage\ Ratio$$

Simply put, the *Leverage Ratio* indicates the amount that is invested or lent out for each unit of capital reserves the bank holds. This means that a higher *Leverage Ratio* indicates a more conservative exposure. The initially proposed *Leverage Ratio* had to be at least 3% and was be phased-in over the beginning period of the Basel III regulation until 2018. It remains at the currently specified levels but can be subject to changes with regard to the way the exposure measure is calculated (BCBS, 2020a). In the above equation the capital measure is defined by the entire Tier 1 capital (CET1 + AT1) as outlined in the previous section. The exposure measure is comprised of the total of the banks' on-balance sheet exposures, derivatives exposures, securities financing transaction exposures, off-balance sheet items (Hull, 2018). The on-balance sheet exposures contain all assets on the balance sheet. Exposures that are created by derivatives are categorized in two categories. First, there is the risk arising from the underlying of the derivative contract. Secondly, the counterparty credit risk exposures have to be taken into account. Securities financing transaction exposures include transactions such as repurchase agreements and security borrowing/lending when the transaction does not include balance sheet assets. Finally, off-balance sheet items refer to loan commitments and substitutes and letters of credit.

Indeed, one of the main reasons for why regulators introduced the *Leverage Ratio* was the concern that banks had too much leeway in calculating the risk-weights for the other capital adequacy measures (Hull, 2018). By limiting the amount of leverage banks can obtain, the BCBS makes sure that banks with a higher share of assets carrying a low risk weight hold additional capital to absorb losses. It can therefore be argued that the *Leverage Ratio* may present a better metric for capping aggregate risk and protecting against rare and highly correlated losses in the financial sector which may not be fully covered by the risk-based approach (Grill et al., 2015). Financial leverage was found to be a significant determinant of idiosyncratic risk in the study conducted by Rosenberg and McKibben (1973). Moreover, there is evidence in the literature that the higher a firm is leveraged financially, the higher and less stable its beta is becoming (Hamada, 1972; Mandelker & Rhee, 1984; DeJong & Collins, 1985). However, there might also be cause for concern when it comes to the *Leverage Ratio* and that it might create perverse incentives for banks. Both Grill et al. (2015) and Hull (2018) also point out that the risk-insensitivity of the ratio that provides benefits on the one hand, might simultaneously cause problems. One of the two capital ratios is likely to be the critical ratio for a bank (i.e., the ratio it is closest to not complying with). If the *Capital Adequacy Ratio* is the critical one, then arguably the *Leverage Ratio* can be justified because it provides useful additional information to regulators. But if the *Leverage Ratio* is the critical one, a bank might be encouraged to hold risky assets because they have the same effect on the *Leverage Ratio* as safe assets but provide a higher expected return. This could be an unintended adverse consequence for regulators. Although it can be argued that the leverage ratio might create perverse incentives, based on the fact that the majority of literature provides evidence of an inverse relationship between lower leverage and beta as well as the theoretical notion that higher leverage makes individual banks more risky (Brealey et al., 2017) we formulate the following hypothesis:

H_3: An increase in the Leverage Ratio will have a negative effect on the level of both systematic and idiosyncratic risk over the observed time-period in the overall banking sector

2.6 Control Variables

In order to develop a better understanding of the true explanatory power of our primary variables of interest, which are the Basel-related metric, we will include two additional variables to our regression equation. Those two variables will control for the influence of profitability and the general global economic activity. Our primary Basel variables cover the relevant areas of equity level, leverage and liquidity. However, profitability and macroeconomic developments have been shown to be significant determinants of risk in the previous literature. Therefore, in order to avoid omitted variable bias we will add two control variables to our regression equation to proxy for profitability and macroeconomic dynamics.

Profitability

On the one hand we will add Return-on-Assets (ROA) as a proxy for the profitability of the firm. ROA is calculated by dividing the period's net income over the amount of total assets. In previous literature it has been established that profitability indicators have significant explanatory power with regard to risk measures in both banks and regular companies (Bessler et al., 2015; Biase & D'Apolito, 2012; Borde et al., 1994; Gu & Kim, 1998; Logue & Merville, 1972; Mohanty et al., 2018; Rosenberg & McKibben, 1973). For idiosyncratic risk, a clear negative relationship was established, while the nature of the impact of profitability on systematic risk only yielded inconclusive results. While being empirically relevant, profitability is also beyond the direct influence of regulators since it reflects the company's ability to effectively manage its assets and control costs (Brealey et al., 2017). In this context it has to be mentioned that alternatively Return-on-Equity (ROE) could have been a relevant profitability metric that has been used in prior work. We refrained from using Return-on-equity to avoid multicollinearity with the *Capital Adequacy Ratio* and *Leverage Ratio*, which by design, impose increased equity levels on banks, therefore directly impacting the ROE achieved by banks.

Economic activity

We have established that apart from micro-economic factors, macroeconomic variables have also been shown to influence risk levels. Therefore, we seek to include one macroeconomic variable into our regression to account for those dynamics. In this context it is important to keep in mind that it is necessary to use a macro-variable that is applicable to the global nature of the sample.

Hence, we want to include a proxy variable to measure the impact of the general global economic activity. Economic activity is represented as the quarterly growth in GDP. The GDP can be defined as the economic value that is created through services and the production of goods over a specified period (OECD, 2020). Economic activity is a relevant descriptor of risk as has been shown in previous research, although GDP was not always the underlying metric of economic activity (Bohachova, 2008; Drobetz et al., 2016; Robichek & Cohn, 1973). With regards to idiosyncratic risk, Bohachova (2008) suggests that banks in developed markets, which make up the majority of our sample, are less risky in times of GDP growth. Robichek (1973) and Drobetz et al. (2016) find that increases in measures of economic activity reduce systematic risk. GDP is usually measured on a country level, which is inapplicable for our research due to the global scope of our sample portfolios. Therefore, we are using an aggregate GDP of the G20 nations which is provided on a quarterly basis by the Organization for Economic Co-operation and Development (OECD). We could have also used the aggregate GDP of the OECD members states but decided for the G20 nations as they provide a better representation of our sample of underlying banks.

3. Methodology

Up until now, Chapter 1 has provided insight into the relevance and motivation underlying or research approach. Chapter 2 embedded said research approach within the relevant economic theory, build a bridge to the work of previous scholars that examined the determinants of risk in companies and formulated research hypotheses for the relationship between Basel III factors and our underlying risk measures. This following Chapter 3 will proceed by outlining the methodological underpinnings of our work. Section 3.1 addresses the more abstract yet important aspects of the philosophical ideas pertaining to our study. Building on this philosophical foundation, Section 3.2 describes the nature and structure of our research approach. Finally, Section 3.3 presents the empirical model at the core of our analysis reflecting how our philosophical and methodological ideas will manifest themselves in the practical analysis process.

3.1 Philosophy of Scientific Research

Even though finance and economics are by and large quantitative disciplines and results can be measured computationally, there are still often discussions to be had about the theories and assumptions underlying a scholar's results. To lend credibility to one's work it is essential to clearly outline the rationale behind decisions that were made over the course of the research process (Crotty, 1998). Saunders et al. (2016) define research as the development of knowledge in a certain field and point out that this knowledge development is subject to a research philosophy. We will base the outline of our research philosophy on Saunders et al. (2016) unless otherwise specified.

Research philosophy refers to the system of assumptions and beliefs underlying the research question and the subsequent knowledge development process. It is important to understand one's own research philosophy by questioning and reflecting upon own belief systems in the same way the belief systems of others are challenged. Before diving into the research philosophy most applicable to our work it is necessary to understand the various assumptions pertaining to different research philosophies. There are three integral types of assumptions being made in the context of every research philosophical approach. *Ontology* refers to questions about the nature of reality and why entities exist in the way do. *Epistemology* concerns assumptions about knowledge, how we know what we know and what we constitute as legitimate knowledge. *Axiology* relates to how the researcher's own values and ethics contribute to the process. Along each of the three categories of assumptions, runs a continuum of *objectivism*, focusing on observable and measurable facts along the lines of natural science, and *subjectivism*, that approaches research from the perspective of social science and focuses on opinions and narrative rather than directly observable facts. The different research philosophies plot along the objectivism-subjectivism continuum for each of the three assumption categories.

Saunders et al. (2016) also underline that in the context of business and economics there is not one "correct" research philosophy. For brevity's sake we will only outline the philosophical underpinnings of our own research approach, which is based on positivism and critical rationalism. For further elaboration on the alternative philosophies we refer to Saunders et al. (2016). Both positivism and critical rationalism run close to the *objectivistic* extreme of the *objectivism-subjectivism* continuum. Ontologically, our work is rooted in critical realism. It explains our experiences and observations in terms of underlying dynamics of reality shaping observable events. For our work this means that we are pursuing objectivity but are also recognizing possible biases that might arise in our work. Epistemologically, however, we define our philosophy more in line with critical rationalism as put forward by Popper (2003). Critical rationalism states that (empirical) theories and knowledge should be rationally criticized and subject to tests that might falsify them. Pertaining to our study, we want to put the theories of how risk determined by micro- and macroeconomic factors under scrutiny and evaluate the intended effects of regulation on banking risk. In the axiological sphere we are also based in critical rationalism where the beliefs, cultural experiences and upbringing of the researchers are detached from what is researched (Popper, 2003).

After reflecting on the research philosophies our work is based upon, the next step involves the decision of how we develop our theories. There exist three major concepts that underlie theory development, which are deduction, induction and abduction. As with the research philosophies we will only elaborate on the approach that is relevant to our work, which is deduction and refer to Saunders et al. (2016) for the further explanation of the remaining approaches. In the context of a deductive framework, theories and hypotheses are developed and consequently tested with a specific research design using a top-down approach. Deduction is the most prominent approach in natural scientific research. One essential characteristic of the deductive research approach is the establishment of causal relationships between concepts in variables like risk and firm-specific accounting metrics in the context of our work. Therefore, the deductive process follows a specific sequence of steps. First, a set of hypotheses is developed based on existing literature and is followed up by testing the hypotheses with a structured methodology and appropriate and measurable data at the core of the analysis. Then, depending on the results of the analysis, the theory or hypothesis are either rejected, reiterated or corroborated.

3.2 Research Methodology

The previous section introduced our fundamental research philosophy and theory development approach. This section addresses our choice of research methodology. According to Saunders et al. (2016), the first methodological choice concerns the question whether the research design will be of quantitative, qualitative or hybrid nature. We will conduct a quantitative study which is in line with our underlying philosophies of critical realism and rationalism as well as our deductive theory approach, since our focus lies on using data to test theory (Saunders et al., 2016). In a quantitative research design the relationship between variables, that can be numerically measured, is analyzed. In the context of our work, this relationship refers to the impact of the Basel III regulatory framework on systematic and idiosyncratic risk. Our quantitative research design can further be characterized as a multi-method quantitative study. The term “multi-method” can refer to the usage of multiple data collection techniques, multiple data analysis processes or both. While only utilizing a single data collection technique, we employ a multi-method quantitative study based on the several econometric techniques underlying our analyses. Those techniques specifically relate to the empirical model used to examine the link between risk and the Basel III metrics as well as the risk calculation methods, all of which is outlined in Chapter 2.

Before going into the actual data collection and analysis it is integral to reflect on the purpose of our research design, which is closely connected to the formulation of the research question and what it exactly is we seek to answer. Research efforts may be conducted on basis of either explanatory, descriptive, evaluative, exploratory or a combination of those (Saunders et al., 2016). The purpose of our own work might be classified as evaluative. At the core of evaluative studies is the question of how well something works. Saunders et al. (2016) point out that evaluative studies are often concerned with examining the effectiveness of policy or regulation, which is central to our thesis. It is the stated objective of the Basel regulation to decrease overall risk in the banking sector, which means that the theoretical relationship between the variables is already made. Therefore, we go beyond just an explanatory or descriptive purpose which would only seek to establish a relationship between the variables. We seek to evaluate the influence and subsequently provide a discussion on not only "how" but also "why" the relationship between the variables is the way that it is. There can be a myriad of research strategies employed in order to answer the research question. The research strategy can be characterized as the methodological bridge that connects research philosophy and the process of data collection (Denzin, 2009). The applied research strategy is to a high degree dependent upon the previous methodological decisions made regarding the theory development and research design, which in our case are specified as deductive and quantitative. Our research strategy lends itself to an experimental design, where hypotheses about relationships between variables are formulated and subsequently tested (Saunders et al., 2016).

The final step before initializing the data collection and analysis process, is defining the time horizon of the study. Research can either be cross-sectional, focused on one particular point in time, or be a representation of events over a certain period defined as a longitudinal or time-series study (Saunders et al., 2016). We will employ a set of panel data for our sample of banks where we are measuring the firm-specific variables for each bank over a six-year time frame between 2014 and 2019. The integral advantage of utilizing time-series data for a panel of entities is the capacity to study change and development (Saunders et al., 2016). This is an essential analytical feature against the backdrop of our analyses, in which we want to examine the development of bank risk over time in the context of specific regulation aimed at mitigating it.

3.3 Empirical Model

3.3.1 Model Presentation

Multivariate Regression Model

The previous paragraphs outlined the philosophical and methodological underpinnings of our research goal which is to examine the relationship between regulation and market-based measures of risk. The following section will outline the empirical methods employed to examine the relationship between the Basel III regulatory framework and market-based measures of risk. At the core of our analysis is a multivariate linear regression model. A linear regression model with one explanatory variable was already introduced in section 2. A multiple regression allows researchers to estimate the effect of an explanatory variable on the dependent variable while holding the additional explanatory variables constant. A general multiple regression model takes the following form:

$$Y_t = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \cdots + \beta_k X_{kt} + u_t \qquad (19)$$

where $t = 1, \ldots, n$, Y_t is the tth observation of the dependent variable, $X_{1t}, X_{2t}, \ldots, X_{kt}$ are the tth observations on the k regressors and u_t is the error term. The coefficients are estimated via OLS approach that seeks to minimize the sum of the squared prediction mistakes of the multiple regression model. The assumptions underlying an OLS estimation were already outlined in section 2.1 in the context of the beta estimation in the CAPM framework. However, since we are applying a time series regression, we are replacing the assumption of *i.i.d* inputs with the assumption that both dependent and independent variables are stationary.

Our research effort is comprised of several time series multivariate regression models with different dependent variables and sample groups. Applied to our research context the multivariate regression model takes the following base specification:

$$Risk_t = \gamma_0 + \gamma_{LCR} LCR_t + \gamma_{LEV} LEV_t + \gamma_{CAR} CAR_t + \gamma_{ROA} ROA_t + \gamma_{GDP} GDP_t + u_t \qquad (20)$$

where the $Risk_t$ refers to the time-series of quarterly beta estimations by means of either rolling window regression or via Kalman Filter and their corresponding estimates for idiosyncratic risk for each of our three portfolios which is detailed in section 2.1.4. These portfolios are comprised of either G-SIB, non-G-SIB or the complete sample of banks. How the risk estimates are obtained is explained in detail in section 2.4 where the risk measure calculations are laid out. γ_k refers to the coefficients of the explanatory variables. LCR_t, $LEV_t, and\ CAR_t$ are the primary variables of interest in our work and relate to the previously introduced *Liquidity Coverage Ratio*, *Leverage Ratio* and *Capital Adequacy Ratio* from the Basel III framework. ROA_t and GDP_t encompass the relevant control variables employed for Return-on-Assets and Gross domestic Product. Equation *(20)* is the base specification of our model, which includes all the variables of primary interest as well as control variables that were selected based on the findings of previous literature and economic theory in the context of our work (Stock & Watson, 2019).

Distributed Lag Model

We will iterate the above specified multiple regression model by altering the base specification in a way in which we will use the lagged values of our explanatory variables as the new independent variables. We are assuming dynamic causal effects that occur over time which is why we want to incorporate lags into our model to add robustness and get a better understanding of the temporal relationship between the variables in case there might be a delayed reaction of the dependent variable, especially in the context of the OLS-based risk measures. In this context, the dependent variable Y_t can be expressed as a distributed lag of current and past values of explanatory variable X_t, as follows:

$$Y_t = \beta_0 + \beta_{1,t}X_{1,t} + \beta_{1,t-1}X_{1,t-1} + \beta_{1,t-2}X_{1,t-2} \dots + \beta_{2,t}X_{2,t} + \beta_{2,t-1}X_{2,t-1} \dots + \beta_{k,t-q}X_{k,t-q} + u_t \quad (21)$$

where $\beta_{1,t}$ is the coefficient of the contemporaneous value of independent variable $X_{1,t}$. Logically, $\beta_{1,t-1}$ is the coefficient of the lagged independent variable $X_{1,t-1}$. That is, $\beta_{1,t-1}$ is the effect of a change in X on Y one period later and. The same logic applies to the other lags as well as the other explanatory variables. However, while still incorporating lags into the iterations of our baseline specification model (Equation 20), we are only using one lag per regression that is consistent throughout the independent variables. Applied to our research approach the lagged models will take the following form:

$$Risk_t = \gamma_0 + \gamma_{LCR} LCR_{t-1} + \gamma_{LEV} LEV_{t-1} + \gamma_{CAR} CAR_{t-1} + \gamma_{ROA} ROA_{t-1} + \gamma_{GDP} GDP_{t-1} + u_t \tag{22}$$

$$Risk_t = \gamma_0 + \gamma_{LCR} LCR_{t-2} + \gamma_{LEV} LEV_{t-2} + \gamma_{CAR} CAR_{t-2} + \gamma_{ROA} ROA_{t-2} + \gamma_{GDP} GDP_{t-2} + u_t \tag{23}$$

There are two important considerations for the fact that we are only including one and the same lag at a time for each of the independent variables. The first reason is that we want to avoid multicollinearity in the successive lags of the explanatory variables which are usually highly correlated in economic time series (Baltagi, 2013). We utilized the variance inflation factor (VIF) (Robinson & Schumacker, 2009) for models including multiple lags of the same variables found that the VIF values of many factors in these models frequently exceeded the critical value of 10. Moreover, due to our relatively small number of observations we are restricted by the amount of degrees of freedom to spare, which decreases with every additional lag multiplied by 2 multiplied by the number of factors included for models including multiple lags of the same variables (Majid et al., 2018; Parker, 2013). These two considerations led to the decision to include only one lag for each variable in a given model specification.

The models specified in the equations 20, 22, and 23 are used for both subsamples as well as estimation methods. When deciding on a (multivariate) regression model, there is generally the tradeoff between including too many or too few variables (i.e. having multicollinearity issues or the risk of omitted variables – see section 3.3.2). It would certainly have been possible to eliminate (insignificant) variables from each individual model specification. We tested this procedure and found that it made the remaining coefficients in each model specification usually (highly) significant – however also lead to extremely inconsistent results between different model specifications. We decided not to pursue this procedure, for multiple reasons: First and foremost, we set up the various robustness dimensions (risk estimation technique, subsample and lag) because we expected similar results for each of the specifications. Beyond doubt, certain differences in results can be explained by changing the model specification. However, the magnitude of inconsistency that the individual factor selection procedure yielded could not be rationalized by the comparatively slight change in model specification. Moreover, there are no reasons to assume that certain relationships change due to a different model specification. Those assumptions would have violated the hypotheses put forward in section 2.5. For these reasons, we decided to hold our choice of variables constant for each and every model specification. This decision comes with the advantage to be able to compare the results of the model specifications among each other and achieve more robust and generalizable results.

3.3.2 Model Validity Concerns

When conducting a multivariate regression analysis, it is important to consider reasons why the validity of the model could be in question and coefficients might be biased. These threats refer to the instance where the regressors are correlated with the error term, resulting in a violation of the exogeneity assumption underlying the regression.

Omitted Variable Bias

A common problem that can originate within the model is omitted variable bias. It was mentioned in section 2.6 that ROA and GDP were selected based on results of relevant prior research and also to avoid omitted variable bias. Omitted variable bias occurs when one or more regressors are correlated with an omitted variable and this omitted variable is a determinant of the dependent variable (Stock & Watson, 2019). A regression model that leaves out additionally important explanatory variables results in biased coefficients for the included variables since effects of the omitted variables will be attributed to the included variables. However, adding additional variables when in fact they would not cause omitted variable bias, will also decrease the precision of the OLS coefficients by increasing their variance (Stock & Watson, 2019). Thus, it is essential to clearly outline why additional factors beyond the primary variables ought to be included. We rooted the inclusion of ROA and GDP in the findings of prior research to proxy for profitability and macroeconomic development which have been shown to impact our relevant risk measures. To avoid multicollinearity issues, which would lead to an imprecise estimation of the partial effects of the regression coefficients by causing a large sampling variance (Stock & Watson, 2019), we only included one variable for both the profitability and the macroeconomic dimension. The VIF tests of the final model specification shown in equations 20, 22, and 23 that include only one lag at a time for each variable showed values considerably below the critical value of 10, mostly even below 3. Therefore, the correlations between the independent variables are deemed acceptable for this study.

Misspecification of Functional Form

A further threat to the validity of multivariate regression models that might arise is the possibility of functional form misspecification. This issue refers to the instance in which a non-linear relationship is assessed with a linear regression equation (Stock & Watson, 2019). This would lead the coefficients to be biased since the non-linear aspect of the regression would not be represented in the equation akin to an omitted variable bias. The standard test for misspecification of the functional form is the RESET test (Peters, 2000). The p-value was above the threshold of 5% for all model specifications for both systematic and unsystematic risk, wherefore the specific results are of no further importance and are, therefore, not presented in the result tables in the findings section.

Errors-in-Variables Bias

Moreover, our model could suffer from errors-in-variables bias. This threat to a model's validity originates in the case the independent variables are inaccurately measured (Stock & Watson, 2019) . Errors in variables can result in correlation between the regressor and the error term which in the context of the OLS estimation is assumed to have mean zero and no correlation and will result in a biased coefficient (Stock & Watson, 2019). Pertaining to our data collection approach, where we are retrieving accounting data from Thomson Data Stream (TDS), a source of measurement error could be typographical errors. However, we performed random checks for all our variables with quarterly disclosure reports published by banks. Both random checks as well as checks for outliers did not yield any errors in the data obtained from TDS. For GDP, the only macroeconomic variable in the model, we turn to the OECD as a source. The reporting on the quarter-on-quarter GDP growth over the relevant time frame was consistent and complete and we consider the OECD as a reliable source for nationally and internationally relevant data.

Sample Selection Bias

Sample selection bias occurs when the sample selection process influences the availability of data and the same selection procedure is also related to the dependent variable (Stock & Watson, 2019). To circumvent sample selection bias, we chose to stick with the main sample for the G-SIB calculation as outlined in section 2.4. According to the BCBS (2020a), the main sample underlying their assessment of G-SIBs is as a valid proxy for the global banking sector.

Simultaneous Causality

Furthermore, an issue that needs to be considered is the phenomenon of simultaneous causality. In a regression it is investigated how explanatory variable X affects dependent variable Y. Simultaneous causality occurs when not only X causes Y but also vice versa. An OLS estimation will incorporate these effects and it results in biased coefficients for the regressors (Stock & Watson, 2019). We have not explicitly tested for simultaneous causality but are assuming that endogeneity based on a reverse causal relationship between measures of risk and the Basel III factors is unlikely.

Inconsistency of OLS Standard Errors

Finally, it is imperative to mention inconsistency in the estimation of the OLS standard errors. Inconsistent standard errors will produce flawed hypothesis tests due to wrong confidence intervals. Inconsistent standard errors are rooted in two dynamics. The first is heteroskedasticity where the variance of the error term. Heteroskedasticity occurs when the variance of the conditional distribution of the error term is not constant over time. As outlined in section 4.6, all our data was differenced to a degree that made it stationary, therefore implying that heteroskedasticity will not be a problem. Moreover, there is the possibility that autocorrelation might arise since we are using panel data and examining dynamic causal effects. However, since we are separating the lags in the different regression, autocorrelation should not be of essential concern to our models (Stock & Watson, 2019)

3.3.3 Measures of Fit

Finally, after introducing the model specifications and addressing possible concerns underlying it, this section will outline which measures of fit will be utilized to assess the aptness of the model itself.

R^2 and Adjusted R^2

The R^2 of a regression model, a number between zero and one, is the fraction of the variance of dependent variable Y_t that is explained by the independent variables in the model. Mathematically, the R^2 is given by

$$R^2 = 1 - \frac{SSR}{TSS}$$

where, SSR is the sum of the squared regression residuals and TSS is ae the total sum of squares. Therefore, 1 minus R^2 will yield the fraction of the variance that is not explained by the regressors. When an additional regressor is added to the regression equation the value of R^2 will increase every time, unless the coefficient of the new regressor is exactly zero because the value of SSR will be reduced (Stock & Watson, 2019). Nevertheless, simply adding more independent variable and increasing the R^2 does not imply that the model fit will be improved. To avoid overfitting due to an artificially high R^2 it is possible to reduce R^2 by some factor to arrive at the adjusted R^2. The adjusted R^2 multiplies the term $\frac{SSR}{TSS}$ with a factor $(n-1)/(n-k-1)$ where n is the sample size and k is the number of factors in the model. Therefore, adding a factor to the model raises R^2 but also decreases the multiplier $(n-1)/(n-k-1)$. Hence, depending which effect is stronger the adjusted R^2 increases or decreases (Stock & Watson, 2019) and thereby penalizes the addition of additional variables in case these do not contribute enough explanatory power to the model.

Standard Error of the Residuals (SER)

This measure estimates the standard deviation of the error term u_t in the multiple regression. SER measures the spread of the distribution of the actual observations of the dependent variable Y_t around the regression line to show well the regression slope fits the actual observations (Stock &

Watson, 2019). For a multivariate regression, the SER is calculated by dividing the sum of the squared residuals SSR with the divisor $(n - k - 1)$.

F-Statistic

The F-test allows for the comparison of two or more different regression models and their ability to explain the variance in the dependent variable. Specifically, the F-test benchmarks the model in question against the intercept-only model which has no regressors. Therefore, the F-test states the implicit null hypothesis that the fit of the intercept-only model and the specified model are the same, while the alternative hypothesis states that the fit of the specified model is significantly better. Hence, if the p-value for the F-statistic is below the required critical value we can reject the null-hypothesis. It also implies that the value of R^2 is significantly different from zero. Mathematically the F-statistic is calculated according to the following formula:

$$\frac{R^2}{1 - R^2} * \frac{n - k - 1}{k}$$

where n is the number of observations and k is the number of the regressors.

Akaike Information Criterion (AIC)

The AIC allows researchers to test how well their model explains the data without problems of overfitting. Thus, the AIC rewards models that have a high goodness-of-fit and penalizes models that are overly complex (Stock & Watson, 2019). This becomes apparent when looking at the equation for the AIC:

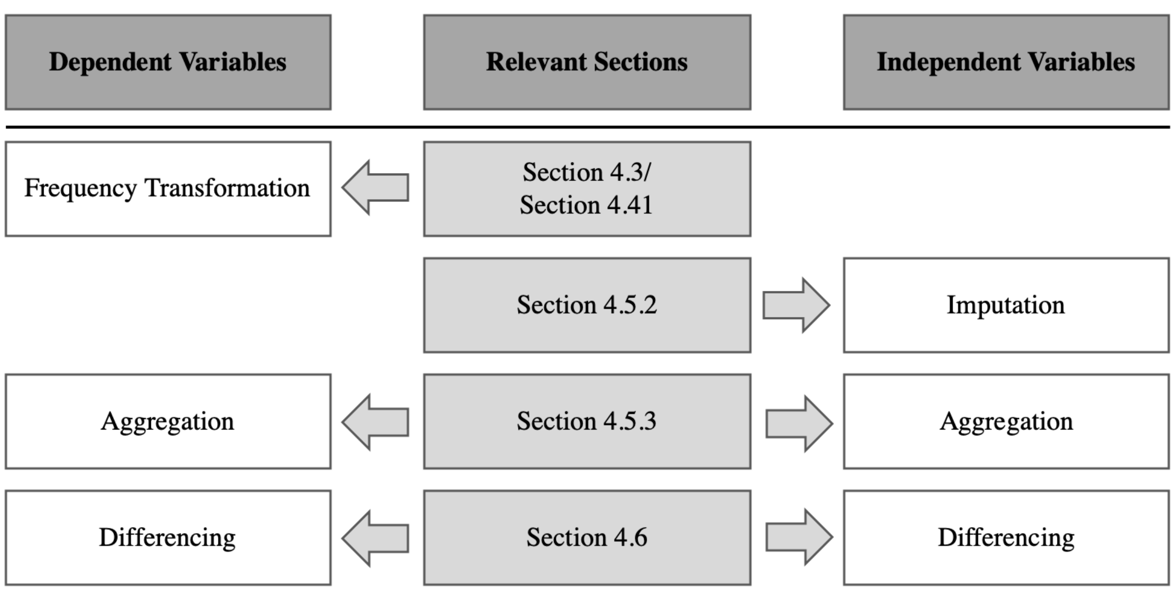
$$AIC = 2 \ln \left[\frac{e^k}{\hat{\mathcal{L}}} \right]$$

where k is number of parameters in the model and $\hat{\mathcal{L}}$ is the maximized likelihood, the measure of goodness-of-fit. A low value of the AIC is preferable, so when the number of parameters k gets increased the AIC increases, while adversely the AIC decreases with an increased measure of fit.

4. Dataset

While Chapter 3 has covered the rather high-level, strategic choices pertaining to the general research approach and econometric models used, this chapter deals with more operational considerations regarding the processing of data and includes all steps from the raw data gathering to the creation of the time series that are used as inputs for the final regression models. The chapter is structured as follows: It will start by giving an overview of the data treatment procedure (section 4.1), then provide a detailed description of how the two subsamples are created (section 4.2), followed by a reasoning for the selected observation period and frequency (section 4.3). Because the processing steps and issues associated with the input variables are fairly different in nature based on the type of variable, we decided to split these into a section for dependent variables (section 4.4) and independent variables (section 4.5). Section 4.6 deals with transformation of non-stationary time series into stationary ones which are required to perform time-series regressions outlined in section 3.3.1.

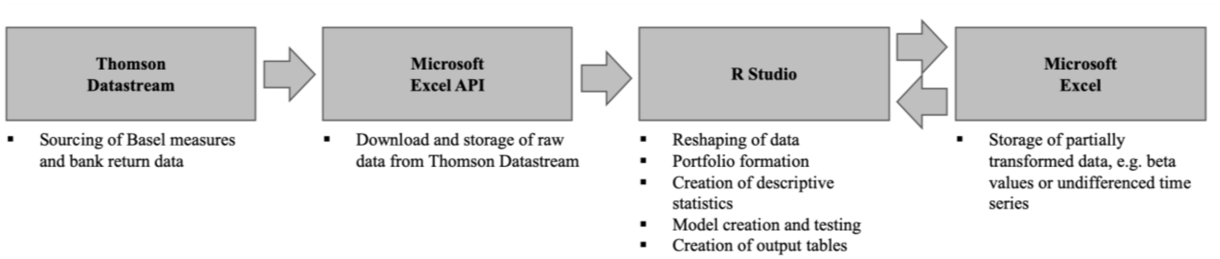
Figure 2: Overview of data transformation procedure



4.1 Data treatment

In order to execute our research approach outlined in chapter 3, large amounts of raw data on various variables of interests needed to be handled. Therefore, this section will give a brief overview of the programs and processing steps performed with each program in order to handle the data that was used for the thesis.

Figure 3: Overview of programs used for data processing



Raw data was sourced from TDS for our complete sample of banks via the respective tickers for each of the variables (see Appendix 3). Via the respective application programming interface, the data was downloaded to Microsoft Excel files. This step was performed solely for storing the data and hence, absolutely no data manipulation was performed in Microsoft Excel. All data processing, cleaning, portfolio formation, model building and statistical tests have been performed in *R Studio* (version 1.2.1335). The code is documented in the appendix and has been written in the most flexible format possible. In the realm of this goal, several calculated variables have been exported to Microsoft Excel files and imported back to *R Studio* when needed in order to decrease the duplication of code or process too many steps within one *R* file. Finally, Microsoft Excel has been used for the visualization of some of the summary outputs of *R Studio*.

4.2 Sample Composition

The creation of the two subsamples, namely the G-SIB and non-G-SIB portfolio, presents an important cornerstone of our research approach. It was already outlined that all the banks in our sample are large internationally active banks, but banks characterized as G-SIBs are especially impacted by the new Basel regulation (BCBS, 2020a). This is because G-SIBs are required to hold more equity capital as a share of risk-weighted assets which in turn influences the *Leverage* and *Capital Adequacy Ratio* which are based on equity capital levels. Based on a cutoff score, G-SIBs are allocated to certain “buckets” as outlined in section 2.4, which are used to determine the degree of required additional loss absorbency. Hence, the division of our overall sample into these two subsamples allows for the possibility to determine differences in sensitivity to the Basel III requirements, especially regarding the two equity-based measures. We want to refine the analysis of our sample in this way, since the systemic threat emanating from G-SIB is substantial as repeatedly pointed out by regulators (BCBS, 2020a). Therefore, distinguishing between G-SIBs and non-G-SIBs allow us to make inferences about the effectiveness of the regulatory framework regarding the most crucial group of banks and provides us with the ability to interpret potentially different dynamics in the development of risk compared to non-G-SIBs.

After the removal of banks for which no data could be obtained, the number of banks for which at least some data was available was 65. In any given year, between two and four of these 65 banks were not included in either of the two subsamples, meaning that the number of the banks which were in the sample changed slightly from 63 (2014-2017) to 61 (2018-2019). This deviation from the total number of 65 banks arose in cases in which banks that have not previously been on in the list for the consideration to be characterized as a G-SIB increases in importance and therefore can be found on the list in a later year, or conversely, a bank was dropped from the list in later years and, therefore, was not included in either of the subsamples. Moreover, some banks made the G-SIB cut in some years, whereas in others they did not, which also lead to subsamples with a changing number and composition of banks. The majority of banks, however, was stable in the sense that they could only be found in one subsample during the entire observation period. A comprehensive table that shows which bank has been included in which subsample in any given year can be found in Appendix 4.

Table 1: Overview of the number of banks in each subsample (2014-2019)

	2014	**2015**	**2016**	**2017**	**2018**	**2019**
G-SIBs	29	29	29	30	28	29
Non-G-SIBs	34	34	34	33	33	32
Not allocated	2	2	2	2	4	4
Overall sample	**65**	**65**	**65**	**65**	**65**	**65**

4.3 Observation Period and Frequency

The choice of the observation period is directly linked to the implementation of the Basel III measures and the frequency of these measures being reported, respectively. Appendix 1 shows an overview of the timeline of the Basel III phase-in arrangements. It can be seen that the Basel III measures we focus on, namely *Liquidity Coverage Ratio, Leverage Ratio and Capital Adequacy Ratio* should have been implemented in 2013 for the latter and January 2015 for the former two. For this reason, an observation period starting a few years before their implementation (e.g. 2012) would have been ideal in order to include levels in the chosen measures prior to their implementation. However, almost no data was reported by banks concerning these measures prior to 2014. This can mainly be attributed to the fact that disclosure requirements and actual enforcement of the measures has only sequentially taken place since measures have first been implemented (BCBS, 2020a). Moreover, our observation period is often regarded as a phase-in period in which the calculation of the ratios (e.g. what type of capital is considered relevant in for certain ratios) can be subject to revision and the final version of the Basel III measures is only planned to be implemented between 2022 to 2027 (BCBS, 2020a).

With regards to frequency, most researchers (e.g. Drobetz et al., 2016; C. H. Lee & Hooy, 2012; W. S. Lee et al., 2015) who employ a similar research design in terms of performing a time series regression of factors hypothesized to influence the level of a risk measure work with monthly data. Based on the fact that the highest available frequency for the chosen Basel III measures is quarterly, we were forced to stick to a quarterly frequency as the highest possible frequency. The lower frequency compared to other studies is still presents a very good fit with our research question, as we are not really interested in frequent changes in the risk measures – but rather on the longer-term effects of Basel III measures on the level of risk in the banking sector, which can adequately captured by quarterly risk measures. Despite the good alignment with our research question, the low observation frequency leads to a significantly lower number of observations for the given period (24 in total[2]), which limits the degrees of freedom in our analysis. To summarize, based on data availability we decided to set the observation period from Q1 2014 to Q4 2019. This

[2] Four observations per year for a period of six years

period – while leaving little room to compare to the pre-implementation period – covers the entire implementation period until the time of writing[3].

4.4 Security Data

4.4.1 Bank return data

Time horizon and frequency

The time horizon and frequency of the return data is mainly dependent on the calculation of the risk estimates via OLS regression and the Kalman Filter, which in turn had to match the time horizon and frequency of the explanatory variables (see section 4.3).

For the OLS regression, we have used a window of two years that is rolled over the entire observation period. In practice, CAPM betas are frequently calculated over a time horizons of four to five years (Groenewold & Fraser, 1999). We decided to use a time window of just two years due to our comparatively short observation period of six years. A time horizon of more than two years would lead to the effect that new information would be reflected in the beta to a more moderate degree and with a significant time lag and, therefore, might decrease in relevance to serve as a dependent variable which is hypothesized to respond to the Basel III measures.

The short time window of two years, on the other hand, leads to issues with the number of observations there are for the risk calculation. In order to match the quarterly time series of our independent variables, a time series of the same length and frequency is required. The calculation based on quarterly returns would have yielded only eight observation during our time window of two years – a number far too small. Draper & Paudyal (1995) investigate the impact of alternative estimation assumptions for beta calculation and find that, using OLS regression, sample size is in fact of high importance, and recommend the use of 400 or more observations[4]. In order to obtain such a high number of observations, increasing the observation frequency to a daily one is the only

[3] At the time of data collection, data for Q1 2020 has not been published yet.
[4] A comparable number of 300 observations has been proposed by Sunder (1980), albeit having a slightly different methodological approach

way to obtain such a high number of observations[5]. Yet, there is a potential issue caused by using daily return data from assets which are infrequently traded – also known as the "thin-trading" effect. The argument, first put forward by Scholes and Williams (1977) and subsequently investigated by many other scholars – often with the goal of finding methods to mitigate the errors arising from thin-trading (e.g. Berglund et al., 1989; Dimson & Marsh, 1983) – does not apply in our context. According to the above-mentioned scholars, using daily return data can result in estimation errors caused by infrequent trading of some securities. For instance, an asset which is not traded on a given day and, for this reason, exhibits a return of 0, can have a reduced measured correlation with the market index and therefore can have a "artificially" low beta.

The "thin-trading" problem - while still being relevant in many emerging markets or for infrequently traded assets in general – is not relevant for our sample of large, internationally active banks with consistently large trading volumes. For this reason, the possibility of interference of such effects can be rejected as well as the need for mitigation techniques like the estimation of outlier-resistant betas as proposed, for instance, by Martin and Simin (2003).

Based on the time window and return frequency, our dataset for security data included daily asset prices from 02/01/2012 to 31/12/2019 – a total of 2087 observations over a period of eight years and 522 observations for each daily rolling OLS beta. For instance, the beta estimate for 01/01/2014 included the 522 observations starting on the 02/01/2012 and ending on the 31/12/2013.

The Kalman Filter, as opposed to an OLS regression, does not work with a fixed rolling time window. Instead, the Kalman Filter determines the beta estimate based on a dynamic estimation algorithm. This means that the Kalman Filter can already provide beta estimates immediately after the initialization, and subsequently increases in its accuracy as more observations are available to be processed by the estimation algorithm. It was theoretically possible to use return data starting only on 01/01/2014 for the Kalman Filter estimates. However, in order to provide estimation techniques with the same data, the same time window starting on 02/01/2012 was used for both

[5] Monthly frequency would lead to 2*12=24 observations; Weekly frequency would lead to 2*52=104 observations; Daily frequency would lead to 2*261 = 522 observations

estimation techniques, and subsequently, only data starting from 01/01/2014 was used for the regression. After the creation of the two daily beta estimates for our sample of 65 banks, the daily beta estimates had to be transformed into quarterly ones. To achieve this, the average of each quarter from the daily beta estimates were used.

The calculation of idiosyncratic risk estimates, which have been derived according to the formula in section 2.14, has been performed according to the same procedure that was outlined in this section for the systematic risk estimates.

Outliers and return distributions

As noted in section 2.1.2, the CAPM requires investors to be rational, mean-variance optimizers. Behind this assumption lies the rather implicit assumption that higher moments of the return distribution are irrelevant in terms of pricing an asset. However, it is very likely that investors do take higher moments of the return distribution, namely skewness and kurtosis, into consideration. In fact, Chamberlain (1983) was able to show that pure mean-variance relationship holds true only if returns exhibit an elliptical distribution. Based on this finding, a large body of literature emerged which dealt with the implications of higher moments of return distributions on asset pricing (e.g. (C. R. Harvey & Siddique, 2000; Zhou, 1993). While most scholars agree on the fact that higher moments of return are indeed relevant, the picture is a less clear with regards to the exact relationships between return and skewness and kurtosis, respectively. One explanation for the inconsistency in findings might be due to the many factors that influence this relationship; for instance, which time horizon is used, whether total measures of higher moments are used rather than relative (e.g. the relative contribution of skewness of an additional asset to an existing portfolio – being the relevant one from a CAPM point of view as only incremental risk is relevant) or whether the interdependencies of various moments are considered (C. R. Harvey & Siddique, 2000).

However, the scope of this paper strictly limits the number of triangulations pertaining to the methods we calculate and treat variables. Regarding the assumptions of the CAPM, we found that a triangulation pertaining to time-invariance assumption (incorporated by using two estimation techniques for beta) provides is of much higher relevance than adjusting our risk measures for the incorporation of a third and fourth moment of asset returns. The main reason for this is rooted in the high complexity and ambiguity that would be involved with an adjustment of our risk measures for higher moments of return on the one hand, and on the importance of the risk-estimation method for our research question on the other hand.

Table 2: Complete sample summary statistics[6]

Min	*Max*	*Mean*	*Std*	*Skewness*	*Kurtosis*
-8,32%	3,54%	0,03%	0,93%	-0,58	7,95

Nonetheless, the measure of kurtosis presents potentially important information on the existence of outliers. As per definition, a normally distributed variable exhibits a Pearson's measure of kurtosis of three is described as mesokurtic, a value of less than three defines a distribution as platykurtic, whereas a value of more than three defines a distribution as leptokurtic. In the latter case, the distribution is found to have more extreme observations as compared to a standard normal distribution (i.e. is said to have fat tails). While leptokurtic distributions are, in fact, not uncommon in financial contexts (e.g. Choi & Nam, 2008; Scherer et al., 2012), they can potentially indicate outliers. For this reason, we have conducted random checks of extreme returns and found that all of them are correct and therefore decided not to truncate our distribution and leave all return data as it is. This decision is backed by the fact that our sample consists of highly liquid assets which are frequently traded and, on top of that, there is no valid reason to question the trustworthiness of TDS as a source for asset prices.

Adjustment for dividends, stock splits and non-trading days

The adjusted closing price (:P), which accounts for both stock splits and the payout of dividends, was used for return calculations. While there was no need to adjust for outliers, there was the need to account for days on which no trading happened. To calculate daily returns for the beta estimation, the variable adjusted closing price was used to obtain price data for all securities. In case there is no trading on a particular day, the variable :P returns the value of the last known value. This convention implies that days on which the price remained unchanged compared to the

[6] Kurtosis is measured as Pearson's measure of kurtosis, for which the value of 3 indicates a normal distribution

previous trading day should be imputed with NAs rather than left as days that show zero return. The occurrence of days with zero returns can be attributed to the fact that the days on which a security is traded is non-homogenous for our sample, because the exchanges from which stock price data is sourced are closed during different days. Sourcing the price data for all assets in one matrix results in a larger number of overall trading days (2087 for our observation period), but consequently in a lower number of actual trading days for each individual asset and consequently, in a lower number of return observations that are being used for the risk calculation. The number of missing values, however, did not present a problem to our beta estimation as the number of observations within the two-year time horizon was still beyond the recommended 300 observations. On the other hand, not imputing zero return values would have – ceteris paribus – lead to a lower correlation of an asset to the market index and resulted in a lower systematic risk estimate.

4.4.2 Market Index

To compute systematic risk estimates as outlined in section 2.1.4, a market index as a proxy for the market return was needed. As Harris et al. (2003) point out, the decision between a global and a local index for the market portfolio is one of the many decisions to be taken during the implementation of the CAPM. We decided to use a global index – mainly for two reasons: Firstly, Stehle (1977), among other scholars, state that the use of a local index is only suitable for “closed, national financial markets”. Second, local biases might be introduced from domestic market returns. While it could be argued that companies are often tied closest to their domestic markets, this argument applies less strongly to our sample of large, internationally active banks, which are heavily exposed to the global financial market. Based on these arguments, we decided to use the Morgan Stanley Capital International (MSCI) World Index with dividend reinvestment as our benchmark index for a global market portfolio. As of March 31, 2020, the index has 1,643 constituents from 23 developed countries and covers approximately 85% of the free-float adjusted market capitalization (MSCI, 2020). Hence, with its large coverage of developed economies it presents a good fit to our sample of globally dispersed, internationally active banks.

4.4.3 Risk-free Asset

The decision which asset to use for the approximation of risk-free returns is another decision in the context of the beta estimation. We decided to stick with the most common approach of using the 3-month US treasury bill as a proxy for risk-free returns, which prevents the incorporation of local biases which may originate from the usage of domestic risk-free rates. Furthermore, other scholars with a similar approach of performing time series regressions of factors against beta, who are also using a sample from mixed geographies, rely on US treasury bill rates in the context of beta estimation (e.g. Drobetz et al., 2016).

4.5 Accounting Data

4.5.1 In-sample missing data

While there are no quality issues pertaining to the security data, in-sample data availability of the accounting variables has been one of the most serious issues in this study, forcing us to impute and aggregate data in the most sensible way. Details regarding data imputation and aggregation are outlined in section 4.5.2 and 4.5.3, respectively.

While the data availability for the *Capital Adequacy Ratio* (69%) as well as for the controlling variable *Return on Assets* (63%) can be considered fair, the availability, or the lack thereof, has been serious for the *Liquidity Coverage Ratio* and *Leverage Ratio*, which only had, on average, 34% and 40% observations available, respectively[7]. The availability of data for the three Basel measures was specifically bad during the first two years and improved over the course of the observation period, presumably due to stricter publication requirements. An overview of the number of available observations for each variable in each time period can be found in Appendix 5. Whether missing observations threaten the validity of our data depends on the reason for the missingness of these observations. TDS states that data regarding equities and fundamentals is sourced "directly from exchanges, leading international and local suppliers, and published reports"[8]. For the Basel III measures, data is presumably sourced from published reports, meaning

[7] Percentage numbers refer to available fraction of overall possible data points per variable, which is 65 (number of banks) x 24 (number of observations per bank) = 1560 data points

[8] https://www.eui.eu/Documents/Research/Library/ResearchGuides/Economics/PDFs/Datastream-2019-Factsheet.pdf

there is no direct evidence for the introduction of bias pertaining to which data points are included and which ones are not, i.e. all published data points should be reported. However, as discussed in section 6.2, there could be a potential motivation for banks with unfavorable ratios not to disclose these. Whether and to which extent this is the case is hard to determine. However, a large part of missing data stems from the fact that banks have simply reported data in a lower than quarterly frequency and there is no reason to assume that banks decided not to report the measures in a given quarter because they deemed it to be too unfavorable to report it. This argument is strengthened by the fact that the ratios are generally not very volatile between quarters, as can be seen from banks with complete time series. Moreover, the number of missing values seems to be dependent on both overall time period and the specific quarter. The former is likely due to the fact that disclosure requirements have only been introduced throughout the observation period, whereas the latter, i.e. that the number of observations is significantly higher in Q4 compared to Q3, may be rooted in the fact that banks publish some of the measures only in annual reports for their last quarter; especially in the earlier parts of the observation period where quarterly compliance reports which are solely focused on Basel measures are not as common as in later years. The dependence of missing data on both observation period and quarter does not necessarily introduce bias into the data. However, we noticed that the fluctuating number of observations between quarters also introduces some fluctuation of the average of each of the Basel III measures as well as *Return on Assets*. As there was no clear pattern observable (i.e. the average value was not consistently below or above average in quarters with less observations), we decided to impute missing data points up to a certain degree – the detailed procedure is outlined in the following section.

4.5.2 Imputation

To account for the fluctuation presumably introduced by the small sample size in some quarters, we decided that imputation is a feasible way to reduce fluctuation and arrive at a more robust time series. Imputation of data is, of course, subject to certain perils and should be performed in a careful manner. Hence, the following paragraph will outline the imputation procedure and the reasoning behind it and will refer to Peng & Lei (2005).

As the reduction of fluctuation was the primary concern behind the data imputation procedure, we had to ensure that this goal was met while at the same time, the imputed data should be as close to the real values as possible. The Basel measures are all exhibiting considerable time-variance and are non-stationarity (see section 4.6). A simple mean or median imputation would, therefore, likely lead to distortion of the dataset – especially as most time series exhibit a significant trend. For this reason, we decided to implement a model-based imputation with a simple linear model.

In order to mitigate (seasonal) fluctuation, we set the maximum number of gaps to be imputed between to datapoints to the value of 3. This number could have been increased up to 22 so that even in the most extreme case (having only two values – the minimal amount required to perform the chosen linear imputation model on) the processes would have yielded a complete time series. However, increasing the number of allowed gaps to such a high number is potentially harmful and might compromise data integrity severely. For instance, having the value of 100 in the first quarter and 110 in the second quarter of the observation period for the *Liquidity Coverage Ratio*, but no values for the remaining 22 quarters would have lead the model to extrapolate the remaining values up to a value of 230 in the last quarter, a number which is not unlikely to present an overestimation of the measure. Sticking with the number of three clearly puts a limit to scenarios like the one illustrated and rather imputes few values between two or more existing and, therefore, correct values. For instance, if the *Liquidity Coverage Ratio* in Q4 2014 is 100 and in Q4 2015 is 120, the three missing quarters in between would have been imputed with the values 105, 110 and 115, respectively. However, if there was only data in Q4 2014 and Q1 2016 and no data in the for all four quarters in 2015, no imputation would have been performed. By setting an upper limit to the number of data points to be imputed, we also limit the potential damage that arises from the fact that the underlying linear model may not be an appropriate representation of the evolution of the time series for the complete observation period. A linear model might not present a good fit for the Basel measures over a longer period of time, because some measures are not increasing or decreasing at the same rate after, e.g. a desired or enacted threshold has been reached. Nonetheless, a linear model is likely to still be the best approximation for shorter gaps of up to three missing values.

4.5.3 Data Aggregation

One of the primary goals of this thesis is to explore the relationship between the Basel III measures and the systematic and unsystematic risk estimates by using multivariate time series regressions.

Given our research design of sourcing data for both the dependent as well as independent variables for each object (i.e. bank) individually, the default approach would have been to regress the relevant time series pertaining to a given bank against that same bank's risk estimate, resulting in 65 multivariate time series regression for each risk estimate and 260 regressions in total[9]. The regression results could then be evaluated according to various measures: For instance, the coefficients could have been analyzed by obtaining their mean values. Moreover, assessing standard deviations of the coefficients as well as the distribution of p-values for each of the coefficient would have provided meaningful ways to assess the robustness of the results. Unfortunately, however, even after the imputation procedure, many time series remained incomplete, making it impossible to perform robust time series regressions. One (theoretical) option would have been to further increase the number of gaps on which data imputation is performed on, which has not been done for reasons outlined in the above section.

Based on these difficulties to perform individual time series regressions for each bank, we decided to aggregate the data by taking the observation-weighted mean for each of our two portfolios for each quarter for all our input variables, respectively. The decision to use observation-weighted averages instead of market-capitalization weighted averages stems from the fact that in our case, the realization of the information system is relevant rather than the market capitalization, meaning that each financial report is equally relevant and there is no reason to assign a larger weight to information from a report stemming from a bank with a larger market capitalization and there is no sensible indication on other potential variables that could provide a feasible proxy for some sort of weighting procedure.

It should be noted that there are potential perils and implicit assumptions regarding the aggregation procedure we decided on. First and foremost, aggregating values of each of the subsamples assumes that the development of both depend are independent variables is homogeneous across banks within each of the two subsamples. Homogeneity is, therefore, a requirement to generalize the results obtained for a subsample for every bank in that sample. While it is likely that this assumption does not hold in its strictest form, the approach to aggregate the data is defensible on

[9] 260 = 65 regressions against each OLS and KF beta as well as 65 regression against the idiosyncratic risk measure derived from OLS and Kalman Filter beta

multiple grounds. First, the fact that the three Basel III measures apply – with few exemptions – to all internationally active banks, already implies a considerable degree of homogeneity with regards to the measures and their implication on the bank's risk. Whilst we account for additional requirements regarding the CET1 capital for G-SIBs (relevant for *Capital Adequacy Ratio*) by using the subsamples, there is still some residual heterogeneity due to the fact that the additional required CET1 capital differs depending on which G-SIB a bank might be allocated to (BCBS, 2020a). Second, the goal of this thesis is to investigate the impact of the Basel III regulation on the banking sector as a whole – not on individual banks and the aggregation procedure is, therefore, still in line with the research question. Yet, one issue of the aggregation is that averages calculated for the various factors are not from the same sample and number of banks compared to the average of the dependent variable it is regressed against[10]. Doing this is not an issue as long as the data points are missing at random, i.e. remaining points are not biased – an assumption that was discussed in section 4.5.1.

By aggregating the variables, we reduced the number of regressions sharply. This, evidently, strictly constraints to assess the distribution of regression outcomes as outlined above, yet still is likely to be the most viable procedure doing the least harm to the integrity of our data[11]. Moreover, the implications of reducing the number of regressions performed are counteracted by introducing robustness to our analysis by means of incorporating 1) two different risk estimates 2) having two portfolios and 3) performing regressions with lagged regressors.

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[10] The issue can be illustrated by taking an imaginative sample of Banks A, B, C and D. While the *Liquidity Coverage Ratio* might be missing for Bank D, the remaining average from the Banks A, B and C is still (and always) regressed against the complete average of the dependent variable (e.g. average of the beta values of Bank A, B, C *and* D. An adjustment of the sample that is used to calculate the average for the dependent variable is impossible, because for one of the other independent variables, the values of another bank could be missing in a given period, which in turn would result in a significant reduced sample size.

[11] There was no bank where all data points for all three Basel measures as well as Return on Assets available, wherefore it was impossible to gauge the degree of deviation from the homogeneity assumption. Yet, especially for the OLS beta estimates and to a lesser degree also for the Kalman Filter beta estimates (for both types of risk), the movement of the risk estimates was astonishingly similar (see Appendix 8). From this finding it can be concluded that, at least to the degree that risk is dependent on the factors included in our analysis), the explanatory variables are likely to also behave homogenously to a certain degree.

4.6 Stationarity

A time series in considered stationary if its "joint probability distribution does not change over time", meaning that the "cross-sectional requirement of each draw being identically distributed is replaced by the time-series requirement that the joint distribution of the variables, including lags, does not change over time" (Stock & Watson, 2019). Non-stationarity can introduce several problems when performing (multivariate) time series regressions. According to Stock and Watson (2019), this pertains especially to the interpretations drawn from "OLS-based statistical inferences", meaning that if a regressor has a stochastic trend, this can lead to spurious regression results, i.e. the regression results may indicate a high probability that the time series are related when, in fact, there is no relation. Hence, every time series need to be tested for stationarity before it is used as an input for the regression. There are several tests available to test for (non)-stationarity. The Augmented Dickey Fuller (ADF) test, which was introduced by Dickey and Fuller (1979) and has subsequently been refined, is one of the most commonly used as well as reliable stationarity tests and has been used by several researchers with similar research topics to ours (e.g. Adam et al., 2016; Groenewold & Fraser, 1999; Reboredo, 2015). The ADF test evaluates if the null hypothesis (that time series has a unit root and is, therefore, non-stationary) can be rejected at a certain confidence level[12]. Hence, the test result should be below 0.05. However, the ADF test comes with some specifications pertaining to the (1) the occurrence of serial autocorrelations in the time series as well as (2) testing against the alternative hypothesis of stationarity around a deterministic trend. Serial autocorrelation is introduced, for instance, by seasonality – e.g. if the value of Y(t) is connected to Y(t+4) – and, if present, should be accounted for in the ADF test (da Silva Lopes, 2003). Yet there is no reason to assume seasonality in either the dependent or the independent variables. A brief check by fitting a linear model (see Appendix 6) has confirmed seasonal variation as being insignificant for every time series. Hence, we do not include a lag into the test specification.

The decision whether to assume a time trend is reasonable and fairly straightforward for some macroeconomic variables such as absolute values of GDP, which exhibit long-term persistent growth. For our variables, yet, is not a trivial question. For instance, measures of systematic risk (i.e. betas) are likely not to exhibit a time trend for longer observation periods, since this would

[12] We used the 5% level, which is the default confidence level.

imply that the relative risk of an asset (or industry) would increase long-term, ultimately leading to infinity. During a period of just six years, as in this case, there might, in fact, be a time trend – especially given the case of the introduction of new regulatory requirements which are hypothesized to influence risk measures. The overall assessment of the independent variable time series, namely the Basel III measures and control variables, is similarly ambiguous. For this reason, we chose not to regard every time series uniformly as trend or non-trend exhibiting, but instead by fitting a linear model to every series and check for the significance of an intercept and trend, respectively. The results of the test as well as the resulting type of stationarity test can be seen in Appendix 6.

Based on whether a time series is assumed to exhibit an intercept and trend, the time series are tested according to the respective ADF specifications. The differentiation between the two ADF test types does not lead to different results regarding the classification into stationary and non-stationary time series – all time series are found to be non-stationary according to the ADF test. However, the ADF test type does make a difference when it comes to the amount of differencing needed, which will be covered next.

In order to remove the stochastic trend identified by the ADF test, the time series need be differenced. The order of integration (d) depends on the magnitude of the autoregressive root within the time series (Stock & Watson, 2019). This implies that, once again, common treatment with regards to differencing would be inappropriate in our context and every time series is integrated individually. We chose to integrate all time series starting with an order of differencing of d=0.1 and increased d by increments of 0.1 until the predetermined type of ADF test displayed significance and the null hypothesis of non-stationarity had to be rejected at the 5% significance level. The amount of integration performed on each time series varied materially, which proved the approach of handling each time series individually as being the right one since differencing may lead to a time series not being stationary and differencing to much may take away too much information, decreasing the potential to show a relation of dependent and independent variables when there, in fact, exists one.

5. Results

With the exception of the *evaluation of risk measures* (part of section 5.1.2) and *model performance* (section 5.4), this chapter will focus primarily on the presentation of the results – the analysis and interpretation of our findings will be covered in the discussion section. Hence, this chapter is rather short and has a simple structure: First, we will present the time series of all dependent and independent variables in section 5.1 and 5.2, respectively. While these two sections are not at the core of our analysis, they allow the reader to gain a better understanding of the evolution of the relevant variables. The discussion, however, will mainly focus on section 5.3, in which the findings of the regression results across all model specifications pertaining to risk estimation method, lag, subsample as well as an interpretation of the test statistics are presented. This chapter concludes with a brief overview on the model performance in section 5.4.

The descriptive statistics (mainly relevant for sections 5.1 and 5.2) can be found in Appendix 7 and refer to the aggregated values with quarterly frequency. Additionally, plots displaying time series with unaggregated values for the risk estimates can be found in Appendix 8.

5.1 Analysis of Dependent Variables

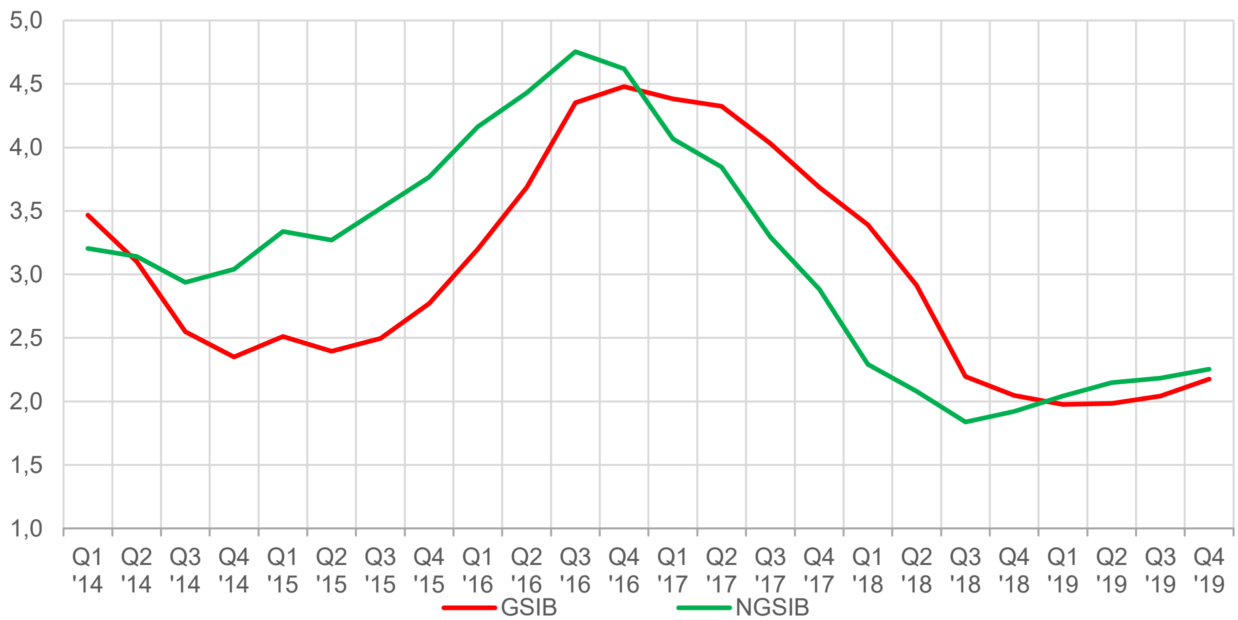
5.1.1 Total Risk

Despite not serving as an input into the regressions, total risk will be briefly addressed as well. Since both systematic and idiosyncratic risk make up the total risk of a stock according to CAPM theory, the inclusion serves the purpose to allow the reader to gain an understanding of the composition of the total risk as well as its development over the observation period[13]. The total risk (variance) of the sample fluctuated significantly during the period and takes approximately an upside-down V-shape, and its maximum values in Q2/Q3 2016 are approximately two times as high compared to the minimum values for both portfolios. While the samples run approximately in parallel, non-G-SIBs exhibit higher variance for the period preceding the peak – a trend that

[13] The total risk is calculated by using two-year rolling windows of daily variances, and then aggregated to quarterly values the same way as the systematic and idiosyncratic risk estimates

reverses after the peak. Idiosyncratic risk makes up 80% (81%[14]) of the total risk and takes ranges of approximately 5%-points around the mean over the observation period. For both estimates, the two subsamples move almost in parallel. Yet, unsystematic risk presents a considerably higher fraction of total risk – 86% (87%) – for G-SIBs compared to non-G-SIBs with 72% (74%)[15]. Unsurprisingly, periods with lower fractions of unsystematic risk are coinciding with periods of higher beta estimates, as can be seen in the next section. The plots showing the estimated fractions of idiosyncratic risk throughout the observation period can be found in Appendix 9.

Figure 4: Total Risk (Variance)



5.1.2 Systematic Risk

OLS Beta estimates

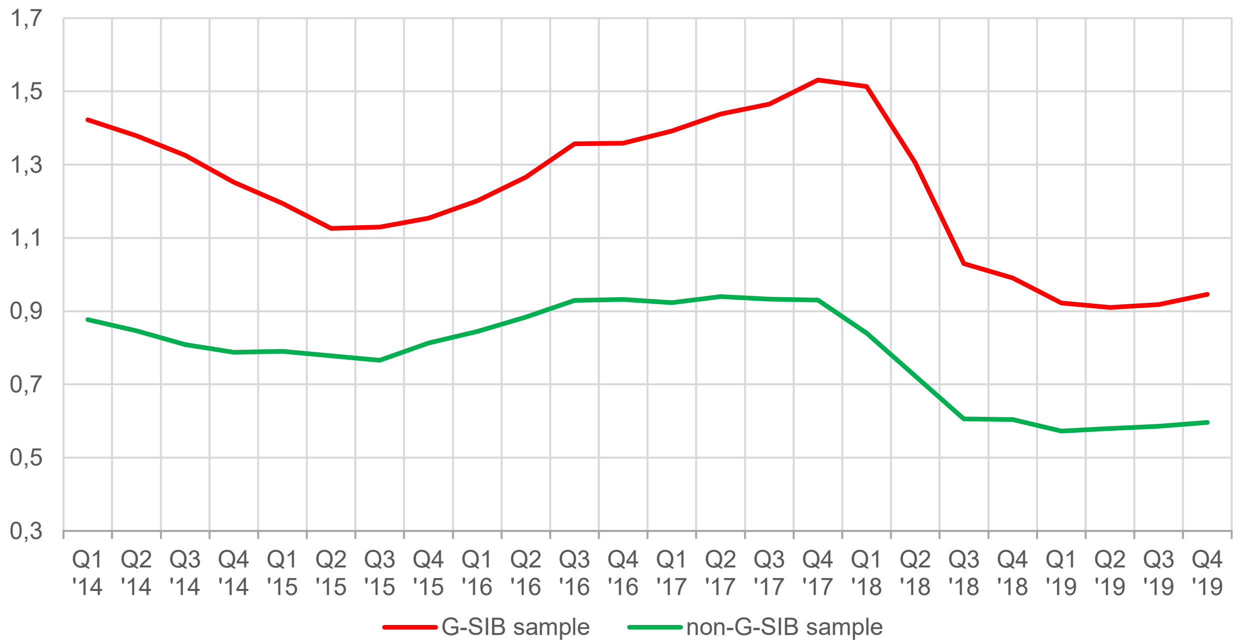
The OLS beta estimates show substantial time-variance, yet the time-variance is slightly more pronounced for the G-SIB portfolio with a delta of 0.62 between the maximum value of 1.53 in Q1 2018 and the minimum value of 0.91 in Q3 2019 than for the non G-SIB portfolio, which exhibits a delta of 0.37 between the highest beta estimate of 0.94 in Q3 2017 and the lowest

[14] In this subsection (5.1.1), values without brackets pertain to OLS estimates, values within brackets pertain to Kalman Filter estimates

[15] Plots showing the fractions of idiosyncratic risk for the two portfolios can be found in Appendix 9

estimate of 0.57 in Q1 2019. Despite the lower degree of time-variance for the non-GSIB portfolio, the beta estimates for both portfolios show very similar movement throughout the observation period and run almost in parallel. The movement of the OLS beta estimates can be roughly divided into four sections: First, betas are falling from Q1 2014 to Q3 2015, are then steadily increasing to the maximum in Q1 2018, then decreasing again for the following four quarters and remain approximately steady for the whole year of 2019. The level of the OLS beta estimates is considerably lower in the beginning for both G-SIBs (1.42) and non-GSIBs (0.88) than for the end of the observation period with values of 0.95 and 0.60, respectively.

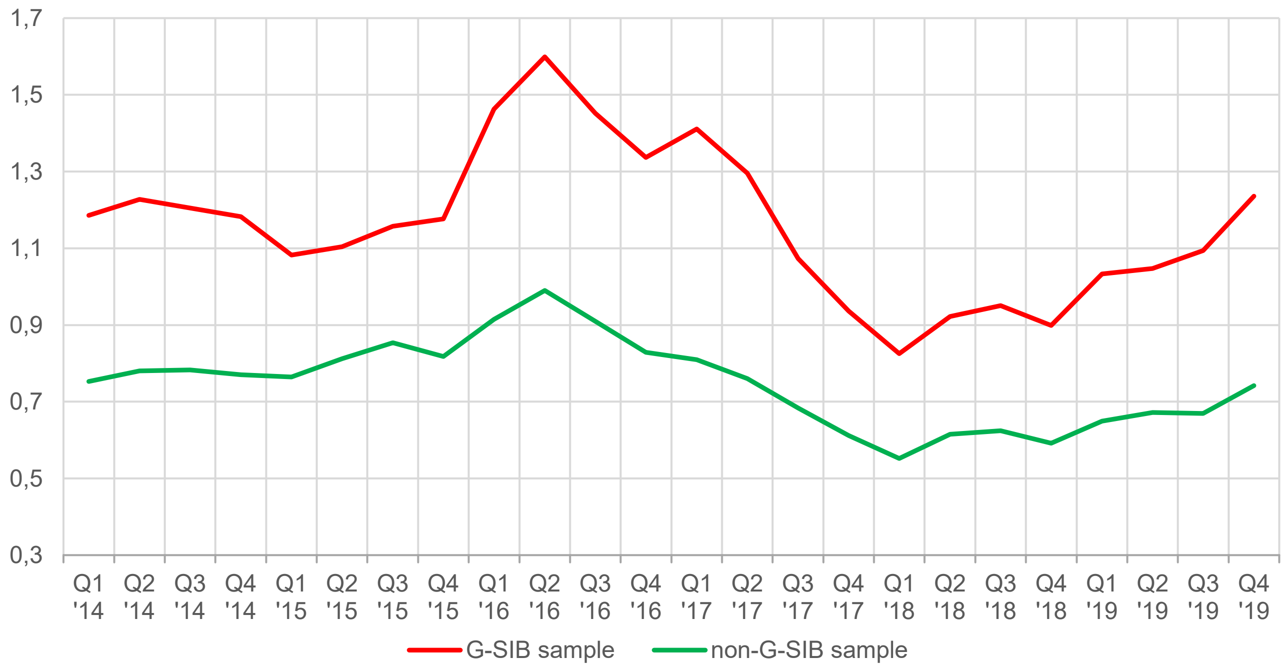
Figure 5: OLS Beta Estimates



Kalman Filter Beta estimates

The Kalman Filter beta estimates show even more time-variance compared to the OLS estimates, and again the time-variance is more pronounced for the G-SIB portfolio with a delta of 0.77 between the maximum value of 1.60 in Q2 2016 and the minimum value of 0.83 in Q1 2018 than for the non G-SIB portfolio, which exhibits a delta of 0.44 between the highest beta estimate of 0.99 in Q2 2016 and the lowest estimate of 0.55 in Q1 2018. Despite the lower degree of time-variance for the non-GSIB portfolio, the Kalman Filter beta estimates for both portfolios again show a very similar movement throughout the observation period and run nearly in parallel and the movement of the beta estimates can also be roughly divided into four sections, though with differing time spans and behavior: First, betas are approximately stable from Q1 2014 to Q4 2015, are then sharply increasing to the maximum in Q2 2016, then decreasing again for the following seven quarters (with the exception of Q1 2017 for the G-SIB sample) and are then increasing steadily until the end of the observation period with the exception of Q4 2018. Another difference of the Kalman Filter beta estimates compared to the OLS estimates is that the level of the betas is similar in the beginning for both G-SIBs (1.19) and non-GSIBs (0.75) and in the end of the observation period with values of 1.24 and 0.74, respectively.

Figure 6: Kalman Filter Beta Estimates



Evaluation of risk measures

As already implicitly touched upon in the descriptive sections, the two main differences between the OLS and Kalman Filter beta estimates are the degree of time-variance, which is higher for the Kalman Filter than for the OLS estimates – and the "reaction" time. The OLS beta is estimated with a two-year rolling window and the observation that is two years back carries the same weight as the observation on the day before the beta estimate. This results in smoother estimates and explains the lower degree of time-variance compared to the Kalman Filter betas as well as the fact that trends are usually not broken by exceptions, as applicable to the Kalman filter as mentioned above. The second difference resulting from the two-year rolling window with equal-weighted observation manifests itself in the considerable time lag with which the OLS betas are reacting to a change in underlying risk. If the OLS betas were shifted a couple of periods backwards, they would (apart from still lower time-variance) almost match the trend of the Kalman Filter estimates. The fact that the Kalman Filter betas are reacting far quicker[16] than the OLS estimates makes them more appropriate for our research purpose. This is because in the base specification, the Basel measure are regressed against the risk measure of the same quarter. Even by extending our model by adding up to two lags for the explanatory variables, a beta that reacts too slowly to the underlying risk might, therefore, not be suitable for our research. The degree of appropriateness for the two beta estimates cannot be answered conclusively, although the observed features for both estimates strongly suggest a superiority of the Kalman Filter over the OLS estimation, which is supported by research mentioned in section 2.3. Finally, we performed an analysis of the mean absolute error for both daily and quarterly beta estimates, which yields a slightly better performance of the Kalman Filter for both observation frequencies[17]. Nonetheless, it should be mentioned that the relevance of the performance of the betas in a CAPM context has, as pointed out above, only limited power to evaluate the appropriateness of the risk measure for our research context.

5.1.3 Idiosyncratic Risk

The level of idiosyncratic risk, which accounts for approximately 80% of the total risk (see section 5.1.1) is very similar for both the estimates based on OLS and Kalman Filter beta. This is due to the fact that unsystematic risk essentially presents the remainder of the total risk that is not systematic risk. The amount of systematic risk is determined by the beta. Because (1) the fraction of systematic risk is comparatively small and (2) the two beta estimates are not differing immensely from each other, the remainder (unsystematic risk) does not differ significantly between the two systematic risk estimates which the unsystematic risk calculation ultimately depends on.

[16] noteworthy is the instant incorporation of rising systematic risk in Q2 2016 which is presumably due the market turbulences caused by the Brexit referendum which only occurred a week before the end of the quarter

[17] A summary table of the mean absolute errors can be found in appendix 10

The variance of the residuals shows considerable time-variance for both OLS and Kalman Filter based estimates and can, similarly to the plot of the overall variance, be described as a upside down V-shape. For both estimation methods, the subsamples do not move completely in parallel, and the level of idiosyncratic risk of the non-G-SIB portfolio exceeds that of the G-SIB portfolio, except for the period from Q3 2017 to Q3 2018, where G-SIBs exhibit higher unsystematic risk compared to non-G-SIBs. Over the entire observation period, however, the average value of idiosyncratic risk is still considerably higher for non-G-SIBs with 2.74 (Kalman Filter: 2.78) than for G-SIBs with 2.19 (Kalman Filter: 2.26). The average, therefore, is significantly below the maximum value, which is 4.03 (Kalman Filter: 4.09) for non-GSIBs and 3.09 (Kalman Filter: 3.13) for G-SIBs.

Figure 7: Idiosyncratic Risk (OLS Estimate)

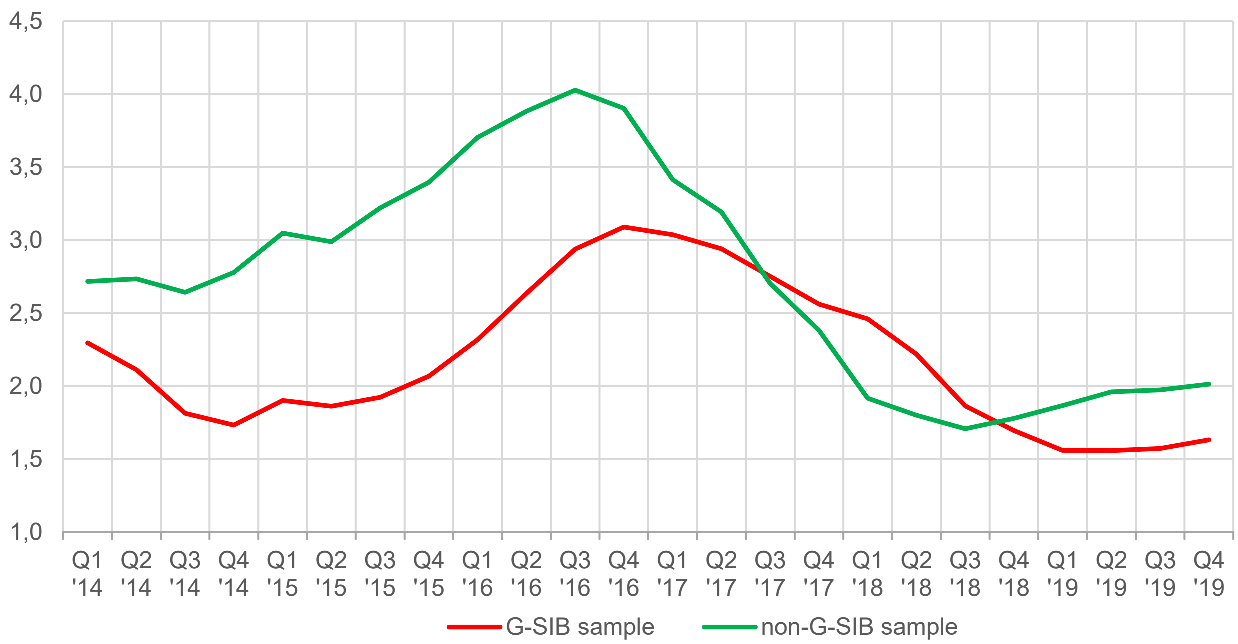
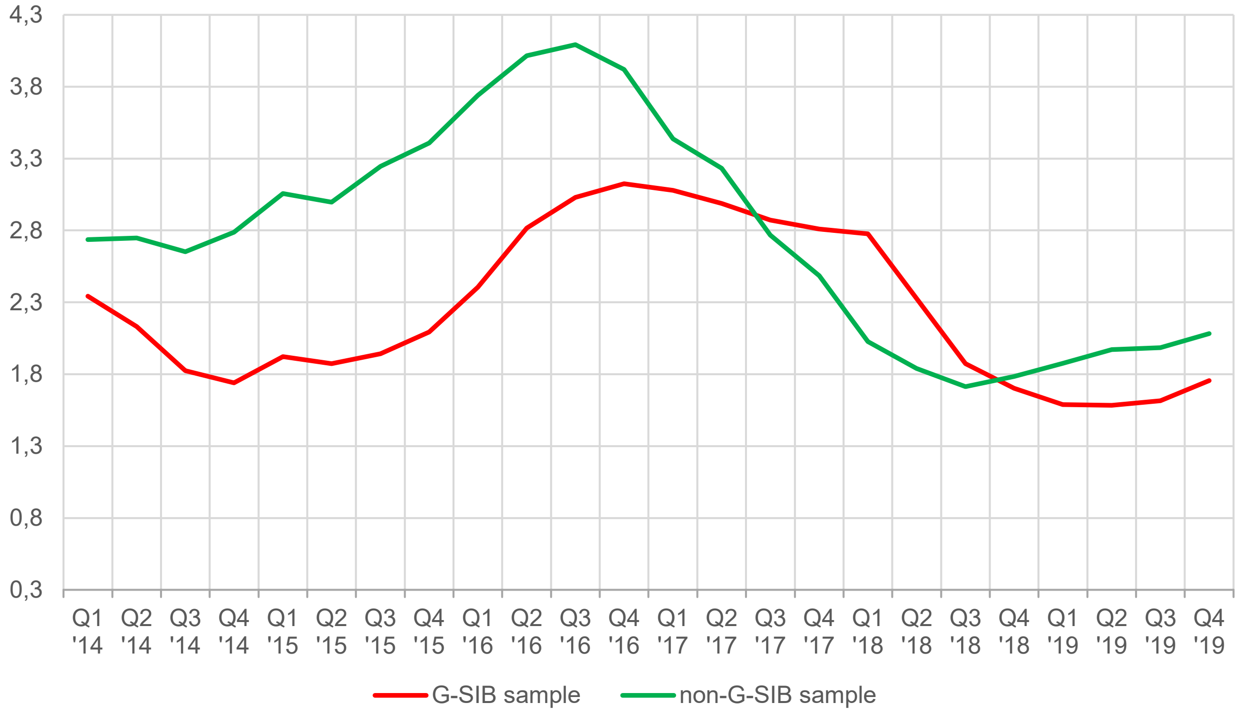


Figure 8: Idiosyncratic Risk (Kalman Filter Estimate)



Concluding remarks on homogeneity across banks

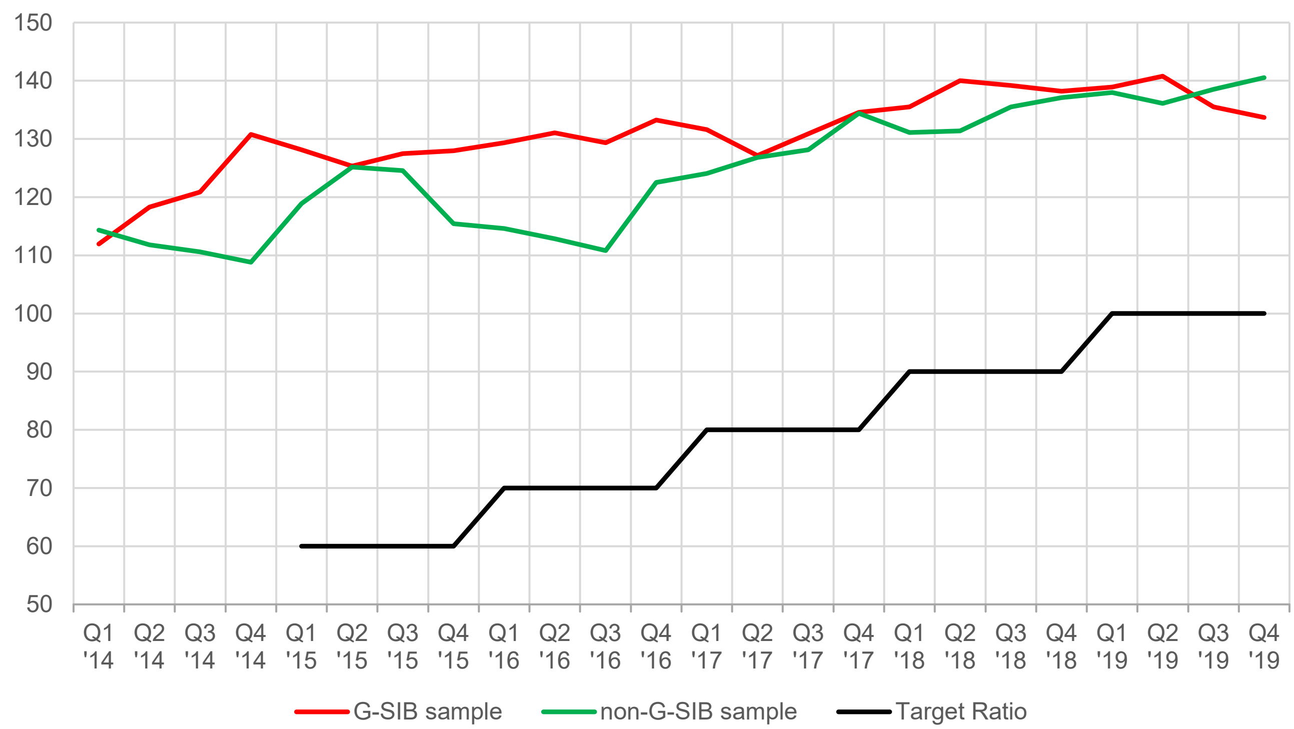
So far, only the aggregated average risk estimates for the two subsamples have been taken into consideration as they are the only ones relevant as inputs into the regression. However, it is highly noteworthy that the development of risk measures of the vast majority of banks in our sample has occurred very much in parallel to each other for both OLS as well as Kalman Filter estimation, though for the latter one to a lesser degree[18]. While the levels of systematic risk still differ considerably between banks, the parallel movement over time is an important finding since it proves the assumption of homogeneous movement (and therefore also reaction to potential influence factors) of risk within the subsamples that was made in section 4.5.3.

[18] Plots for the systematic risk estimates on a bank level can be found in the appendix

5.2 Analysis of Independent Variables

5.2.1 Liquidity Coverage Ratio

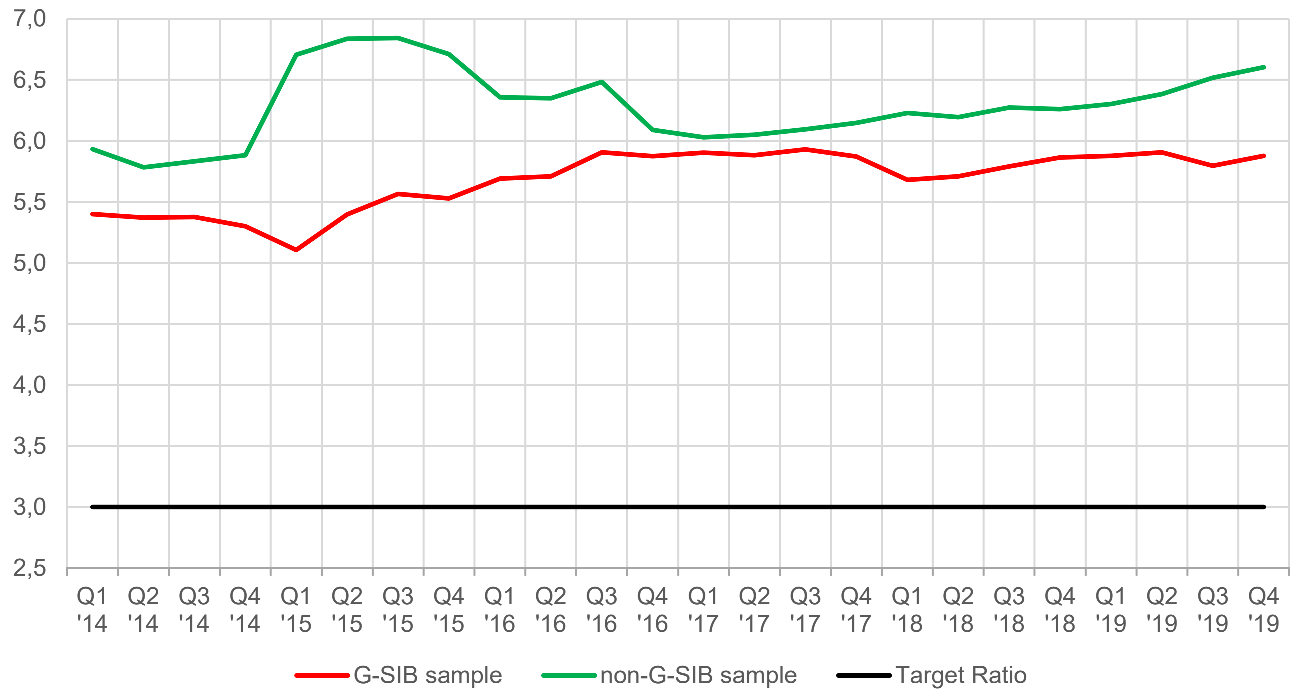
Figure 9: Liquidity Coverage Ratio (in %)



Most remarkably, both G-SIBs and non-GSIBs do not only exceed the required *Liquidity Coverage Ratio* before its implementation, which starts with a requirement of 60% in 2015, but also its final requirement of 100%, which was implemented in 2019. Despite exceeding the final requirement in the beginning of the observation period, the average *Liquidity Coverage Ratio* increases for both subsamples by approximately 25% points from 113% in Q1 2014 to 138% in Q4 2019. However, the trends moderate, yet significant trend slightly diminishes towards the end of the observation period. The *Liquidity Coverage Ratio* is slightly lower for non-GSIBs compared to G-SIBs for the majority of the observations.

5.2.2 Leverage Ratio

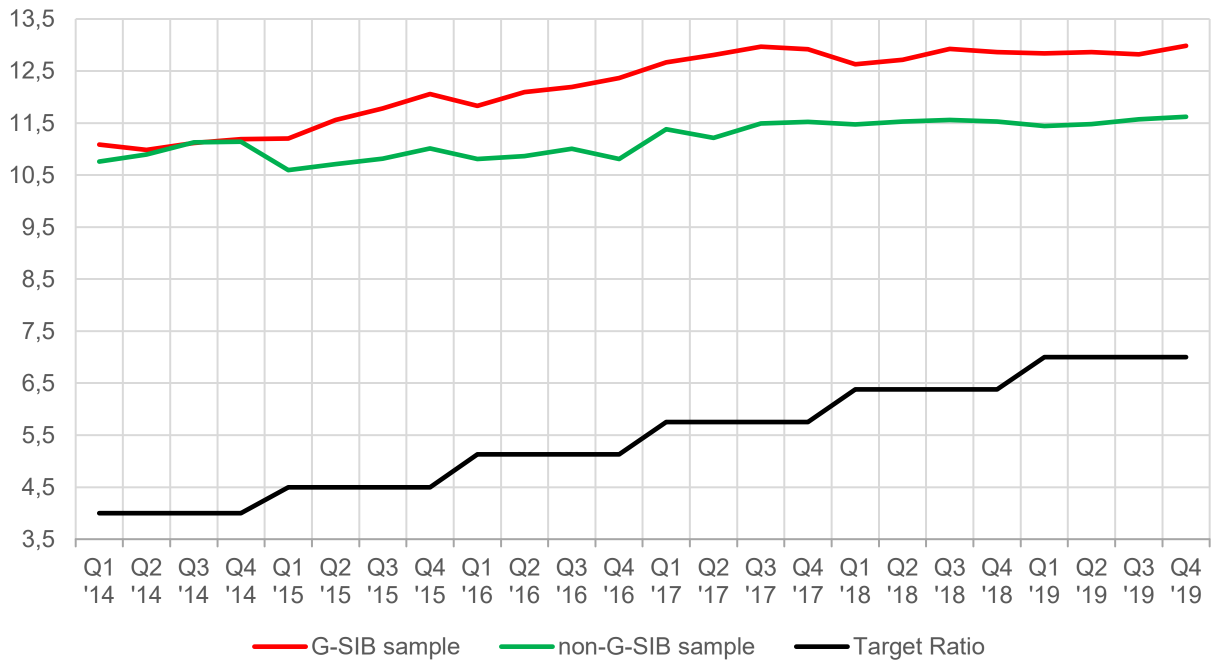
Figure 10: Leverage Ratio (in %)



The *Leverage Ratio* shows patterns similar to that of the development of the *Liquidity Coverage Ratio*: Despite exceeding the Basel III requirement of 3% already in the beginning by more than 2% points, the *Leverage Ratio* again exhibits a moderate, but noteworthy upward trend during the observation period. In contrast to the *Liquidity Coverage Ratio*, G-SIBs show a slightly lower *Leverage Ratio* of an average of 5.68% compared to an average of 6.29% for non-G-SIBs.

5.2.3 Capital Adequacy Ratio

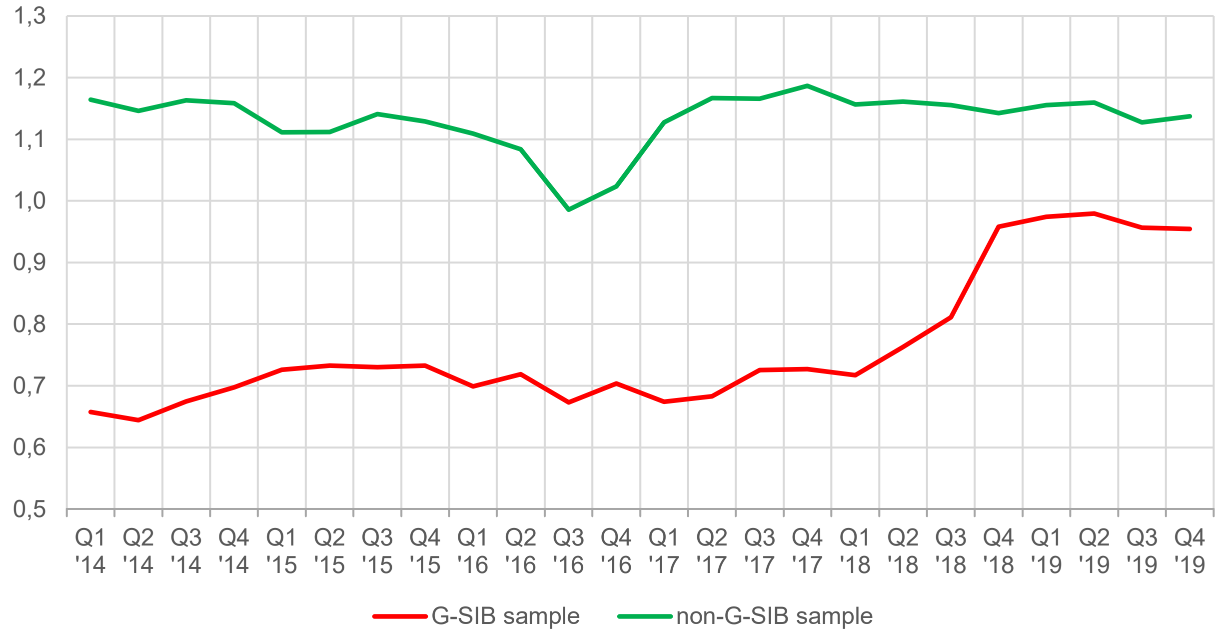
Figure 11: Capital Adequacy Ratio (in %)



The *Capital Adequacy Ratio* shows a very similar behavior when compared to the two other Basel III measures, yet it resembles the *Liquidity Coverage Ratio* more closely due to the fact that the ratio is lower for the non-G-SIB (average of 11.18%) than for the G-SIB sample (average of 12.23%). While the two subsamples have nearly the same level in 2014, the delta only emerges starting in Q1 2015. This can be explained by the fact that G-SIBs are required to hold additional equity capital depending on their allocation to a bucket (BCBS, 2020a). Similar to the two other ratios, both subsamples exhibit a moderate upward trend despite exceeding the final target ratio by far already in 2014.

5.2.4 Return on Assets

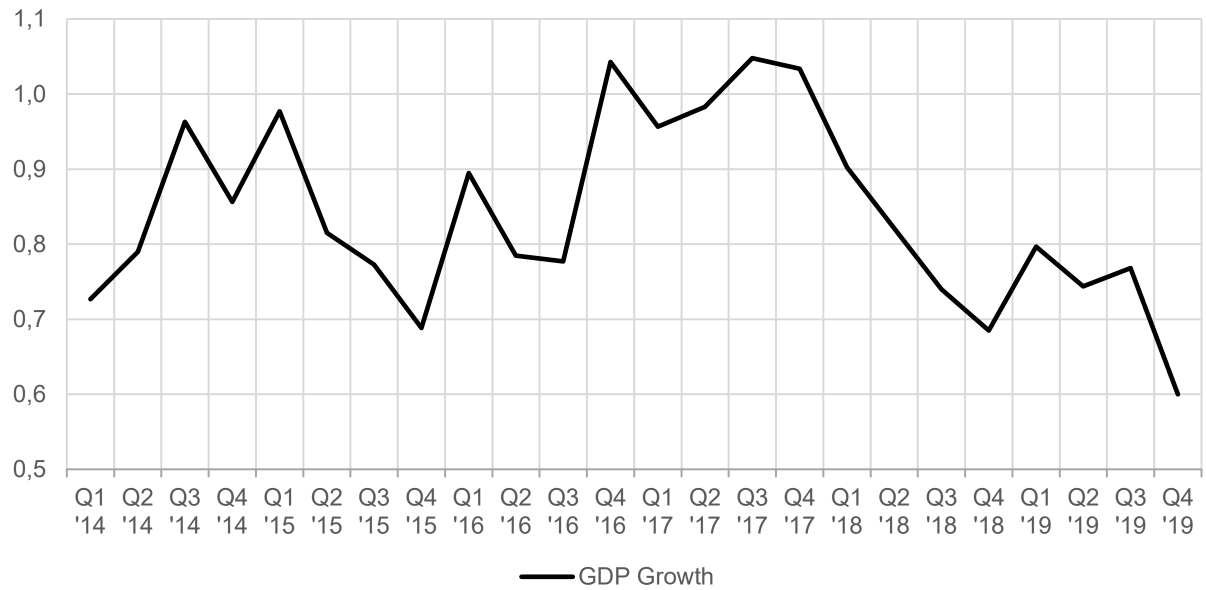
Figure 12: Return on Assets (in %)



The *Return on Assets* as a profitability ratio, and therefore as a potential factor to impact risk, shows a considerable difference between G-SIBs, which have an average return of 0.76% compared to non-G-SIBs, which have an average return of 1.13% over the entire observation period. Additionally, G-SIBs experience a clear upward spike in 2018 and then maintain the newly reached level of near 1%, whereas the non-G-SIBs exhibit an almost constant level throughout the observation period with the exception of a downward dent in Q3 2016 which is likely due to the market turmoil caused by the Brexit.

5.2.5 GDP Growth

Figure 13: Quarter on Quarter GDP Growth (in %)



The quarter on quarter GDP growth presents a macroeconomic variable and is, therefore, not specific to the two subsamples. Over the observation period, there is no clear trend in GDP growth observable, yet there is considerable time-variance around the mean of 0.84% - with a maximum of 1.05% reached in Q3 2017 and a minimum of 0.60% in Q4 2019. Moreover, the GDP always exhibits growth that is substantially above 0%, indicating that there is no recession during the entire observation period.

5.3 Regression Results

The following section will detail the results of our regression of the systematic and idiosyncratic risk estimates on the Basel III liquidity and capital requirements as well as the relevant control variables. Since we are working with time-series that exhibit a unit root, the necessity of differencing arises in order to make all time series that are being used in the regression stationary. Few researchers that employ a similar approach of explaining time-variance of risk in the banking sector, perform regressions of time series data with the assumptions pertaining to cross-sectional data. One example for scholars who do not consider unobserved heterogeneity across time and use a pooled regression and observations are viewed as independent are Biase and D'apolito (2012). For completeness' sake, the undifferenced regression results can be found in Appendix 11 & 12, but should not be interpreted without concern since the occurrence of spurious results (as discussed in section 4.6) cannot be ruled out. For this reason, the remaining sections of this chapter as well as chapter 6 deal exclusively with the results obtained from differenced time-series data.

5.3.1 Systematic Risk

Liquidity Coverage Ratio

For the *Liquidity Coverage Ratio*, no clear relationship with levels of beta is identifiable. This pertains to all three major robustness dimensions (lag, risk estimation technique and subsample). Apart from the base specification (no lag) for the OLS beta for the G-SIB portfolio, which indicates a negative relationship at the 95% confidence level and is in line with the assumed negative relationship, all other model specifications[19] do not exhibit significance and have varying signs. *Hence, the null hypothesis, stating that the Liquidity Coverage Ratio has no effect on systematic risk, cannot be rejected by the results.*

Leverage Ratio

Contrary to the hypothesis and regulator's intention that the *Leverage Ratio* is supposed to have a negative impact on systematic risk, our analysis contradicts this assumption by producing two significant results (both for the Kalman Filter beta with lag 2) for the G-SIB portfolio (at the 95% level) and for the non-G-SIB portfolio (at the 90% level). All other models show varying signs at insignificant levels. Hence, we conclude a slight contradiction with the assumed negative relationship, which will be further investigated in the discussion part. *Yet, the null hypothesis, stating that the Leverage Ratio has no effect on systematic risk, cannot be rejected by the results.*

Capital Adequacy Ratio

For the *Capital Adequacy Ratio*, we find varying results. The OLS model at lag 0 shows a positive relationship with beta for the G-SIB sample, whereas the OLS model at lag 2 indicates a negative relationship for the non-G-SIB sample (both at the 90% significance level). All other results have varying signs without clear patterns. *Therefore, the null hypothesis, stating that Capital Adequacy Ratio has no effect on systematic risk, cannot be rejected by the results.*

[19] From here onwards mostly referred to as models

Return on Assets

Return on Assets are not a great predictor of systematic risk either, as signs are varying and none of the coefficients are significant.

GDP Growth

GDP Growth is the indicator for systematic risk with the highest number of significant coefficients. Three models show a significant (one at the 90% and two at the 95% level) negative relationship to systematic risk. Overall, 10 out of the 12 models exhibit a negative sign.

Table 3: Regression Results - Systematic Risk

	G-SIBs						non-G-SIBs					
	OLS Beta			Kalman Filter Beta			OLS Beta			Kalman Filter Beta		
Lag	no lag	lag (t-1)	lag (t-2)	no lag	lag (t-1)	lag (t-2)	no lag	lag (t-1)	lag (t-2)	no lag	lag (t-1)	lag (t-2)
Variables												
Liquidity Coverage Ratio	-0.011**	-0.006	-0.003	0.009	0.003	0.005	-0.001	0.0004	0.002	0.0005	-0.0005	-0.002
	(0.005)	(0.005)	(0.006)	(0.007)	(0.008)	(0.006)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
Leverage Ratio	-0.003	0.013	0.012	-0.136	-0.033	0.210**	0.003	0.021	-0.020	0.008	0.025	0.115*
	(0.075)	(0.081)	(0.088)	(0.103)	(0.117)	(0.095)	(0.055)	(0.053)	(0.047)	(0.065)	(0.071)	(0.063)
Capital Adequacy Ratio	0.085*	0.077	0.019	-0.075	-0.065	-0.024	-0.042	-0.024	-0.056*	-0.032	0.004	0.041
	(0.045)	(0.050)	(0.054)	(0.062)	(0.072)	(0.058)	(0.032)	(0.032)	(0.029)	(0.038)	(0.042)	(0.039)
Return on Assets	-0.356	0.150	0.389	-0.579	0.297	-0.352	0.079	0.144	0.093	0.361	-0.117	0.217
	(0.473)	(0.508)	(0.548)	(0.653)	(0.734)	(0.592)	(0.306)	(0.298)	(0.268)	(0.363)	(0.396)	(0.356)
GDP Growth	0.005	0.085	-0.029	-0.462**	-0.354	-0.565**	-0.092	-0.081	-0.191*	-0.204	-0.091	-0.117
	(0.150)	(0.172)	(0.185)	(0.207)	(0.249)	(0.200)	(0.104)	(0.108)	(0.096)	(0.123)	(0.144)	(0.127)
Constant	-0.003	-0.018	-0.017	0.007	-0.0001	0.003	-0.004	-0.009	-0.010	-0.001	0.001	0.002
	(0.017)	(0.018)	(0.020)	(0.023)	(0.026)	(0.022)	(0.010)	(0.010)	(0.009)	(0.012)	(0.013)	(0.011)
Test statistics												
Observations	24	23	22	24	23	22	24	23	22	24	23	22
AIC	-46.5	-41.2	-36.3	-31.1	-24.3	-32.9	-72.9	-71	-73.1	-64.8	-57.9	-60.6
R2	0.385	0.139	0.046	0.295	0.162	0.494	0.170	0.074	0.268	0.177	0.076	0.317
Adjusted R2	0.214	-0.114	-0.253	0.100	-0.085	0.336	-0.060	-0.198	0.039	-0.052	-0.196	0.103
Residual Std. Error	0.079	0.085	0.09	0.109	0.123	0.098	0.046	0.044	0.039	0.054	0.059	0.052
F Statistic	2.251*	0.551	0.153	1.51	0.655	3.128**	0.738	0.272	1.171	0.774	0.28	1.483

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

5.3.2 Idiosyncratic Risk

Liquidity Coverage Ratio

As for systematic risk, the *Liquidity Coverage Ratio* does not seem to have a clear impact on unsystematic risk. This pertains to all three major robustness dimensions (lag, risk estimation technique and subsample). Apart from the for the OLS beta for the G-SIB portfolio for lag (t-1), which indicates a negative relationship at the 90% confidence level and is in line with the assumed negative relationship, all other model specifications do not exhibit significance and have varying signs. *Hence, the null hypothesis, stating that the Liquidity Coverage Ratio has no effect on unsystematic risk, cannot be rejected by the results.*

Leverage Ratio

With regards to the *Leverage Ratio*, all 12 model specifications exhibit a positive sign, indicating that the *Leverage Ratio* is, contrary to our assumption, positively correlated with unsystematic risk. Yet, only one model – the estimation via the Kalman Filter at lag (t-2) for the G-SIB sample – shows significance at the 90% level. While these findings signify a potential contradiction with the assumed negative relationship, which will be further investigated in the discussion part, *we cannot reject the null hypothesis, stating that the Leverage Ratio has no effect on unsystematic risk.*

Capital Adequacy Ratio

For the *Capital Adequacy Ratio*, we find that 11 out of 12 models confirm the assumed negative relationship with idiosyncratic risk. However, none of the coefficients proved to be significant. *Therefore, the null hypothesis, stating that Capital Adequacy Ratio has no effect on unsystematic risk, cannot be rejected by the results.*

Return on Assets

As opposed to the effect on systematic risk, *Return on Assets* shows a predominantly positive relationship with idiosyncratic risk at lag (t-1) and lag (t-2) across the two portfolios and risk estimates. Out of these eight models, two are significant – both for lag (t-2) for both risk estimates of the G-SIB and non-G-SIB portfolio, respectively. The remaining four model specifications with no lag exhibit a negative, albeit insignificant, coefficient.

GDP Growth

As with systematic risk, *GDP Growth* was found to have an overwhelmingly negative relationship, with all 12 models showing a negative sign, however just one (OLS for non-G-SIBs at lag (t-1)) was found to be significant at the 90% level.

5.4 Model performance

The following subsection provides a brief overview on the performance of the models used based on the measures of fit explained in section 3.3.3. As we put forward in section 3.3.1, we decided to include the same set of variables for every model specification, which makes it easier to compare the various model specifications.

According to the F-statistic, the null hypothesis, which states that the fit of the intercept-only model and the specified model are the same, can be rejected for only two out of the 12 models used for the investigation of systematic risk. For unsystematic risk, the same amount of two models are significant. Unsurprisingly in this context, the average values of R^2 and adjusted R^2 is relatively low. For the models describing systematic risk, the average value is 0,217 and -0,014, respectively. For unsystematic risk, these values are slightly higher with 0,254 and 0,034. Even for the significant models, values of 0.494 (systematic risk) and 0.507 (unsystematic risk) for R^2 are not exceeded. These rather moderate values for the R^2 and adjusted R^2 are not inherently good or bad, they simply indicate that the chosen factors do – on average – only help to explain a comparatively small fraction of the variance in the dependent variable, i.e. risk measure. Furthermore, patterns in the measures of fit regarding model specifications are explored. Contrary to our assumptions, we could not prove that a lag of (t-1) or (t-2) generally increases the predictive power of the independent variables. With regards to the risk estimation method, the Kalman Filter models achieve considerably higher predictive power in terms of R^2 and adjusted R^2 for systematic risk compared to the OLS models – 0.254 vs. 0.180 for R^2 and 0.034 vs -0.062 for adjusted R^2. Yet, for the idiosyncratic risk estimates, the OLS models show higher predictive power (0.285 vs 0.223 for R^2 and 0.075 vs -0.006 for adjusted R^2). Based on the assumption that the Kalman Filter estimates present a more accurate representation of risk, this would imply that more weight should be put on the models based on the Kalman Filter and their respective measures of fit.

Table 4: Regression Results - Idiosyncratic Risk

	G-SIBs						***non-G-SIBs***					
	OLS estimate			Kalman Filter estimate			OLS estimate			Kalman Filter estimate		
Lag	no lag	lag (t-1)	lag (t-2)	no lag	lag (t-1)	lag (t-2)	no lag	lag (t-1)	lag (t-2)	no lag	lag (t-1)	lag (t-2)
Variables												
Liquidity Coverage Ratio	0.008	0.013	-0.003	0.001	0.006	-0.007	-0.003	-0.017*	0.007	-0.003	-0.015	0.005
	(0.009)	(0.009)	(0.008)	(0.012)	(0.012)	(0.010)	(0.010)	-0.009	-0.012	-0.01	-0.009	-0.012
Leverage Ratio	0.190	0.050	0.061	0.210	0.023	0.100	0.130	0.315*	0.175	0.15	0.285	0.24
	(0.136)	(0.142)	(0.124)	(0.176)	(0.182)	(0.157)	(0.213)	-0.18	-0.249	-0.223	-0.195	-0.247
Capital Adequacy Ratio	-0.077	-0.099	-0.102	-0.027	-0.054	-0.071	-0.059	0.141	-0.032	-0.066	0.14	-0.027
	(0.082)	(0.087)	(0.077)	(0.105)	(0.112)	(0.097)	(0.125)	-0.107	-0.153	-0.131	-0.116	-0.152
Return on Assets	-0.876	0.095	1.898**	-0.326	0.764	2.065*	-1.081	1.438	0.878	-0.589	1.516	1.172
	(0.865)	(0.893)	(0.776)	(1.117)	(1.146)	(0.983)	(1.184)	-1.005	-1.412	-1.239	-1.089	-1.405
GDP Growth	-0.327	-0.268	-0.035	-0.183	-0.133	-0.242	-0.506	-0.702*	-0.159	-0.537	-0.661	-0.259
	(0.274)	(0.303)	(0.261)	(0.354)	(0.389)	(0.331)	(0.401)	-0.365	-0.503	-0.42	-0.396	-0.501
Constant	-0.001	-0.015	-0.019	-0.003	-0.016	-0.014	-0.008	0.01	-0.014	-0.008	0.012	-0.01
	(0.031)	(0.032)	(0.028)	(0.039)	(0.041)	(0.036)	(0.038)	-0.032	-0.045	-0.039	-0.035	-0.045
Test statistics												
Observations	24	23	22	24	23	22	24	23	22	24	23	22
AIC	-17.6	-15.3	-21	-5.3	-3.8	-10.6	-8	-15.1	0	-5.8	-11.3	-0.3
R2	0.229	0.206	0.378	0.102	0.101	0.328	0.272	0.507	0.118	0.223	0.435	0.148
Adjusted R2	0.014	-0.027	0.184	-0.147	-0.163	0.118	0.070	0.363	-0.157	0.007	0.268	-0.119
Residual Std. Error	0.145	0.149	0.128	0.187	0.191	0.162	0.177	0.15	0.206	0.185	0.162	0.205
F Statistic	1.067	0.883	1.947	0.41	0.382	1.56	1.347	3.502**	0.429	1.034	2.613*	0.555

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

6. Discussion

This chapter is structured as followed: First, we provide interpretations for the results of the regression analysis. In this part, we aim set our findings into a larger context by using concepts in the realm of finance and economics. Moreover, we point out the limitations of our thesis. Based on the first two sections, we derive implications for regulators as well as recommendations for future research.

6.1 Interpretations

Our research questions sought to answer how the capital and liquidity requirements from Basel III affected systematic and idiosyncratic risk levels for internationally active banks. In the literature review, we have established how various factors are impacting both systematic as well as idiosyncratic risk of companies in general and banks in particular. We also investigated the underlying logic of the Basel III regulations in this context and found that based on findings from existing research that establishes links between risk and similar accounting factors, the Basel III regulations are reasonable and likely to decrease risk. Moreover, our dataset clearly shows that the average values of the ratios from the banks in our two samples are moving in the intended, upward direction. However, our regression analysis can – in general - not confirm a strong relationship of risk and the Basel measures in the hypothesized negative direction and our models are only able to explain a fairly small fraction of the overall variation in risk measures. This finding raises questions as to why there is no significant relationship of the Basel factors and risk and, on top of that, whether the regulations are as effective as they are claimed to be. The following paragraphs, therefore, aims to put our findings into a larger context by drawing from various economic and financial theories and concepts which we deem relevant for the explanation of our findings.

First of all, it should be noted that we are using market-based measures of risk. This implies that both systematic and unsystematic risk measures are ultimately dependent on the market's (i.e. investor's) perception of risk (Bohachova, 2008). Hence, a good representation of the (fundamental) risk is only given in an efficient market. According to the strong form of market efficiency, all data, historic and current as well as public *and* private is reflected in the stock price (Malkiel & Fama, 1970). There is some consensus among scholars that the strong form of market efficiency is rather a theoretical construct. The degree of how much this strong form of market efficiency is impaired has been the subject of a vast amount of academic discourse, which shall not be the center of the discussion in this context. However, it is paramount to note that many regulations which are targeted at unifying accounting standards and increase disclosure of information are, to an important extent, aiming at reducing inefficiencies of the market in terms of information availability (Healy & Palepu, 2001; Linsley & Shrives, 2005). The lack of appropriate information can cause information asymmetries and, in turn, agency problems of various kinds. Hence, we will take a closer look at the relevance of disclosure mechanisms within the Basel III framework in the context of reducing information asymmetries and evaluate these subsequently.

The disclosure mechanisms are likely to be of paramount importance since Basel III is not legally binding but is intended to provide a general foundation for banking supervision (Alexander, 2019): All 45 member states of the Basel Committee have agreed to fully implement the standards and apply them to all internationally active banks in their jurisdiction (BCBS, 2020). The enforcement is carried out via national legislative action like the "Final US rule" and the "CRD IV" for the European Union. Consequently, there is no central sanctioning entity to ensure comprehensive and diligent implementation and it is each jurisdiction's own responsibility to make sure that banks are adhering to the required standards. This also applies for sanctioning activities and penalties that come into play when Basel III standards are violated. The relevance of sanctioning is likely not very high for our sample and observation period since we show that, on average, both G-SIBs and non-G-SIBs adhere to the minimum standards throughout the observation period. However, even in the case that banks do not adhere to the Basel requirements, there are theoretical arguments to be made why ex-post sanctions after regulatory violations might be ineffective: Estrella (2004) points out that ex-post penalties are hardly a practical solution when banks that are failing or struggling to make the proper ratios, are then penalized by fines from the regulators. Also, it is stated in the Basel Accords that in stress periods banks are allowed to miss specified thresholds without facing regulatory punishment. The BCBS (2015) acknowledges these arguments and proclaims that the improved market discipline and disclosure requirements are the main driver of compliant behavior, especially for large banks, like the ones encompassed in our sample. It is argued that the perception of market participants such as traders and rating agencies provides far more incentive to be compliant when banks are forced to disclose regulatory capital levels or are part of monitoring exercises (Weil et al., 2006), an argument which is also supported empirically by various scholars (e.g. Martinez Peria & Schmukler, 2001; Haq et al., 2013).

There are several factors which determine the effectiveness of the regulations in terms of reducing information asymmetries, and thereby, agency costs through excessive risk taking. First, the disclosed information must be useful for investors to get a better picture of the underlying risk of an asset (Anderson, 1981). The underlying rationale of the Basel III measures has extensively been dealt with in the literature review and can, based on existing research, generally be confirmed. Second, the frequency of disclosure as well as accessibility and comprehensibility of information is vital (Drake et al., 2016). The three investigated measures are principally published through quarterly reports, for which the BIS has set certain guidelines with the aim of pushing banks to presenting the information contained in these reports as comprehensible as possible (BCBS, 2020a). Yet, the degree of utility of these reports to investors is questionable. First, the guidelines are, again, not legally binding. Moreover, the guidelines merely present qualitative recommendations and are, in this sense, not comparable to the high standards for annual reports, such as the 10-K filing standard by the Securities and Exchange Commission. The lack of enforced disclosure standards severely limits the market participants' ability to effortlessly compare measures across banks. Certainly, this argument applies to a much stronger degree to non-institutional investors with limited resources to assess information than to institutional investors with their own equity research resources. However, the fact that the Basel III measures have only been implemented sequentially throughout the observation period and, on top of that, even for the most recent quarters, a significant amount of banks have still not reported (at least not in the frequency prescribed by the Basel committee), severely questions the argument that the Basel III regulations can be effective by laying out a common framework for the disclosure of certain capital and liquidity measures.

In summary, it is doubtful that backward-looking quarterly reports without comprehensive enforcement of common disclosure standards, which have not been published in the prescribed frequency by all banks in the sample can be an effective tool for decreasing information asymmetries and thereby reducing risk-taking behavior. The nature of reporting can also serve as an explanation why the assessment of the bank's risk was found to be lagged and in various cases, significance in reaction of market participants was only reflected in the risk measure one or even two quarters after the actual change in a given accounting measure has occurred.

It can certainly be argued that banks which are not following the suggested disclosure requirements might do so because they are not being compliant with the regulations or have less favorable ratios compared to their competitors. According to Akerlof (1970), this non-disclosure of information, therefore, also yields information to investors and has the potential to label non-disclosing banks as "lemons". Despite the argument of adverse selection being suitable also in our context, it is still arguable whether non- or infrequent disclosure of Basel III related information is, in fact, viewed by investors as hiding bad news, since it depends on how valuable investors perceive this information in general. The importance that investors assign to the Basel III framework might also depend on other factors as will be discussed in the next paragraph. A final argument that could undermine the effectiveness of the Basel measures is investor irrationality: Kahneman and Tversky (1979), founders of the prospect theory, argue that various cognitive and heuristic biases prevent decision makers from making rational decisions. Since the proposition of the prospect theory, a growing body of literature and even a new school of thought, often referred to as behavioral economics, has emerged and often confirms irrationality of investors in certain situations. The question whether information provided through the Basel III regulations mitigates or exacerbates investor irrationality is beyond the scope of this thesis; yet it might serve as another potential explanation as to why the Basel III regulations have not played out as theory predicts during the observation period.

Moreover, the economic environment plays an important role when interpreting our results. Banks can be characterized as performing intermediary functions between the financial sector and the real economy and are therefore affected by the business cycle conditions that affect the real economy (Bohachova, 2008). Previous literature already established an inverse relationship between the business cycle and systematic and idiosyncratic risk in banks as well as real sector companies (Bessler et al., 2015; Bohachova, 2008; Drobetz et al., 2016; Robichek & Cohn, 1973). While cyclical downturns are not necessarily causing higher risks, they might reveal hidden weaknesses in bank risk structure that were created in economically sound times like in the build-up to the 2008 financial crisis (Bohachova, 2008). The inverse relationship between economic growth and risk is supported to a certain extent by our regression results for quarterly GDP growth which show almost exclusively negative, albeit mostly insignificant coefficients for the idiosyncratic and systematic risk measures. GDP growth as seen in Figure 13 was constantly positive during the observation period. Yet, the prosperous economic conditions without sustained periods of stress over the observed time horizon might be an indicator for why our regression results fail to establish a more significant relationship between the Basel III metrics and systematic and idiosyncratic risk. One of the main goals of the Basel III regulation in this context is to ensure that the banking system will be able to support the real economy throughout the business cycle (BCBS, 2020). It could be argued that without the presence of a period of financial distress, the Basel requirements are not as relevant when determining risk but become crucial determinants in times of distress. This would go along the lines of Bohachova's (2008) argumentation regrading beta, which states that in economically good times banks move pro-cyclically with the market. When conditions deteriorate in the overall economy, the increased capital and liquidity ratios would moderate the sensitivity of banks to overall market movements effectively reducing betas. The implied higher importance of the Basel III measures in economically bad times compared to sound times also serve as a crucial explanation for why the overall explanatory power during the observation period is fairly low. Simultaneously, the higher capital and liquidity ratios would ensure a lower default probability of banks when borrowers from the real economy run into difficulties and fail to meet their obligations, significantly reducing idiosyncratic risk. However, our observation period does not allow to draw conclusions on what might happen in case of an economic downturn and if the Basel metrics would significantly decrease risk in that context.

Moreover, it was observed that the relevant capital and liquidity ratios were already substantially higher than the required levels over our observation period as can be seen in Figures 9, 10 and 11. It is reasonable to assume that because the required metrics exceeded the requirements from the start, any marginal change in the ratios did not make a significant impact on the risk measures. This, however, might also imply a relationship between the explanatory variables and the measures of risk that is conditional on the level of the explanatory variables themselves.

With regards to the Liquidity Coverage Ratio, no clear relationship could be identified, wherefore it is interesting to look at potential explanations for a positive relationship that some of the models showed – despite being insignificant. A high *Liquidity Coverage Ratio* generally ensures that banks are able to meet their short-term financial obligations without being in financial distress, so an adequate *Liquidity Coverage Ratio* should have a negative impact especially on idiosyncratic risk. However, it might be argued that too much liquidity might adversely affect bank risk. Banks might be perceived to hold too many liquid assets like cash and high-quality sovereign bonds that only yield a low return. This dynamic creates a paradox since, on the one hand, banks are reducing their profitability - by reducing loans that would not qualify as HQLA under the *Liquidity Coverage Ratio* requirements – and profitability has been shown to be inversely correlated to risk. On the other hand, banks are making sure that they do not run into short-term liquidity pressure by holding too few readily convertible assets. This dichotomy might be a reason why the *Liquidity Coverage Ratio* shows varying signs throughout the models.

An unanticipated aspect of the regression results includes the overwhelmingly positive signs of the *Leverage Ratio* coefficients, even though only a few of the coefficients are actually significant. However, the BCBS (2020b) shows that while capital levels increased, the exposure measure also increased but was offset by the increase in total Tier 1 Capital. This increase in the exposure measure might be the source of the positive impact of *Leverage Ratio* on the risk measures. It is suggested that banks might use the increased capital levels for further lending in order to maximize the utility of the additional capital (Janda & Kravtsov, 2019). Due to the increased levels of capital banks might be incentivized to engage in asset substitution since those riskier assets have the same effect on the *Leverage Ratio* than the safer assets (Hull, 2018). These riskier assets subsequently might not have a significant impact on the *Capital Adequacy Ratio* which is based on the RWA since especially large banks have some leeway with regards to how they calculate their RWA. This dynamic might also be framed as an agency conflict between the stock and bondholders of the banks, in which banks make riskier investments decisions ex-post that maximize the shareholder value at the potential expense of the debtholders interest payments in case of default, when debtholder were expecting less risky investments ex-ante (Jensen & Meckling, 1976). Thus, potential returns might be higher, but the stock becomes riskier as it would make the earnings stream of the banks more volatile, thereby increasing systematic risk and increasing the probability of default which would explain the positive relationship with idiosyncratic risk.

To summarize our interpretations of the research results, it becomes apparent that there are a multitude of conceptual considerations that might affect how the Basel III measures impact systematic and idiosyncratic risk. We argue that the lack of rigorous and rational enforcement, market efficiency and the prosperous economic environment might cause the lack of a more significant relationship between the variables. Subsequently, in direct connection to the Basel III metrics, we outline how specific dynamics inherent to the measures could be the root of unanticipated signs in the coefficients due to agency conflicts and hidden risk-taking.

6.2 Limitations

Due to various factors, the transferability of our results is limited to certain extents. Therefore, a brief overview of what can and cannot be concluded from our study will be outlined and serve as important considerations when discussing implications for regulators as well as recommendations for further research.

The first limitation pertains to the degree of data availability, which is presumably linked to the relative newness of the regulations. The lack of complete time series for all banks forced us to build averages across the two samples – a procedure that implicitly assumes homogenous development of the Basel III measures across banks, which may not be the case. This approach does not jeopardize the goal of investigating the impact of Basel III on risk in the banking sector in general, but it constrains the possibility to draw further conclusions whether the impact differs within the samples of banks and how the Basel III measures can explain this differing behavior of banks. The second important limitation arises from the observation period. The fact that no major economic shocks or recessions occurred during the observation horizon suggests that our results might have limited transferability to periods of serious economic turmoil, as the Basel III measures are specifically designed to make banks safer during such periods and could not show their "strengths" during the investigated time horizon. However, such a question formulation would likely also require a different type of analysis, e.g. an event-based study that compares different periods of economic turmoil and the associated development of risk in the banking sector in order to arrive at conclusions about the effectiveness of regulation – a type of analysis that would have been out of the scope of this thesis.

6.3 Implications

Basel III as a macroprudential framework has the objective to strengthen the resilience of the international banking ecosystem by providing a framework that combines capital and liquidity requirements for the individual banking institutions with a macroprudential layer that takes into account the interactions among banks and the feedback loop with the real economy in order to mitigate systemic risks. There are certain implications regulators might want to consider in the context of our research. We recommend an improved alignment with national legislators when it comes to disclosure requirements of the relevant capital and liquidity requirements. A comprehensive framework with regards to the reporting of ratios is of integral importance for assessing the effectiveness of the imposed metrics on market-based measures of risk as in the context of our study but also for specifically for market participants. Furthermore, it would establish a more credible accountability structure throughout the global financial system. This would go along with introducing a standard filing form for the relevant regulatory requirements that is easily comparable across jurisdictions.

Pertaining to the capital and liquidity ratios, our main recommendation aims at improving the interplay between the *Capital Adequacy Ratio* based on the RWA and the *Leverage Ratio* based on total assets. As we have discussed, banks might be incentivized to engage in asset substitution which is reflected in the positive coefficients for the *Leverage Ratio*. When banks use internal models to calculate RWA, they can easily influence their own estimates in order to reduce the amount of capital required to be put aside or alter the risk weights in favorable ways to veil riskier assets which are not captured by the *Leverage Ratio*, therefore meeting both capital standards.

Finally, we suggest that the BCBS consider further research into the underlying dynamics between risk and the Basel III measures. It has to be considered that our research mostly encompassed the phase-in period of the Basel III framework. The next few years will give potentially more meaningful insight into how the interplay between the ratios and market-based measures of risk behaves. Moreover, it would allow for a more heterogenous observation period that would also be characterized by more volatile economic environments that will put the Basel measures to the test.

6.4 Recommendations

To our knowledge, this study is the first to directly investigate the relationship between Basel III measures and risk in the banking sector over time without falling back on proxy factors. While we have managed to set up a rigorous research design, there are still some limitations which have been enumerated in section 6.3. Subsequently, we will present argue how these limitations present potentially fruitful departure points for future research.

First, fellow scholars could adopt a very similar methodology at a later point in time. Not only would this enable one to draw conclusions from a larger and, therefore, more robust dataset, but it would also allow for the possibility to gauge the impact of the Basel factors during periods of sustained stress. At the time of writing, the likelihood of a recession which by far exceeds that of the 2008 global financial crisis is deemed very high due to the recent spread of Covid-19 (International Monetary Fund, 2020). The occurrence of such a recession would increase the importance to evaluate how the Basel III measures contribute to the resilience of the banking sector in such a period. Second, if more banks were to report the measures as frequently as commanded by the Basel Committee, this would open up for the possibility to perform individual time series regressions instead of aggregated ones as was done in this study due to the lack of continuous time series of individual banks. Furthermore, as we have pointed out, there is a great level of sensitivity of the results to varying methodological choices. Looking at the individual banks as a more granular approach instead of taking a high-level perspective through aggregation of banks in portfolios might provide additional insights with regards to how individual banks are affected through the Basel regulation. Finally, it may be worthwhile to also include the qualitative aspects of the Base regulatory framework into the analysis. We have only considered the isolated effects of the quantifiable measures, but in combination with the effects of market discipline and supervision there is the possibility to reveal new insights.

7. Conclusion

The objective of this thesis was to gain an understanding of how the liquidity and capital requirements imposed by the Basel III regulations influence systematic and idiosyncratic risk levels of internationally active banks. Based on previous empirical research on the relationship between firm-specific accounting and measures and risk, we assumed a uniformly negative impact of the *Liquidity Coverage Ratio*, *Leverage Ratio* and *Capital Adequacy Ratio* on both systematic and idiosyncratic risk. However, we did not detect a significant impact of the Basel III measures over the observation period. We acknowledge that the concept of risk is a multifaceted and complex topic that warrants careful consideration when attempted to be examined in an empirical context like our thesis. Therefore, methodological integrity of our research has been central to the way we investigated the topic. We ensured valid results, by adding sufficient layers of robustness. First, this was performed by dividing our sample of internationally active banks into subsamples of G-SIBs and non-G-SIBs. Moreover, two different risk estimation methods, one of which allowed for the empirically confirmed time-varying nature of beta, were employed. Finally, we accounted for potential lagged effects of the explanatory variables by utilizing a distributed lag model.

A solid methodological foundation was of crucial importance, yet we also sought to provide new insights. To our knowledge, our thesis is the first empirical study that employs the actual Basel III measures in the context of regressing firm-specific variables against measures of systematic and idiosyncratic risk instead of using proxy variables. Consequently, we contributed to the body of literature in several ways. First, we show that higher capital and liquidity ratios do not necessarily imply lower risk levels and suggest that the macroeconomic context during the observation period, information asymmetry as well as particular dynamics between the individual Basel III measures are also important considerations in assessing the effectiveness of the Basel regulatory framework. Moreover, it should be pointed out that there are potentially other factors influencing bank risk that are out of the control of the regulators and beyond the scope of the Basel III regulatory framework. Finally, we want to emphasize the sensitivity of the results with regards to the methodological choices. The manner with which risk is calculated and input data is treated has a significant effect on how the results turn out.

At their core, the findings of this study underline the complex and often opaque nature of risk in the banking sector. Developing sound regulation that encompasses resolute risk-mitigation methods without impeding banks in their role as effective financial intermediaries in the economy has been a key challenge for policy makers ever since. Thus, as regulation develops, so do banks and the financial ecosystem. The fact that Basel III is going to be refined during the 2020s and Basel IV is already underway will ensure the continued relevance of this thesis for the foreseeable future, with hopes that it may provide guidance for researchers in years to come.

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Appendix

Appendix 1: Timeline of Basel III phase-in arrangements

Basel Committee on Banking Supervision
BANK FOR INTERNATIONAL SETTLEMENTS

Basel III phase-in arrangements
(All dates are as of 1 January)

	Phases	2013	2014	2015	2016	2017	2018	2019
Capital	Leverage Ratio	Parallel run 1 Jan 2013 – 1 Jan 2017 Disclosure starts 1 Jan 2015					Migration to Pillar 1	
	Minimum Common Equity Capital Ratio	3.5%	4.0%	4.5%				**4.5%**
	Capital Conservation Buffer				0.625%	1.25%	1.875%	**2.5%**
	Minimum common equity plus capital conservation buffer	3.5%	4.0%	4.5%	5.125%	5.75%	6.375%	**7.0%**
	Phase-in of deductions from CET1*		20%	40%	60%	80%	100%	**100%**
	Minimum Tier 1 Capital	4.5%	5.5%	6.0%				**6.0%**
	Minimum Total Capital	8.0%						**8.0%**
	Minimum Total Capital plus conservation buffer	8.0%			8.625%	9.25%	9.875%	**10.5%**
	Capital instruments that no longer qualify as non-core Tier 1 capital or Tier 2 capital		Phased out over 10 year horizon beginning 2013					
Liquidity	Liquidity coverage ratio – minimum requirement			60%	70%	80%	90%	**100%**
	Net stable funding ratio						Introduce minimum standard	

* Including amounts exceeding the limit for deferred tax assets (DTAs), mortgage servicing rights (MSRs) and financials.
- - transition periods

Appendix 2: Liquidity Coverage Ratio Components

Item	Factor
Stock of HQLA	
A. Level 1 assets:	
• Coins and bank notes • Qualifying marketable securities from sovereigns, central banks, PSEs, and multilateral development banks • Qualifying central bank reserves • Domestic sovereign or central bank debt for non-0% risk-weighted sovereigns	100%
B. Level 2 assets (maximum of 40% of HQLA):	
Level 2A assets	
• Sovereign, central bank, multilateral development banks, and PSE assets qualifying for 20% risk weighting • Qualifying corporate debt securities rated AA- or higher • Qualifying covered bonds rated AA- or higher	85%
Level 2B assets (maximum of 15% of HQLA)	
• Qualifying RMBS • Qualifying corporate debt securities rated between A+ and BBB- • Qualifying common equity shares	75% 50% 50%
Total value of stock of HQLA	

Cash Outflows	
A. Retail deposits:	
Demand deposits and term deposits (less than 30 days maturity) • Stable deposits (deposit insurance scheme meets additional criteria) • Stable deposits • Less stable retail deposits	 3% 5% 10%
Term deposits with residual maturity greater than 30 days	0%
B. Unsecured wholesale funding:	
Demand and term deposits (less than 30 days maturity) provided by small business customers: • Stable deposits • Less stable deposits	 5% 10%
Operational deposits generated by clearing, custody and cash management activities • Portion covered by deposit insurance	25% 5%
Cooperative banks in an institutional network (qualifying deposits with the centralised institution)	25%
Non-financial corporates, sovereigns, central banks, multilateral development banks, and PSEs • If the entire amount fully covered by deposit insurance scheme	40% 20%
Other legal entity customers	100%
C. Secured funding:	
• Secured funding transactions with a central bank counterparty or backed by Level 1 assets with any counterparty. • Secured funding transactions backed by Level 2A assets, with any counterparty • Secured funding transactions backed by non-Level 1 or non-Level 2A assets, with domestic sovereigns, multilateral development banks, or domestic PSEs as a counterparty • Backed by RMBS eligible for inclusion in Level 2B • Backed by other Level 2B assets • All other secured funding transactions	0% 15% 25% 25% 50% 100%
D. Additional requirements:	
Liquidity needs (eg collateral calls) related to financing transactions, derivatives and other contracts	3 notch downgrade
Market valuation changes on derivatives transactions (largest absolute net 30-day collateral flows realised during the preceding 24 months)	Look back approach
Valuation changes on non-Level 1 posted collateral securing derivatives	20%
Excess collateral held by a bank related to derivative transactions that could contractually be called at any time by its counterparty	100%
Liquidity needs related to collateral contractually due from the reporting bank on derivatives transactions	100%

Increased liquidity needs related to derivative transactions that allow collateral substitution to non-HQLA assets	100%
ABCP, SIVs, conduits, SPVs, etc:	
• Liabilities from maturing ABCP, SIVs, SPVs, etc (applied to maturing amounts and returnable assets)	100%
• Asset Backed Securities (including covered bonds) applied to maturing amounts.	100%
Currently undrawn committed credit and liquidity facilities provided to:	
• retail and small business clients	5%
• non-financial corporates, sovereigns and central banks, multilateral development banks, and PSEs	10% for credit 30% for liquidity
• banks subject to prudential supervision	40%
• other financial institutions (include securities firms, insurance companies)	40% for credit 100% for liquidity
• other legal entity customers, credit and liquidity facilities	100%
Other contingent funding liabilities (such as guarantees, letters of credit, revocable credit and liquidity facilities, etc) • Trade finance • Customer short positions covered by other customers' collateral	National discretion 0-5% 50%
Any additional contractual outflows	100%
Net derivative cash outflows	100%
Any other contractual cash outflows	100%
Total cash outflows	

Cash Inflows	
Maturing secured lending transactions backed by the following collateral:	
Level 1 assets	0%
Level 2A assets	15%
Level 2B assets • Eligible RMBS • Other assets	 25% 50%
Margin lending backed by all other collateral	50%
All other assets	100%
Credit or liquidity facilities provided to the reporting bank	0%
Operational deposits held at other financial institutions (include deposits held at centralised institution of network of co-operative banks)	0%
Other inflows by counterparty: • Amounts to be received from retail counterparties • Amounts to be received from non-financial wholesale counterparties, from transactions other than those listed in above inflow categories • Amounts to be received from financial institutions and central banks, from transactions other than those listed in above inflow categories.	 50% 50% 100%
Net derivative cash inflows	100%
Other contractual cash inflows	National discretion
Total cash inflows	
Total net cash outflows = Total cash outflows minus min [total cash inflows, 75% of gross outflows]	
LCR = Stock of HQLA / Total net cash outflows	

Appendix 3: Overview of Input Variables[20]

Ticker	Variable
P	Adjusted Closing Price (Equities)
MSPI	Price Index (MSCI)
IR	Middle Rate (T-Bills)
WC18609A	Basel III Liquidity Coverage Ratio
WC18607A	Basel III Leverage Ratio
WC18604A	Basel III Capital Adequacy Ratio
WC08326A	Return on Assets

[20] GDP Growth has been sourced from OECD (2020)

Appendix 4: Overview of Panel Composition[21]

Bank	2014	2015	2016	2017	2018	2019
Agricultural Bank of China	2	2	2	2	2	2
Australia and New Zealand Banking Group	1	1	1	1	1	1
Banco Bradesco	1	0	1	0	0	0
Banco do Brasil	1	1	1	1	0	0
Bank of America	2	2	2	2	2	2
Bank of Beijing	0	1	1	1	1	1
Bank of China	2	2	2	2	2	2
Bank of Montreal	1	1	1	1	1	1
Bank of Nova Scotia	1	1	1	1	1	1
Barclays	2	2	2	2	2	2
Banco Bilbao Vizcaya Argentaria	2	1	1	1	1	1
BNP Paribas	2	2	2	2	2	2
Bank of New York Mellon	2	2	2	2	2	2
Bank of Communications	1	1	1	1	1	1
Caixabank	1	1	1	1	1	1
Capital One	0	1	1	1	1	1
China Construction Bank	1	2	2	2	2	2
China Everbright Limited	1	1	1	1	1	1
China Guangfa Bank	1	1	1	1	1	1
China Minsheng Bank	1	1	1	1	1	1
CITIC Group	1	1	1	1	1	1
Citigroup	2	2	2	2	2	2

Bank	2014	2015	2016	2017	2018	2019
Commerzbank	1	1	1	1	1	1
Commonwealth Bank of Australia	1	1	1	1	1	1
Crédit Agricole	2	2	2	2	2	2
Credit Suisse	2	2	2	2	2	2
Danske Bank	1	1	1	1	1	1
DBS Bank	1	1	1	1	1	1
Deutsche Bank	2	2	2	2	2	2
Goldman Sachs	2	2	2	2	2	2
Hana Financial Group	1	1	1	1	1	1
Handelsbanken	1	0	0	1	0	0
HSBC	2	2	2	2	2	2
Industrial and Commercial Bank of China	2	2	2	2	2	2
Industrial Bank	1	1	1	1	1	1
ING Groep	2	2	2	2	2	2
Intesa Sanpaolo	1	1	1	1	1	1
Itaú Unibanco	1	1	1	1	1	1
JPMorgan Chase	2	2	2	2	2	2
Lloyds Banking Group	1	1	1	1	1	1
Mizuho Bank	2	2	2	2	2	2
Morgan Stanley	2	2	2	2	2	2
Mitsubishi UFJ Financial Group	2	2	2	2	2	2
National Australia Bank	1	1	1	1	1	1

[21] Explanation: 0 = not considered in the sample; 1 = considered in the non-G-SIB sample; 2 = considered in the G-SIB sample

Bank	2014	2015	2016	2017	2018	2019
Nordea	2	2	2	2	1	1
Ping An Bank	1	1	1	1	1	1
PNC Financial Services	1	1	1	1	1	1
Royal Bank of Scotland	1	1	1	2	2	2
Royal Bank of Canada	2	2	2	2	1	1
Banco Santander	2	2	2	2	2	2
Sberbank	1	1	1	1	1	1
Skandinaviska Enskilda Banken	1	1	0	0	0	0
Shanghai Pudong Development Bank	1	1	1	1	1	1
Shinhan Bank	1	1	1	1	1	1
Sumitomo Mitsui Financial Group	2	2	2	2	2	2
Sumitomo Mitsui Trust Holdings	1	1	1	1	1	1
Société Générale	2	2	2	2	2	2
Standard Chartered Bank	2	2	2	2	2	2
State Bank of India	1	1	1	1	1	1
State Street Corporation	2	2	2	2	2	2
Toronto-Dominion Bank	1	1	1	1	1	2
UBS	2	2	2	2	2	2
Unicredit	2	2	2	2	2	2
Wells Fargo	2	2	2	2	2	2
Westpac	1	1	1	1	1	1

Appendix 5: Data Availability

Number of observations for each of the regressors used (on complete portfolio level)

Period	Liquidity Coverage Ratio	Leverage Ratio	Capital Adequacy Ratio	Return on Assets
Q1 2014	7	9	28	28
Q2 2014	7	9	35	38
Q3 2014	6	8	31	28
Q4 2014	12	15	50	66
Q1 2015	7	17	35	28
Q2 2015	13	17	42	40
Q3 2015	6	13	34	29
Q4 2015	20	26	52	66
Q1 2016	17	24	45	30
Q2 2016	24	27	58	49
Q3 2016	16	19	40	32
Q4 2016	29	35	62	67
Q1 2017	25	32	51	29
Q2 2017	33	35	56	47
Q3 2017	27	28	44	30
Q4 2017	42	40	63	65
Q1 2018	28	31	43	27
Q2 2018	33	31	49	39
Q3 2018	22	24	36	27
Q4 2018	39	42	56	56
Q1 2019	28	35	43	29
Q2 2019	29	33	48	42
Q3 2019	22	25	35	30
Q4 2019	44	45	41	61
Average	**34%**	**40%**	**69%**	**63%**

Appendix 6: Stationarity Testing and Differencing[22]

Time Series	Time Series Properties					ADF Test Specifications		ADF Test Result	Degree of Differencing
	drift	trend	lag1	lag2	lag3	lag	type	p-value	d
Liquidity Coverage Ratio									
G-SIB	0.00	0.00	0.88	0.95	0.41	0	3	0.15	0.2
non-GSIB	0.00	0.00	0.79	0.62	0.69	0	3	0.34	0.7
Leverage Ratio									
G-SIB	0.00	0.00	0.81	0.54	0.89	0	3	0.65	0.7
non-GSIB	0.00	0.62	1.00	0.73	0.96	0	2	0.39	0.7
Capital Adaquecy Ratio									
G-SIB	0.00	0.00	0.82	0.66	0.64	0	3	0.88	0.5
non-GSIB	0.00	0.00	0.99	0.36	0.50	0	3	0.19	0.2
Return on Assets									
G-SIB	0.00	0.00	0.96	0.93	0.92	0	3	0.85	0.8
non-GSIB	0.00	0.02	0.90	0.81	0.62	0	3	0.51	0.9
GDP Growth									
G-SIB/non-G-SIB	0.00	0.39	0.53	0.76	0.54	0	2	0.25	0.3
Systematic Risk									
OLS									
G-SIB	0.00	0.04	0.83	0.69	0.79	0	3	0.93	1.2
non-GSIB	0.00	0.01	0.94	0.82	0.99	0	3	0.95	1.3
Kalman Filter									
G-SIB	0.00	0.09	0.71	0.93	0.95	0	2	0.55	1.0
non-GSIB	0.00	0.01	0.49	0.59	0.81	0	3	0.78	1.2
Unsystematic Risk									
OLS									
G-SIB	0.00	0.49	0.93	0.77	0.76	0	2	0.85	1.5
non-GSIB	0.00	0.00	0.91	0.88	0.76	0	3	0.82	1.5
Kalman Filter									
G-SIB	0.00	0.65	0.87	0.68	0.72	0	2	0.79	1.5
non-GSIB	0.00	0.01	0.90	0.89	0.77	0	3	0.82	1.5

[22] **Explanation**: Numbers in the first five columns indicate significance with which the null hypothesis (stating that the time series does *not* exhibit the respective property) can be rejected. For every time series a drift (intercept) was detected), wherefore all ADF tests are performed with the respective specification of having no lag. Furthermore, type 2 or 3 of the ADF test was chosen based on whether the time series shows a significant trend. The second column to the right indicates the p-value of the ADF test result based on the respective test specification. Finally, the right column shows the degree of differencing needed to make the time series stationary at the 5% significance level.

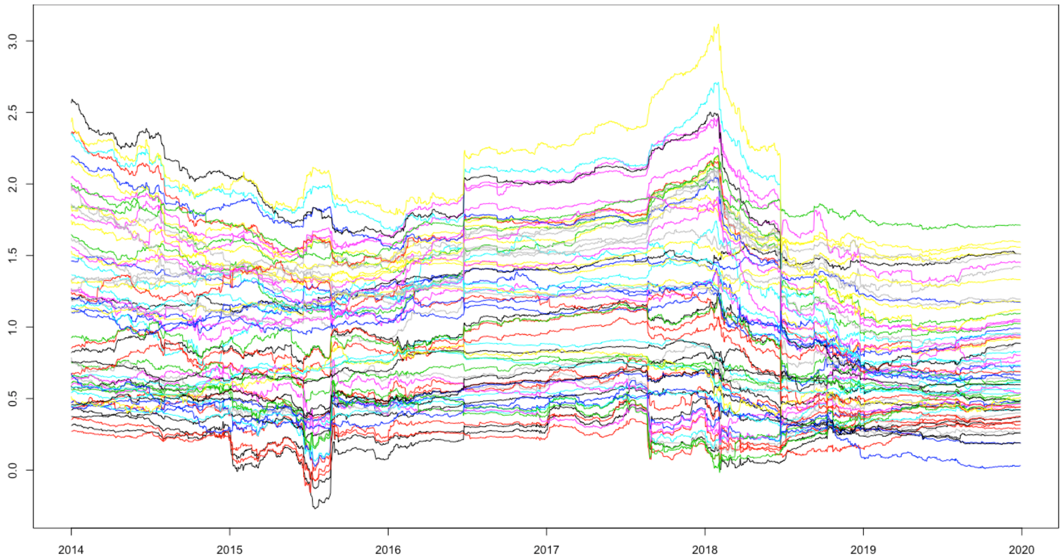
Appendix 7: Descriptive Statistics[23]

Time Series	Mean	St. Dev.	Min	Max
Liquidity Coverage Ratio (Average)	128.23	7.63	112.67	138.42
G-SIB	130.82	7.02	111.94	140.79
non-GSIB	124.67	10.43	108.81	140.54
Leverage Ratio (Average)	5.92	0.22	5.47	6.26
G-SIB	5.68	0.24	5.11	5.93
non-GSIB	6.29	0.31	5.78	6.84
Capital Adequacy Ratio (Average)	11.69	0.51	10.88	12.29
G-SIB	12.23	0.71	10.98	12.98
non-GSIB	11.18	0.34	10.6	11.62
Return on Assets (Average)	0.96	0.06	0.84	1.08
G-SIB	0.76	0.11	0.64	0.98
non-GSIB	1.13	0.05	0.99	1.19
GDP Growth (Average)	0.84	0.12	0.6	1.05
Systematic Risk				
OLS (Average)	0.99	0.16	0.74	1.22
G-SIB	1.23	0.2	0.91	1.53
non-GSIB	0.79	0.13	0.57	0.94
Kalman Filter (Average)	0.94	0.15	0.68	1.27
G-SIB	1.16	0.2	0.83	1.6
non-GSIB	0.75	0.11	0.55	0.99
Unsystematic Risk				
OLS (Average)	2.48	0.58	1.72	3.53
G-SIB	2.19	0.51	1.56	3.09
non-GSIB	2.74	0.75	1.71	4.03
Kalman Filter (Average)	2.54	0.59	1.74	3.6
G-SIB	2.26	0.54	1.58	3.13
non-GSIB	2.78	0.76	1.71	4.09
Total Risk (Average)	3.08	0.82	1.98	4.57
G-SIB	3.02	0.86	1.98	4.48
non-GSIB	3.13	0.9	1.84	4.75
Idiosyncratic Risk (Fraction)				
OLS (Average)	0.80	0.04	0.73	0.88
G-SIB	0.72	0.05	0.65	0.84
non-GSIB	0.86	0.03	0.81	0.92
Kalman Filter (Average)	0.81	0.04	0.75	0.89
G-SIB	0.74	0.05	0.66	0.84
non-GSIB	0.87	0.03	0.82	0.92

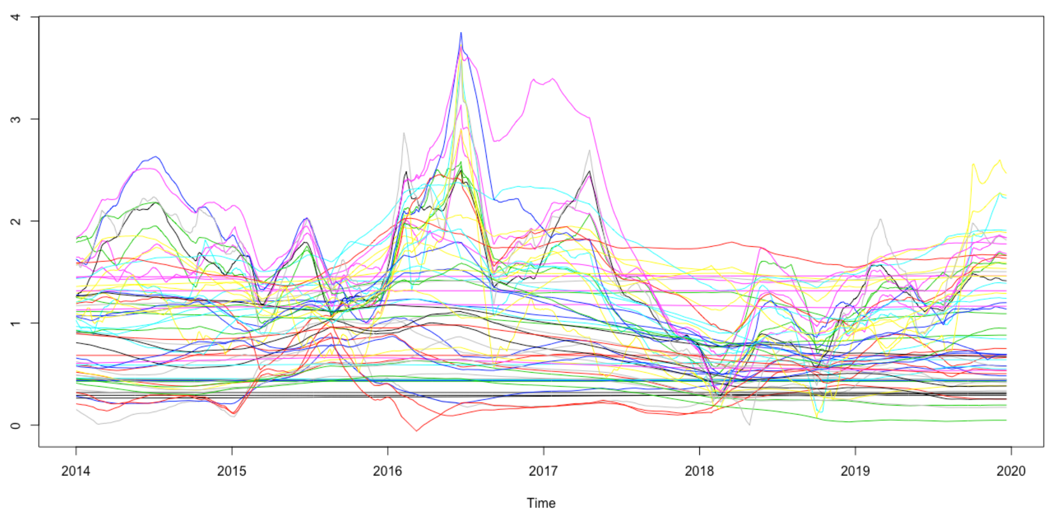
[23] All explanatory variables in %

Appendix 8: Daily Risk Estimates on Bank Level

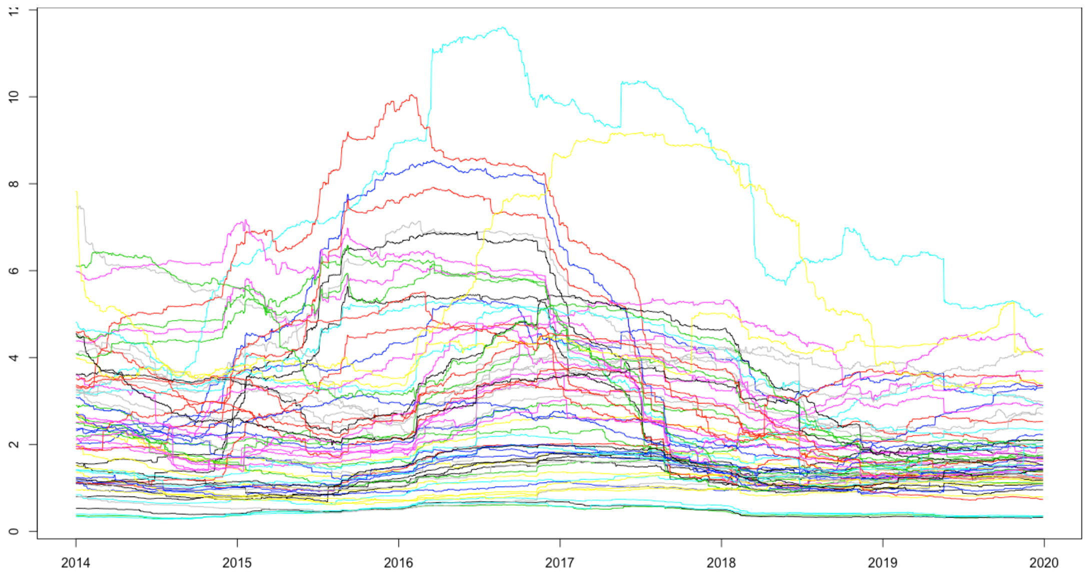
Systematic Risk – Daily OLS Betas



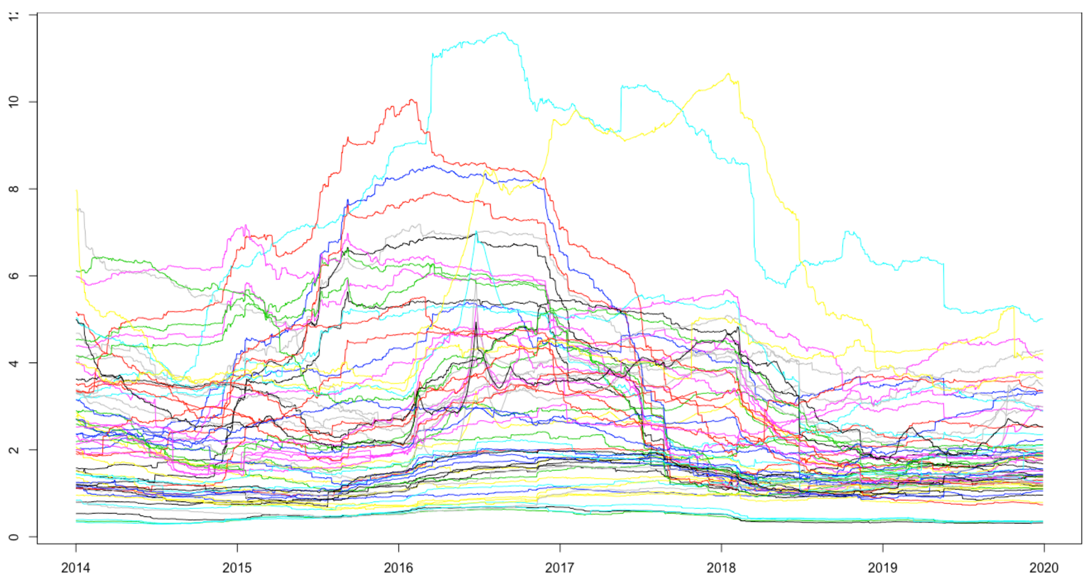
Systematic Risk – Smoothed Daily Kalman Filter Betas



Idiosyncratic Risk – Estimates based on OLS Beta

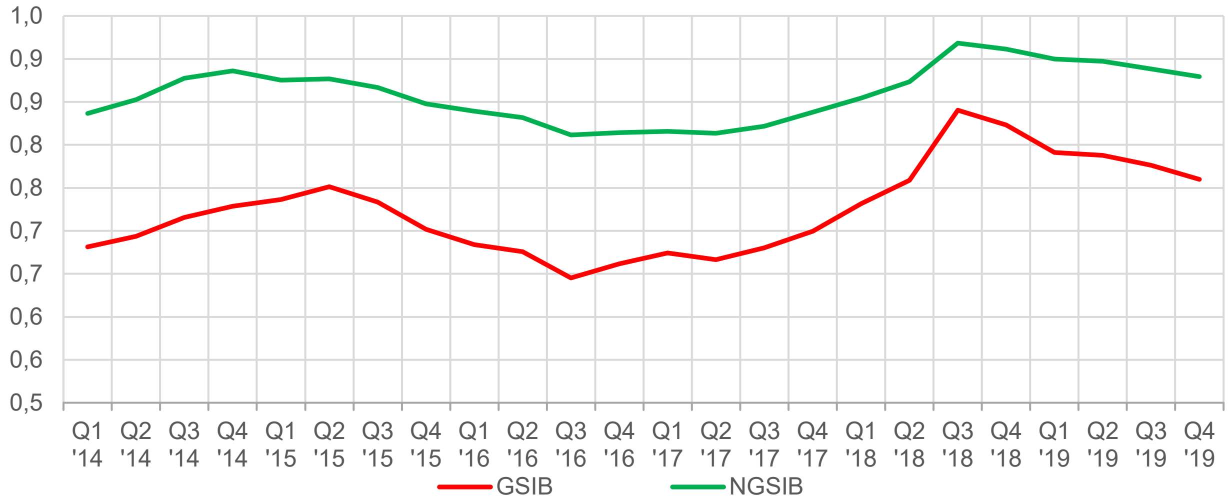


Idiosyncratic Risk – Estimates based on Kalman Filter Beta

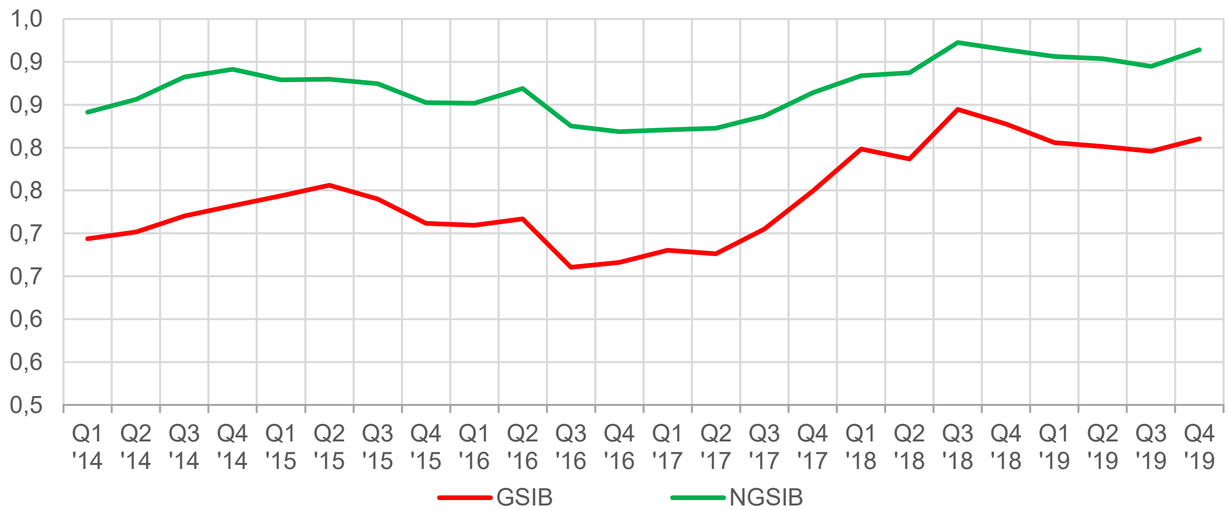


Appendix 9: Risk Composition

Fraction of idiosyncratic risk based on OLS Beta Estimates



Fraction of idiosyncratic risk based on Kalman Filter Beta Estimates



Appendix 10: Mean Absolute Error for Beta Estimates

	OLS Beta	Kalman Filter Beta
Daily	0 0105	0,0103
Quarterly	0,0847	0,0831

Appendix 11: Regression Results for Undifferenced Time Series (Systematic Risk)

	G-SIBs						***non-G-SIBs***					
	OLS Beta			Kalman Filter Beta			OLS Beta			Kalman Filter Beta		
Lag	no lag	lag (t-1)	lag (t-2)	no lag	lag (t-1)	lag (t-2)	no lag	lag (t-1)	lag (t-2)	no lag	lag (t-1)	lag (t-2)
Variables												
Liquidity C. Ratio	-0.007	-0.012***	-0.013**	0.002	0.006	0.012	-0.006*	-0.008**	-0.007*	-0.006**	-0.005**	-0.006***
	(0.005)	(0.004)	(0.006)	(0.009)	(0.010)	(0.010)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Leverage Ratio	-0.063	0.290*	0.595***	1.158***	1.012**	0.770**	-0.010	0.033	0.053	0.073	0.098	0.167***
	(0.183)	(0.146)	(0.201)	(0.322)	(0.368)	(0.361)	(0.082)	(0.085)	(0.089)	(0.065)	(0.059)	(0.053)
Capital A. Ratio	0.153*	0.068	-0.046	-0.410**	-0.443**	-0.405**	0.012	0.0002	-0.051	-0.051	-0.114	-0.104
	(0.082)	(0.067)	(0.092)	(0.144)	(0.168)	(0.166)	(0.097)	(0.101)	(0.107)	(0.078)	(0.071)	(0.064)
Return on Assets	-1.514***	-1.219***	-0.969**	-0.444	-0.196	-0.425	-0.348	-0.432	-0.605	-0.710*	-0.354	0.201
	(0.282)	(0.226)	(0.338)	(0.496)	(0.571)	(0.607)	(0.434)	(0.452)	(0.476)	(0.348)	(0.317)	(0.286)
GDP Growth	0.364*	0.492***	0.457**	-0.184	-0.329	-0.827**	0.582***	0.570***	0.424**	-0.033	-0.121	-0.228**
	(0.186)	(0.153)	(0.209)	(0.326)	(0.385)	(0.376)	(0.153)	(0.168)	(0.176)	(0.123)	(0.118)	(0.106)
Constant	1.470**	0.868*	0.452	-0.186	0.474	1.181	1.397	1.528	2.226	2.440**	2.567**	1.614*
	(0.548)	(0.438)	(0.600)	(0.963)	(1.106)	(1.081)	(1.283)	(1.333)	(1.404)	(1.028)	(0.935)	(0.843)
Test statistics												
Observations	24	23	22	24	23	22	24	23	22	24	23	22
AIC	-43.2	-51.8	-35.6	-16.1	-9.3	-9.8	-45.6	-41.7	-37.8	-56.2	-58.1	-60.2
R2	0.857	0.911	0.840	0.543	0.441	0.498	0.699	0.687	0.675	0.737	0.795	0.845
Adjusted R2	0.817	0.885	0.789	0.416	0.276	0.341	0.615	0.595	0.574	0.664	0.735	0.797
Res. Std. Error	0.085	0.067	0.092	0.149	0.17	0.165	0.081	0.084	0.088	0.065	0.059	0.053
F Statistic	21.551***	34.908***	16.740***	4.280***	2.679*	3.176**	8.363***	7.474***	6.658***	10.072***	13.193***	17.493***

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Appendix 12: Regression Results for Undifferenced Time Series (Idiosyncratic Risk)

	G-SIBs						***non-G-SIBs***					
	OLS estimate			Kalman Filter estimate			OLS estimate			Kalman Filter estimate		
Lag	no lag	lag (t-1)	lag (t-2)	no lag	lag (t-1)	lag (t-2)	no lag	lag (t-1)	lag (t-2)	no lag	lag (t-1)	lag (t-2)
Variables												
Liquidity C. Ratio	-0.004	0.013	0.026	-0.003	0.008	0.016	-0.036**	-0.052***	-0.049***	-0.037**	-0.053***	-0.051***
	(0.011)	(0.016)	(0.024)	(0.012)	(0.018)	(0.026)	(0.014)	(0.014)	(0.013)	(0.015)	(0.014)	(0.014)
Leverage Ratio	1.363***	2.023***	2.397**	1.251**	1.993***	2.340**	0.471	0.827**	1.028***	0.503	0.870**	1.094***
	(0.401)	(0.594)	(0.843)	(0.446)	(0.639)	(0.925)	(0.366)	(0.343)	(0.330)	(0.377)	(0.364)	(0.346)
Capital A. Ratio	0.079	-0.309	-0.642	0.186	-0.211	-0.501	-0.250	-0.159	-0.552	-0.184	-0.118	-0.502
	(0.179)	(0.271)	(0.387)	(0.199)	(0.292)	(0.425)	(0.433)	(0.408)	(0.395)	(0.447)	(0.433)	(0.415)
Return on Assets	-4.091***	-4.100***	-3.858**	-4.525***	-4.113***	-3.771**	-6.374***	-4.403**	-1.440	-6.490***	-4.327**	-1.312
	(0.617)	(0.921)	(1.419)	(0.687)	(0.992)	(1.556)	(1.943)	(1.830)	(1.767)	(2.004)	(1.938)	(1.855)
GDP Growth	0.485	0.214	0.038	0.455	0.503	0.229	1.696**	0.720	0.078	1.778**	0.896	0.200
	(0.406)	(0.621)	(0.879)	(0.452)	(0.669)	(0.964)	(0.685)	(0.681)	(0.654)	(0.707)	(0.721)	(0.686)
Constant	-3.326**	-4.299**	-4.121	-3.664**	-4.804**	-4.364	12.851**	10.136*	10.101*	12.186*	9.334	9.126
	(1.199)	(1.784)	(2.524)	(1.335)	(1.921)	(2.768)	(5.749)	(5.402)	(5.207)	(5.931)	(5.722)	(5.466)
Test statistics												
Observations	24	23	22	24	23	22	24	23	22	24	23	22
AIC	-5.6	12.7	27.6	-0.5	16.1	31.6	26.4	22.6	19.9	27.9	25.3	22
R2	0.894	0.783	0.593	0.886	0.781	0.573	0.817	0.848	0.869	0.809	0.832	0.859
Adjusted R2	0.865	0.719	0.466	0.854	0.716	0.439	0.767	0.803	0.829	0.756	0.783	0.814
Res. Std. Error	0.186	0.274	0.386	0.207	0.295	0.423	0.362	0.34	0.324	0.373	0.36	0.341
F Statistic	30.483***	12.245***	4.661***	27.937***	12.091***	4.292**	16.105***	18.986***	21.306***	15.236***	16.895***	19.416***

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

R-Code

Part A: R-Code for Security Data

OLS Beta Estimate

```
library(readxl)
library(dplyr)
library(tseries)
library(ggplot2)
library(xts)

# DAILY OLS betas
betaD_df <- read_excel("~/Dropbox/02_Master/Master_Thesis/Data/Asset_prices_f
orR.xlsx",
                       sheet = "E_Beta_D", col_names = FALSE,
                       na = "NA")
betaD_df2 <- (betaD_df[-(7830:7830),])
betaD_df3 <- select(betaD_df2,-c(1:2,33:34))

#adjust column names
features <- c(sprintf("X%d", seq(1,65)))
colnames(betaD_df3) <- features
betaD_df4 <- (betaD_df3[-(1:6264),])
betaD_df5 <- data.matrix(betaD_df4, rownames.force = NA)
betaD_ts <- ts((betaD_df4), start = c(2014,01,01), frequency = 261)
plot(betaD_ts, plot.type = "single", col=1:65)


#QUARTERLY OLS betas
#create date index
date_idx <- read_excel("~/Dropbox/02_Master/Master_Thesis/Data/Asset_prices_f
orR.xlsx",
                       sheet = "Date_Index")
date_idx2 <- date_idx[-(1:6262),]
colnames(date_idx2) <- "Date"
date_idx3 <- as.Date(date_idx2$`Date`, date_system = "modern")

#create quarterly time series
beta.final <- xts(tbl_df(betaD_ts), order.by = date_idx3)
ep <- endpoints(beta.final,'quarters')
beta.q <- period.apply(beta.final, INDEX = ep, FUN = mean)
beta.q2 = (beta.q[-(25:25),])
beta.q3 <- data.matrix(beta.q2, rownames.force = NA)
plot(beta.q2, plot.type = "single", col=1:68)
```

```
#portfolio averaging (only for quarterly betas)
#AVG
AVG <- read_excel("~/Dropbox/02_Master/Master_Thesis/Data/Bank Index Overview
_v2.xlsx",
                  sheet = "AVG")
AVG2 <- select(AVG,-c(1:3))
AVG3 <- data.matrix(AVG2[-(1:9),])

OLSbeta.AVG <- tbl_df(AVG3*beta.q3)
OLSbeta.AVG2 <- OLSbeta.AVG %>%
  mutate_all(funs(ifelse(. == 0, NA, .)))
OLSbeta.AVG.ts <- ts((OLSbeta.AVG2), start = c(2014,01), frequency = 4)
plot(OLSbeta.AVG.ts, plot.type = "single", col=1:68)
#AVG average
OLSbeta.AVG.ts <- ts(rowMeans(x=OLSbeta.AVG.ts, na.rm = TRUE, dims = 1),start
= c(2014,01), frequency = 4)
plot(OLSbeta.AVG.ts, plot.type = "single", col=1:68)

#portfolio creation
#G-SIB
#create GSIB matrix
GSIB <- read_excel("~/Dropbox/02_Master/Master_Thesis/Data/Bank Index Overvie
w_v2.xlsx",
                                     sheet = "GSIB")
GSIB2 <- select(GSIB,-c(1:3))
GSIB3 <- data.matrix(GSIB2[-(1:9),])

OLSbeta.GSIB <- tbl_df(GSIB3*beta.q3)
OLSbeta.GSIB2 <- OLSbeta.GSIB %>%
  mutate_all(funs(ifelse(. == 0, NA, .)))
OLSbeta.GSIB.ts <- ts((OLSbeta.GSIB2), start = c(2014,01), frequency = 4)
plot(OLSbeta.GSIB.ts, plot.type = "single", col=1:68)
#G-SIB average
OLSbeta.GSIB.AVG.ts <- ts(rowMeans(x=OLSbeta.GSIB.ts, na.rm = TRUE, dims = 1)
, start = c(2014,01), frequency = 4)
plot(OLSbeta.GSIB.AVG.ts, plot.type = "single", col=1:68)

#Non-GSIB
#create non-GSIB matrix
N.GSIB <- read_excel("~/Dropbox/02_Master/Master_Thesis/Data/Bank Index Overv
iew_v2.xlsx",
                   sheet = "NGSIB")
N.GSIB2 <- select(N.GSIB,-c(1:3))
N.GSIB3 <- data.matrix(N.GSIB2[-(1:9),])

OLSbeta.N.GSIB <- tbl_df(N.GSIB3*beta.q3)
OLSbeta.N.GSIB2 <- OLSbeta.N.GSIB %>%
  mutate_all(funs(ifelse(. == 0, NA, .)))
OLSbeta.N.GSIB.ts <- ts((OLSbeta.N.GSIB2), start = c(2014,01), frequency = 4)
plot(OLSbeta.N.GSIB.ts, plot.type = "single", col=1:68)
```

```
#N.G-SIB average
OLSbeta.N.GSIB.AVG.ts <- ts(rowMeans(x=OLSbeta.N.GSIB.ts, na.rm = TRUE, dims
= 1),
                                start = c(2014,01), frequency = 4)
plot(OLSbeta.N.GSIB.AVG.ts, plot.type = "single", col=1:68)

#comparison
OLS.beta.comp <- ts(t(rbind(OLSbeta.AVG.ts,OLSbeta.GSIB.AVG.ts,OLSbeta.N.GSIB
.AVG.ts)),start = c(2014,01), frequency = 4)
#chart.TimeSeries(OLS.beta.comp, main="OLS Beta Estimates - sample comparison
",
               #  ylim = c(0.3,2.1), colorset=c(1:65), lty=c(1,2,3),
               #  legend.loc = "topright", legend(), cex.legend = 1.0)



#merging portfolio and individual betas (for quartlery betas only)
betaD_df6 <-cbind(beta.q2, OLSbeta.AVG.ts, OLSbeta.GSIB.AVG.ts, OLSbeta.N.GSI
B.AVG.ts)
colnames(betaD_df6) <- c(features, "AVG", "GSIB", "NGSIB")


#exporting beta time series
library(openxlsx)
write.xlsx(tbl_df(betaD_df6), 'OLSbetaQ.xlsx') #quarterly (65 + 3 columns)
write.xlsx(tbl_df(betaD_ts), 'OLSbetaD.xlsx') #daily (65 columns)
```

Kalman Filter Beta Estimate

```
library(readxl)
library(dplyr)
library(tseries)
library(ggplot2)
library(tidyselect)
library(imputeTS)
library(xts)
library(stats)

features <- c(sprintf("X%d", seq(1,65)))

#create date index
date_idx <- read_excel("~/Dropbox/02_Master/Master_Thesis/Data/Asset_prices_f
orR.xlsx",
                         sheet = "Date_Index", col_names = FALSE)
date_idx <- (date_idx[-(7828:7828),])
date_idx2 <- date_idx[-(1:5740),]
colnames(date_idx2) <- "Date"
date_idx3 <- as.Date(date_idx2$`Date`, date_system = "modern")
```

```r
#import return series
rf <- data.frame(read_excel("RiskfreeD.xlsx"))
rf.matrix <- data.frame(rep(array(rf), times = 65))
colnames(rf.matrix) <- features
market <- data.frame(read_excel("MarketD.xlsx"))
banks <- data.frame(read_excel("BanksD.xlsx"))

#excess returns
r1.market <- ts(market - rf)
banks.matrix <- (banks - rf.matrix)

#create xts series
MSCIW_D.xts <- xts(x=r1.market, order.by = date_idx3)

colnames(MSCIW_D.xts) = "MSCIW_D.xts"
s2v = 1
s2a = 0.01
s2b = 0.01

library(dlm)
tvp.dlm = dlmModReg(X=MSCIW_D.xts, addInt=TRUE,
                        dV=s2v, dW=c(s2a, s2b))

tvp.dlm[c("FF","V","GG","W","m0","C0")]
tvp.dlm[c("JFF","JV","JGG","JW")]
head(tvp.dlm$X)


#loop
i <- 3
res <- beta.s  # Store initial value on "res"

    repeat {
       banks4 <- ts(select(banks.matrix,c(i)))
     ind.bank.return <- xts(banks4, order.by = date_idx3)

     # ols fit - constant equity beta
     ols.fit = lm(banks4 ~ r1.market, na.action = na.omit)
     summary(ols.fit)

       # function to build TVP ss model
         buildTVP <- function(parm, x.mat){
          parm <- exp(parm)
          return( dlmModReg(X=x.mat, dV=parm[1],
                            dW=c(parm[2], parm[3])) )
        }
       # maximize over log-variances
         start.vals = c(1,1,1)
      names(start.vals) = c("lns2v", "lns2a", "lns2b")
       TVP.mle = dlmMLE(y=ind.bank.return, parm=start.vals,
```

```
                         x.mat=MSCIW_D.xts, build=buildTVP,
                         hessian=T)

       class(TVP.mle)
       names(TVP.mle)
       TVP.mle

        # get sd estimates
         se2 <- sqrt(exp(TVP.mle$par))
       names(se2) = c("sv", "sa", "sb")
        sqrt(se2)

         # fitted ss model
           TVP.dlm <- buildTVP(TVP.mle$par, MSCIW_D.xts)
         # filtering
           TVP.f <- dlmFilter(ind.bank.return, TVP.dlm)
         class(TVP.f)

          names(TVP.f)

           # smoothing
            TVP.s <- dlmSmooth(TVP.f)
           class(TVP.s)
            names(TVP.s)
             # extract smoothed states - intercept and slope coefs
               alpha.s = xts(TVP.s$s[-1,1,drop=FALSE],
                               as.Date(rownames(TVP.s$s[-1,])))
            beta.s = xts(TVP.s$s[-1,2,drop=FALSE],
                            as.Date(rownames(TVP.s$s[-1,])))
             colnames(alpha.s) = "alpha"
             colnames(beta.s) = "beta"
             #### extract std errors - dlmSvd2var gives list of MSE matrices
               mse.list = dlmSvd2var(TVP.s$U.S, TVP.s$D.S)
            se.mat = t(sapply(mse.list, FUN=function(x) sqrt(diag(x))))
             se.xts = xts(se.mat[-1, ], index(beta.s))
             colnames(se.xts) = c("alpha", "beta")

             i = i+1
             if (i == 68){
               break
             }
             res <- cbind(res, beta.s)
     }

library(PerformanceAnalytics)
chart.TimeSeries(cbind(alpha.s), main="Smoothed estimates of alpha",
        ylim=c(-0.1,0.1), colorset=c(1,2,2), lty=c(1,2,2),ylab=expression(alp
ha),xlab="")

chart.TimeSeries((res), main="Smoothed estimates of beta",
```

```r
        colorset=c(1:65), lty=c(1,2,2),ylab=expression(beta),xlab="")

plot(res, plot.type = "single", col=1:68)

#adjust column names
features <- c(sprintf("X%d", seq(0,65)))
colnames(res) <- features

#create quarterly time series
beta.final <- xts(select(tbl_df(res), -c(1)), order.by = date_idx3)
ep <- endpoints(beta.final,'quarters')
beta.q <- period.apply(beta.final, INDEX = ep, FUN = mean)
beta.q2 = (beta.q[-(33:33),])
beta.q3 = (beta.q2[-(1:8),])
beta.q4 <- data.matrix(beta.q3, rownames.force = NA)


betaKF_ts <- ts((beta.q3), start = c(2014,01), frequency = 4)
plot(betaKF_ts, plot.type = "single", col=1:67)


#portfolio averaging (only for quarterly betas)
#AVG
AVG <- read_excel("~/Dropbox/02_Master/Master_Thesis/Data/Bank Index Overview
_v2.xlsx",
                  sheet = "AVG")
AVG2 <- select(AVG,-c(1:3))
AVG3 <- data.matrix(AVG2[-(1:9),])

KFbeta.AVG <- tbl_df(AVG3*beta.q4)
KFbeta.AVG2 <- KFbeta.AVG %>%
  mutate_all(funs(ifelse(. == 0, NA, .)))
KFbeta.AVG.ts <- ts((KFbeta.AVG2), start = c(2014,01), frequency = 4)
plot(KFbeta.AVG.ts, plot.type = "single", col=1:68)
#AVG average
KFbeta.AVG.ts <- ts(rowMeans(x=KFbeta.AVG.ts, na.rm = TRUE, dims = 1),
                    start = c(2014,01), frequency = 4)
plot(KFbeta.AVG.ts, plot.type = "single", col=1:68)

#G-SIB
#create GSIB matrix
GSIB <- read_excel("~/Dropbox/02_Master/Master_Thesis/Data/Bank Index Overvie
w_v2.xlsx",
                                sheet = "GSIB")
GSIB2 <- select(GSIB,-c(1:3))
GSIB3 <- data.matrix(GSIB2[-(1:9),])

KFbeta.GSIB <- tbl_df(GSIB3*beta.q4)
KFbeta.GSIB2 <- KFbeta.GSIB %>%
  mutate_all(funs(ifelse(. == 0, NA, .)))
```

```
KFbeta.GSIB.ts <- ts((KFbeta.GSIB2), start = c(2014,01), frequency = 4)
plot(KFbeta.GSIB.ts, plot.type = "single", col=1:68)
#G-SIB average
KFbeta.GSIB.AVG.ts <- ts(rowMeans(x=KFbeta.GSIB.ts, na.rm = TRUE, dims = 1))
plot(KFbeta.GSIB.AVG.ts, plot.type = "single", col=1:68)

#Non-GSIB
#create Non-GSIB matrix
N.GSIB <- read_excel("~/Dropbox/02_Master/Master_Thesis/Data/Bank Index Overv
iew_v2.xlsx",
                                  sheet = "NGSIB")
N.GSIB2 <- select(N.GSIB,-c(1:3))
N.GSIB3 <- data.matrix(N.GSIB2[-(1:9),])

KFbeta.N.GSIB <- tbl_df(N.GSIB3*beta.q4)
KFbeta.N.GSIB2 <- KFbeta.N.GSIB %>%
mutate_all(funs(ifelse(. == 0, NA, .)))
KFbeta.N.GSIB.ts <- ts((KFbeta.N.GSIB2), start = c(2014,01), frequency = 4)
plot(KFbeta.N.GSIB.ts, plot.type = "single", col=1:68)
#N.G-SIB average
KFbeta.N.GSIB.AVG.ts <- ts(rowMeans(x=KFbeta.N.GSIB.ts, na.rm = TRUE, dims =
1))
plot(KFbeta.N.GSIB.AVG.ts, plot.type = "single", col=1:68)

#comparison
KF.beta.comp <- ts(t(rbind(KFbeta.AVG.ts,KFbeta.GSIB.AVG.ts,KFbeta.N.GSIB.AVG
.ts)),start = c(2014,01), frequency = 4)
plot(KF.beta.comp, plot.type = "single", col=1:68)


#merging portfolio and individual betas (for quartlery betas only)
features2 <- c(sprintf("X%d", seq(1,65)))
beta.q5 <- cbind(beta.q3,KFbeta.AVG.ts, KFbeta.GSIB.AVG.ts,KFbeta.N.GSIB.AVG.
ts) #quarterly
colnames(beta.q5) <- c(features2, "AVG", "GSIB", "NGSIB")

#exporting beta time series
library(openxlsx)
write.xlsx(tbl_df(beta.q5), 'KFbetaQ.xlsx') #KF beta quarterly
object1 <- select(tbl_df(res),-c(1))
object2 <- object1[-(1:522),]
write.xlsx(tbl_df(object2), 'KFbetaD.xlsx') #KF beta daily
```

Idiosyncratic Risk – exemplary for estimate based on OLS Beta

```
library(readxl)
library(dplyr)
library(tseries)
library(ggplot2)
library(matrixStats)

features <- c(sprintf("X%d", seq(1,65)))

#import return series
rf <- data.frame(read_excel("RiskfreeD.xlsx"))
rf.matrix <- data.frame(rep(array(rf), times = 65))
colnames(rf.matrix) <- features
market <- data.frame(read_excel("MarketD.xlsx"))
banks <- data.frame(read_excel("BanksD.xlsx"))

#import OLS beta
OLSbeta <- data.frame(read_excel("OLSbetaD.xlsx"))

#create time series
r1.market <- ts(market, start = c(2012,1,2), frequency = 261)
banks.matrix <- ts(banks - rf.matrix)
r2.riskfree <- ts(rf, start = c(2012,1,2), frequency = 261)

#loop
k <- 1
res <- idio_ts  # Store initial value on "res"

repeat {

#create 1565 two-year time windows of the market return
rolling_slice.market <- function(r1.market,window){
  rows = 522
  m <- matrix(0,rows,window)
  for(i in 1:rows){m[i,] <- r1.market[i:(i+window-1)]}
  return(m)
}
rolling.market <- rolling_slice.market(r1.market,1565)


#create 1565 two-year time windows of the risk-free
rolling_slice.rf <- function(r2.riskfree,window){
  rows = 522
  m <- matrix(0,rows,window)
  for(i in 1:rows){m[i,] <- r2.riskfree[i:(i+window-1)]}
  return(m)
}
rolling.rf <- rolling_slice.rf(r2.riskfree,1565)
```

```
#create 1565 two-year time windows of the beta
#array of same variance of residuals
OLSbeta_BankX <- as.numeric(t(select(OLSbeta,c(k))))
OLSbeta_BankX <- array(as.numeric(OLSbeta_BankX))
rolling.beta=matrix(rep(OLSbeta_BankX,522),
         ncol=1565,
         byrow=T)


#create 1565 two-year time windows of ind. asset returns (real returns)
return.BankX <- ts(select(banks,c(k)), start = c(2012,1,2), frequency = 261)
rolling_slice.bank <- function(return.Bank1,window){
  rows = 522
  m <- matrix(0,rows,window)
  for(i in 1:rows){m[i,] <- return.Bank1[i:(i+window-1)]}
  return(m)
}
rolling.bank <- rolling_slice.bank(return.BankX,1565)


#apply CAPM formula to get expected returns
rolling.exp.returns <- rolling.rf + rolling.beta * (rolling.market-rolling.rf
)

# calculate residuals
residuals <- rolling.exp.returns - rolling.bank

# calculate variance for each time point
idio_ts <- ts(colVars(residuals, na.rm = TRUE), start = c(2014,1,1), frequenc
y = 261)
plot(idio_ts, plot.type = "single", col=1:67)

k = k+1
if (k == 69){
  break
}
res <- cbind(res, idio_ts)
}

library(dplyr)
columns <- c(sprintf("X%d", seq(0,65)))
colnames(res) <- columns
idioD_ts <- ts(select(tbl_df(res),-c(1)), start = c(2014,1,1), frequency = 26
1)
plot(idioD_ts, plot.type = "single", col=1:68)



#QUARTERLY OLS estimate for variance of residuals
```

```r
#create date index
date_idx <- read_excel("~/Dropbox/02_Master/Master_Thesis/Data/Asset_prices_f
orR.xlsx",
                       sheet = "Date_Index")
date_idx2 <- date_idx[-(1:6262),]
colnames(date_idx2) <- "Date"
date_idx3 <- as.Date(date_idx2$`Date`, date_system = "modern")

#create quarterly time series
idio.final <- xts(tbl_df(idioD_ts), order.by = date_idx3)
ep <- endpoints(idio.final,'quarters')
idio.q <- period.apply(idio.final, INDEX = ep, FUN = mean)
idio.q2 = (idio.q[-(25:25),])
idio.q3 <- data.matrix(idio.q2, rownames.force = NA)
plot(idio.q2, plot.type = "single", col=1:68)



#portfolio averaging (only for quarterly variance of residuals)
#AVG
AVG <- read_excel("~/Dropbox/02_Master/Master_Thesis/Data/Bank Index Overview
_v2.xlsx",
                  sheet = "AVG")
AVG2 <- select(AVG,-c(1:3))
AVG3 <- data.matrix(AVG2[-(1:9),])

OLSidio.AVG <- tbl_df(AVG3*idio.q3)
OLSidio.AVG2 <- OLSidio.AVG %>%
  mutate_all(funs(ifelse(. == 0, NA, .)))
OLSidio.AVG.ts <- ts((OLSidio.AVG2), start = c(2014,01), frequency = 4)
plot(OLSidio.AVG.ts, plot.type = "single", col=1:68)
#AVG average
OLSidio.AVG.ts <- ts(rowMeans(x=OLSidio.AVG.ts, na.rm = TRUE, dims = 1),start
= c(2014,01), frequency = 4)
plot(OLSidio.AVG.ts, plot.type = "single", col=1:68)

#portfolio creation
#G-SIB
#create GSIB matrix
GSIB <- read_excel("~/Dropbox/02_Master/Master_Thesis/Data/Bank Index Overvie
w_v2.xlsx",
                   sheet = "GSIB")
GSIB2 <- select(GSIB,-c(1:3))
GSIB3 <- data.matrix(GSIB2[-(1:9),])

OLSidio.GSIB <- tbl_df(GSIB3*idio.q3)
OLSidio.GSIB2 <- OLSidio.GSIB %>%
  mutate_all(funs(ifelse(. == 0, NA, .)))
OLSidio.GSIB.ts <- ts((OLSidio.GSIB2), start = c(2014,01), frequency = 4)
plot(OLSidio.GSIB.ts, plot.type = "single", col=1:68)
```

```r
#G-SIB average
OLSidio.GSIB.AVG.ts <- ts(rowMeans(x=OLSidio.GSIB.ts, na.rm = TRUE, dims = 1)
, start = c(2014,01), frequency = 4)
plot(OLSidio.GSIB.AVG.ts, plot.type = "single", col=1:68)

#Non-GSIB
#create non-GSIB matrix
N.GSIB <- read_excel("~/Dropbox/02_Master/Master_Thesis/Data/Bank Index Overv
iew_v2.xlsx",
                     sheet = "NGSIB")
N.GSIB2 <- select(N.GSIB,-c(1:3))
N.GSIB3 <- data.matrix(N.GSIB2[-(1:9),])

OLSidio.N.GSIB <- tbl_df(N.GSIB3*idio.q3)
OLSidio.N.GSIB2 <- OLSidio.N.GSIB %>%
  mutate_all(funs(ifelse(. == 0, NA, .)))
OLSidio.N.GSIB.ts <- ts((OLSidio.N.GSIB2), start = c(2014,01), frequency = 4)
plot(OLSidio.N.GSIB.ts, plot.type = "single", col=1:68)
#N.G-SIB average
OLSidio.N.GSIB.AVG.ts <- ts(rowMeans(x=OLSidio.N.GSIB.ts, na.rm = TRUE, dims
= 1),
                            start = c(2014,01), frequency = 4)
plot(OLSidio.N.GSIB.AVG.ts, plot.type = "single", col=1:68)

#comparison
OLS.idio.comp <- ts(t(rbind(OLSidio.AVG.ts,OLSidio.GSIB.AVG.ts,OLSidio.N.GSIB
.AVG.ts)),
                    start = c(2014,01), frequency = 4)
plot(OLS.idio.comp, plot.type = "single", col=1:67)

#merging portfolio and individual variance of residuals (for quartlery varian
ce of residuals only)
idioD_df6 <-cbind(idio.q2, OLSidio.AVG.ts, OLSidio.GSIB.AVG.ts, OLSidio.N.GSI
B.AVG.ts)
colnames(idioD_df6) <- c(features, "AVG", "GSIB", "NGSIB")

#exporting idio time series
library(openxlsx)
write.xlsx(tbl_df(idioD_df6), 'OLSidioQ.xlsx') #quarterly (65 + 3 columns)
write.xlsx(tbl_df(idioD_ts), 'OLSidioD.xlsx') #daily (65 columns)
```

Part B: R-Code for Explanatory Variables

The following code is exemplary for the Liquidity Coverage Ratio and is executed similarly for other explanatory variables.

```
library(readxl)
library(dplyr)
library(tseries)
library(ggplot2)
library(tidyselect)
library(imputeTS)
library(PerformanceAnalytics)

#adjust column names
features <- c(sprintf("X%d", seq(1,65)))

###########Liquidity Coverage Ratio

#Importing the Data
LCR_df <- read_excel("~/Dropbox/02_Master/Master_Thesis/Data/BASELIII_indicat
ors_forR.xlsx",
                        sheet = "LCR", col_names = FALSE,
                        na = "NA")
LCR_df2 <- (LCR_df[-(123:123),])
LCR_df3 <- select(LCR_df2,-c(1:2,33:34))
colnames(LCR_df3) <- features
LCR_df4 <- (LCR_df3[-(1:98),])
LCR_df4 <- ts(LCR_df4, start = c(2014,01), frequency = 4)
LCR_ts <- na_interpolation(LCR_df4, option = "linear", maxgap = 3)
LCR_df5 <- tbl_df(LCR_ts)
LCR_df5 <- data.matrix(LCR_df5, rownames.force = NA)


#AVG
AVG <- read_excel("~/Dropbox/02_Master/Master_Thesis/Data/Bank Index Overview
_v2.xlsx",
                  sheet = "AVG")
AVG2 <- select(AVG,-c(1:3))
AVG3 <- data.matrix(AVG2[-(1:9),])

LCR.AVG <- tbl_df(AVG3*LCR_df5)
LCR.AVG2 <- LCR.AVG %>%
  mutate_all(funs(ifelse(. == 0, NA, .)))
LCR.AVG.ts <- ts((LCR.AVG2), start = c(2014,01), frequency = 4)
plot(LCR.AVG.ts, plot.type = "single", col=1:68)
#AVG average
LCR.AVG.ts <- ts(rowMeans(x=LCR.AVG.ts, na.rm = TRUE, dims = 1),start = c(201
4,01), frequency = 4)
```

```
#G-SIB
GSIB <- read_excel("~/Dropbox/02_Master/Master_Thesis/Data/Bank Index Overvie
w_v2.xlsx",
                   sheet = "GSIB")
GSIB2 <- select(GSIB,-c(1:3))
GSIB3 <- data.matrix(GSIB2[-(1:9),])

LCR.GSIB <- tbl_df(GSIB3*LCR_df5)
LCR.GSIB2 <- LCR.GSIB %>%
  mutate_all(funs(ifelse(. == 0, NA, .)))
LCR.GSIB.ts <- ts((LCR.GSIB2), start = c(2014,01), frequency = 4)
plot(LCR.GSIB.ts, plot.type = "single", col=1:68)
#G-SIB average
LCR.GSIB.ts <- ts(rowMeans(x=LCR.GSIB.ts, na.rm = TRUE, dims = 1),start = c(2
014,01), frequency = 4)


#Non-GSIB
N.GSIB <- read_excel("~/Dropbox/02_Master/Master_Thesis/Data/Bank Index Overv
iew_v2.xlsx",
                     sheet = "NGSIB")
N.GSIB2 <- select(N.GSIB,-c(1:3))
N.GSIB3 <- data.matrix(N.GSIB2[-(1:9),])

LCR.N.GSIB <- tbl_df(N.GSIB3*LCR_df5)
LCR.N.GSIB2 <- LCR.N.GSIB %>%
  mutate_all(funs(ifelse(. == 0, NA, .)))
LCR.N.GSIB.ts <- ts((LCR.N.GSIB2), start = c(2014,01), frequency = 4)
plot(LCR.N.GSIB.ts, plot.type = "single", col=1:68)
#N.G-SIB average
LCR.N.GSIB.ts <- ts(rowMeans(x=LCR.N.GSIB.ts, na.rm = TRUE, dims = 1),start =
c(2014,01), frequency = 4)

#LCR Target
LCR.Target <- read_excel("~/Dropbox/02_Master/Master_Thesis/Data/BASELIII_ind
icators_forR.xlsx",
                         sheet = "Target_Ratios", col_names = FALSE,
                         na = "NA")
LCR.Target2 <- select(LCR.Target,c(2))
LCR.Target.ts <- 100*ts(rowMeans(x=LCR.Target2, na.rm = TRUE, dims = 1),start
= c(2014,01), frequency = 4)
plot(LCR.Target.ts, plot.type = "single", col=1:68)


# LCR - comparison
LCR.comp <- ts((t(rbind(LCR.GSIB.ts,LCR.N.GSIB.ts,LCR.Target.ts))), start = c
(2014,01),
               frequency = 4)
colnames(LCR.comp) <- c("G-SIB sample", "non-G-SIB sample", "Target Ratio")
```

```
chart.TimeSeries(LCR.comp, major.ticks = "auto", ylim = c(55,152),
                 colorset=c(2,3,1), lty=c(1,1,1), lwd = c(3,3,3), legend.loc
= "bottomright", legend(),
                 cex.legend = 1.0,auto.grid = TRUE, plot.engine = "default")`
``

## Including Plots

You can also embed plots, for example:
```

Part C: R-Code Regression Analysis

Exemplary code for the regression pertaining to the systematic risk (via OLS) for the G-SIB portfolio

```
library(readxl)
library(dplyr)
library(tseries)
library(ggplot2)
library(tidyselect)
library(imputeTS)
library(lmtest)

#Importing the Data
ts_diff_lagged <- data.frame(read_excel("ts_lagged_3.xlsx"))

#splitting time series
OLSbeta_AVG <- select(ts_diff_lagged, c(1))
OLSbeta_GSIB <- select(ts_diff_lagged, c(2))
OLSbeta_NGSIB <- select(ts_diff_lagged, c(3))

KFbeta_AVG <- select(ts_diff_lagged, c(4))
KFbeta_GSIB <- select(ts_diff_lagged, c(5))
KFbeta_NGSIB <- select(ts_diff_lagged, c(6))

OLSidio_AVG <- select(ts_diff_lagged, c(7))
OLSidio_GSIB <- select(ts_diff_lagged, c(8))
OLSidio_NGSIB <- select(ts_diff_lagged, c(9))

KFidio_AVG <- select(ts_diff_lagged, c(10))
KFidio_GSIB <- select(ts_diff_lagged, c(11))
KFidio_NGSIB <- select(ts_diff_lagged, c(12))


LCR_AVG <- select(ts_diff_lagged, c(13:15))
LCR_GSIB <- select(ts_diff_lagged, c(16:18))
LCR_NGSIB <- select(ts_diff_lagged, c(19:21))
```

```r
Lev_AVG <- select(ts_diff_lagged, c(22:24))
Lev_GSIB <- select(ts_diff_lagged, c(25:27))
Lev_NGSIB <- select(ts_diff_lagged, c(28:30))

CAR_AVG <- select(ts_diff_lagged, c(31:33))
CAR_GSIB <- select(ts_diff_lagged, c(34:36))
CAR_NGSIB <- select(ts_diff_lagged, c(37:39))

ROA_AVG <- select(ts_diff_lagged, c(40:42))
ROA_GSIB <- select(ts_diff_lagged, c(43:45))
ROA_NGSIB <- select(ts_diff_lagged, c(46:48))

GDP_AVG <- select(ts_diff_lagged, c(49:51))
GDP_GSIB <- select(ts_diff_lagged, c(52:54))
GDP_NGSIB <- select(ts_diff_lagged, c(55:57))


#models

#systematic risk

#OLS beta regression

#GSIB
lm.OLSbeta.GSIB.l0 <- lm(ts(OLSbeta_GSIB) ~ ts(select(LCR_GSIB,c(1))) + 
ts(select(Lev_GSIB,c(1))) +
                       ts(select(CAR_GSIB,c(1))) +  ts(select(ROA_GSIB,c(1))) 
+
                       ts(select(GDP_GSIB,c(1))))
summary(lm.OLSbeta.GSIB.l0)
AIC(lm.OLSbeta.GSIB.l0)

lm.OLSbeta.GSIB.l1 <- lm(ts(OLSbeta_GSIB) ~ ts(select(LCR_GSIB,c(2))) + 
ts(select(Lev_GSIB,c(2))) +
                       ts(select(CAR_GSIB,c(2))) +  ts(select(ROA_GSIB,c(2))) 
+
                       ts(select(GDP_GSIB,c(2))))
summary(lm.OLSbeta.GSIB.l1)
AIC(lm.OLSbeta.GSIB.l1)

lm.OLSbeta.GSIB.l2 <- lm(ts(OLSbeta_GSIB) ~ ts(select(LCR_GSIB,c(3))) + 
ts(select(Lev_GSIB,c(3))) +
                       ts(select(CAR_GSIB,c(3))) +  ts(select(ROA_GSIB,c(3))) 
+
                       ts(select(GDP_GSIB,c(3))))
summary(lm.OLSbeta.GSIB.l2)
AIC(lm.OLSbeta.GSIB.l2)
```